Travel Behavior Over Time

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June 2015

Research Project
Final Report 2015-23

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Using detailed travel surveys (the Travel Behavior Inventory) conducted by the Metropolitan Council of the Minneapolis/Saint Paul (Twin Cities) Region in Minnesota for 1990, 2000-2001, and 2010-2011, this report conducts an analysis of changes in travel behavior over time. Specifically looking at changes in travel duration, time, use, and accessibility; telecommuting and its relationship with travel and residential choices; transit service quality and transit use; effects of age and cohort; and changes in walking and bicycling.

Much has changed in this period, including the size of the region, demographics, economics, technology, driver licensing, and preferences, examining in turn the effects of investment, development, and population change on behaviors for the Minneapolis-St. Paul region as a whole and for areas within the region. While this research cannot hope to untangle all of the contributing factors, it aims to increase understanding of what did happen, with some explanation of why. This will inform transportation engineers, planners, economists, analysts, and decision makers about the prospective effects of future changes to networks, land use, and demographics while also evaluating the effects of previous network investments.</td></tr>
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Travel Behavior Over Time

Final Report

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EXECUTIVE SUMMARY

Using detailed travel surveys (the Travel Behavior Inventory) conducted by the Metropolitan Council of the Minneapolis/Saint Paul (Twin Cities) Region in Minnesota for 1990, 2000-2001, and 2010-2011, this report conducts a detailed analysis of changes in travel behavior over time. Much has changed in this period, including the size of the region, demographics, economics, technology (especially the Internet and mobile phones), driver licensing, and preferences. While this research cannot hope to untangle all of the contributing factors, it aims to increase understanding of what did happen, with some explanation of why.

The first chapter “Accessibility and the allocation of time” looks at the trends in travel duration, time use, and accessibility over this period. For workers, average trip distances, speeds, and travel times increased over this 20-year period (for work, shopping, and other trips). Rising distances and speeds are associated with continued suburbanization (almost all of the region’s growth was outside the core cities of Minneapolis and St. Paul). Suburban locations are spread farther apart (and thus increase distance), but are located on faster roads (thus increasing speed). Time per trip was slightly higher. For non-workers these decreased, perhaps due to changes in who constitutes non-workers (for instance, more elderly people in the population of non-workers may change the overall averages as the underlying demographic composition of the group shifts). The share of workers peaked in 2000, and a somewhat larger share of the sample was non-workers in 2010 than 1990.

While trips for workers were longer, there were fewer of them, and workers spent more time at home and on other activities in 2010 than 1990, and less time at work, shopping, and travel activities. Non-workers also saw less time spent in travel.

The research found accessibility to jobs remained an important factor in predicting travel durations to work and time spent at work. In addition, this study found that a longer commute duration correlated to more time spent at work. Further analysis into the cause of this may be warranted, though it may be due to a blending of the work and home environments when one lives very close to where one works.

The second chapter “Telecommuting and its relationships with travel and residential choices” examines the complementarity and substitution effects between travel to work and telecommuting over this period between 2000 and 2010. The research observes that the number of people who telecommute once per week or more increased, while those who telecommuted 4-5 days per week dropped. For one-worker households, telecommuters tend to be more affluent, more highly educated, older, and more likely to have multiple jobs than non-telecommuters in both 2000 and 2010. For multiple-worker households, telecommuting households tend to be more affluent and have more household members than non-telecommuting households in both years. Furthermore, telecommuters in multiple-worker households tend to live in job-rich areas more than non-telecommuters. The effects of telecommuting on travel in practice are limited, not noticeably affecting measures of travel behavior for multi-worker households, and having limited effects (positive) on single-worker households' total vehicle hours of travel. Telecommuting is negatively associated with average commute distances for multiple-worker households. This suggests that the ability of one worker to telecommute may motivate the household to seek a location closer to the workplace of other household members and thus reduce average commute distance.

The third chapter “Transit service quality and transit use” investigates the question of the degree to which better transit service is associated with higher demand, and whether this relationship has changed over time. Models are conducted at the trip-level (will a trip use transit or not) and person-level (will a person use transit or not). The results show that individuals and trips that are nearer transit are more likely to use transit, and that accessibility (such as the number of jobs reachable within 30 minutes by transit) is an important explanatory factor as well as proximity to high-frequency transit and high-quality transit stops and stations. While there are some changes between 2000 and 2010, the largest part of the structural relationships are relatively stable over this period, and the additional transit demand can in large part be attributed to additional transit service provided in this period. Two interesting exceptions are that individuals with car access and individuals in households with children are more likely to use transit in 2010 than 2000.

The fourth chapter “Cohort analysis of travel behavior” considers simultaneous age effects (which are traditionally examined in travel behavior analysis) and cohort effects (which are not). The question arises as to whether preferences differ correlated with when someone was born and the culture they were raised in rather than how old they are at a given time. This is especially topical with discussion about how the youngest cohort entering adulthood (the “Millennials”) appears to have different travel behaviors than earlier generations. Disentangling this effect from the surrounding economic conditions is difficult. Older birth cohorts tend to have lower overall trip rates (which is mostly a function of age) and these rates have been falling over time. There seems to be a broader trend of declining trip rates across most cohorts during the past two survey years.

Contrary to common perceptions about lower levels of travel, the cohort effects for the Millennials appears to indicate higher levels of travel after controlling for other relevant factors such as licensure, employment and income; however, it must be noted that income and employment status for this group are lower than in previous decades, so we may have some self-selection processes going on. In particular, licensure rates are clearly lower for Millennial men and women compared to older cohorts. Household vehicle ownership rates are not lower, but this may be an indicator of more millennials living in larger households, (either with parents or roommates) as opposed to more vehicles per person. Most male cohorts show a decline in average trip distance as they age.

The fifth chapter, “Biking and walking over time,” documents changes in walking and bicycling. It finds that walking and cycling have both increased from 2001 to 2010. Bicyclists and pedestrians, and their bike and walk trips, differ by demographics, geography, distance, and trip purpose. Biking and walking propensity depends on weather, personal demographic and household characteristics, and trip factors. Some factors differ between modes (e.g., gender), while some factors appear to affect walking and bicycling similarly (e.g., having a driver’s license).

Males and females tend to walk at comparable rates, but despite gains in rates of cycling overall, a gender gap persists among cyclists. Most of the observed growth in cycling from 2001 to 2010 came from increases in commuting by men, with a corresponding reduction in the share of cycling for social and recreational purposes. The gap appears to be in bicycling participation rates of men and women; there was no observed gap in frequency of making bicycle trips among male and female cyclists.

Access to bike lanes in Minneapolis increased substantially between 2000 and 2010, and due to the increased access to facilities, access no longer is a significant factor associated with the likelihood of bicycling in Minneapolis. The usefulness of bicycle facilities in reaching destinations likely remains important in rates of bicycling.

One of the most important findings is that the overall bicycle mode share is about two to three times larger than reported by the US Census (2000) and American Community Survey Journey to Work data, which in the Twin Cities region, tend to underestimate the bicycle mode share for commuting. The Travel Behavior Inventory (TBI) measures are a more accurate portrayal of the importance of bicycling and walking to the region because of the specificity of the information in the trip diaries.

The past decades have seen marked changes in many travel behaviors, including changes in mode choice, trip distances and speeds, drivers license rates among the young, telecommuting, biking, walking, and taking transit. These changes (and others) undoubtedly will affect future transportation needs and wants.

Collectively these chapters investigate in-depth the valuable travel surveys that are conducted approximately every 10 years in the Twin Cities region. They show what underlying behaviors are stable and which ones are changing. It would be especially valuable to have this data collected annually (even with a smaller sample size per year) than to only discover these changes in behavior every 10 years. Other surveys, most notably the American Community Survey, have switched to this annual data collection to reduce the latency between changes in underlying factors (individual travel and location decisions) and the discovery of those changes by planners and researchers. As we enter an era with more rapidly changing transportation technologies, we recommend that the Travel Behavior Inventory be collected continuously on a rolling basis, rather than once a decade, so that we may more rapidly understand and so that policy may more quickly respond to those changes.

Chapter 1

Accessibility and the Allocation of Time: Changes in Travel Behavior 1990-2010

1.1 Introduction

Accessibility is a measure of the potential for interactions [4, 10, 11, 12, 30, 31, 32]. It is inherently linked with mobility, but depends on both mobility and density of destinations. Accessibility as a measure of a transportation system's value has been studied for half a century, and high accessibility is the main objective of transportation planning [5]. This study examines how accessibility affects time spent traveling to and at work.

Previous research has found that in US average commute trip durations have remained relatively stable over time, despite the changing urban landscape [14, 17, 18, 19], with people traveling on faster suburban roads rather than slower urban roads, and their destinations are becoming more decentralized with suburban jobs. [25] found in a detailed literature review that household structure, demographics, destination activity, and the characteristics of the region traveled in all have measurable effects on travel time budgets.

This study extends previous research by examining factors that affect travel and activity behavior. [14] used a gravity based accessibility model for the Washington DC Metropolitan area and applied it to data from a 1988 household survey to test several hypotheses that analyze the relationship between accessibility and the commuting times of various individuals. Increased job accessibility in housing rich areas, and labor accessibility in employment rich areas were expected to decrease commute time.

Using detailed travel surveys conducted by the Metropolitan Council of the Minneapolis/Saint Paul (Twin Cities) Region in Minnesota for 1990, 2000-2001, and 2010-2011, this paper conducts a detailed analysis of journey-to-work times, activity allocation and accessibility. Given the data are collected every 10 years, it is also possible to observe changes in the travel behavior in the region, as well as any changes in the relationships important to the transportation network. This information is key in assessing the transportation landscape, and can be used to help develop policy going forward.

1.2 Theory

The core hypotheses tested in this study are based on previous studies [14, 17]. We expect the relationships between commute duration and accessibility in the Twin Cities to corroborate previous findings. In brief the core hypotheses for auto commuters are below:

- Individuals who live in areas that have high housing accessibility will have longer commutes due to competition for jobs.
- Individuals who work in areas that have high housing accessibility will have shorter commutes because they are more likely to live in said housing.
- Individuals working in areas with many competing jobs will have longer commutes because they will have to search for housing further from their work due to competition in the housing market.
- Individuals living in areas with high job accessibility will have shorter commutes because one of those jobs is more likely to be theirs.
- Distance to the center of a city is important in that accessibility to jobs is higher for those who live near the center, and therefore they should have shorter commutes than those who live further from the center where accessibility is lower.

We would anticipate the same relationships for transit commuters were transit service as uniform as road networks. But the relationship is confounded by significant positive externalities associated with transit service, as observed by the Mohring Effect [24]. The Mohring effect illustrates a positive feedback between transit service and demand. Increasing transit service reduces headways, which makes transit more attractive, which increases ridership, which may, in a virtuous circale, further reduce headways. This tends to occur in thick transit markets, which will occur where either job accessibility is high (i.e.,, high density job centers) or housing accessibility is high. [14] found that transit commute durations drop when employment is higher near either the origin (home) or destination (work) end for trips.

Extending the analysis from travel duration to activity duration, we posit that the relationship between accessibility and time spent at work resembles the relationship between accessibility and commute duration. While there is a finite amount of time and thus a budget [15], so more time at one activity must reduce time available for other activities, there are also complementarities between travel activities and out-of-home activities (travel and out-of-home activities are complements). The more out-of-home activities that are engaged in, the more travel that is required to engage in them. Thus we anticipate that longer work commutes and longer work durations are positively associated, and the factors affecting them are similar. There could be several reasons for this:

- Areas of high employment accessibility are associated with higher salaries [21]. More productive employees (justifying the salary) work longer hours.

- Individuals who work near their place of employment are able to travel back and forth between home and work readily, and may more easily blend the two. A person who lives near their job will, due to the easier commute, have more flexibility in their hours (if the employer allows it), popping into the office as needed rather than needing to camp at their workplace in case something comes up. They may also be more likely to return home for lunch.
- Individuals with long commutes may work fewer days per week, but more hours per day, to compensate for the additional travel time.

1.3 Data

The primary data for this study were collected by the Metropolitan Council for the Travel Behavior Inventories (TBI) conducted in 1990, 2000, and 2010. The TBI collects data on a variety of factors; from information about household size and makeup, employment information, and specific information about trips.

Due to the changing nature of the surveys in each decade, the data needed to be harmonized in order to be compared on a decade-to-decade basis. Also, much of the data is self-reported by the individuals who participated, and therefore there are errors in the reporting.

Certain censoring thresholds were used to address this issue. Trips were excluded if:

- The calculated distance traveled was greater than 200 km (though not technically impossible, any trip greater than this seemed unlikely and out of the realm of the analysis).
- The calculated average speed was greater than 150 $km \cdot H^{-1}$ (again, not technically an impossibility, however an average speed that fast would be highly unlikely, and some calculated speeds were impossibly high).
- Trip durations exceeded than 120 minutes. While durations greater than that may or may not be errors, it was determined that they fell beyond a reasonable application of this study. Or,
- Any of the fields were missing or unreported.

When a trip was omitted, so were all of the other trips made by that respondent, so as not to artificially affect the time allocations.

Table 1.1 shows the censoring filters and the sample size remaining after each filter. Errors in the data may also be due to respondent's tendency to round trip departure and arrival times to the nearest multiple of 5. This causes the data to be skewed towards those times. Figure 1.1 shows this for the 2010 reported trips. The x-axis shows the reported travel times in minutes, and the y-axis is the number of reported trips (after filtering). There are very clear spikes at the 5's (as well as 10 and 30 minutes) that are much larger than the rest of the reported times, which show the anticipated exponential decay relationship. As many activities tend to be scheduled to begin on 5, 15, and 30 minute intervals as well, it is difficult to determine the extent to which the spikes around those times are artifacts of rounding, or actually present in practice, which may affect the precision of any models developed from the data. A check with the GPS study data from the 2010 survey could be done to find the error introduced by these 5-minute spikes.

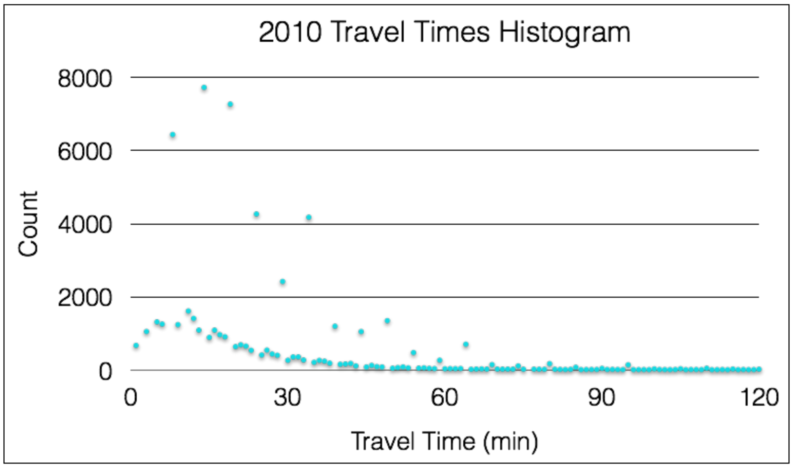

Figure 1.1: Travel Times Histogram

Table 1.1 shows the filtering parameters and the remaining sample size for each year after the filters. Most of the filtering and analysis of the data in this study are the same as [20], which analyzed TBI data from 1990 and 2000, however with a few definitional changes in order to directly compare 2000 with 2010. Only adult respondents of working age were used (between 18 and 65), as well as only respondents who had begun and ended the travel day at home. The latter parameter is needed to calculate the time spent at home. In [20] the respondents were separated by gender and employment status, however telecommuting was not taken into account. Additionally, anyone who made a trip reported to be greater than 120 minutes was excluded. This is due to the assumption that they are making "unusual" trips, rather than a daily routine trip. There is no guarantee that the remaining records represent usual or typical behavior for any particular individual. Telecommuting is becoming a significant means of employment, which may have deep impacts on the transportation network, and is the subject of the second chapter Telecommuting and its relationships with travel and residential choices. However, for the purposes of comparison to [20], it was decided to omit the work-at-home category for this chapter as well.

The trip purposes for each separate TBI were harmonized, as defined in Table 47 from [28]. A worker is defined as someone who made a work-trip on the travel day. A work-at-home respondent is defined as someone who did not have a work outside of home trip on the travel day but did have work-at-home listed as an activity.

One significant difference between this study and [20] is the inclusion of "work-related" trips as work trips, and the inclusion of formerly "non-workers" who made work related trips into the worker category. This change was made due to the 2010 TBI lacking a "work-related trip" purpose. In the 2010 survey, a work trip included any trip made for work outside of the home, regardless of whether that trip was to the primary place of employment or not. This change slightly altered the 1990 and 2000 results, and as such were recalculated, as discussed later in this report. The sample size of each category can be seen in Figure 1.2. Filtering may introduce bias compared to the original sample, though the original sample is, despite efforts, not unbiased either compared to the population. Weights are not used in the analysis below.

Table 1.1: Filtering

Description of Constraints	1990	2000	2010
Subtotal	24509	14671	30286
Reason for Dropping Records			
Gender not recorded	0	0	45
Age [18,65]	7513	6279	11992
Did not start travel day at home	975	237	700
Did not end travel day at home	385	209	1820
Trip Duration > 120	31	17	653
Travel+activity duration > 1440	63	5	91
Missing 1 or more trips	60	266	535
Work-at-home only	20	70	698
Total dropped	9047	7083	16534
Net total	15462	7588	13572

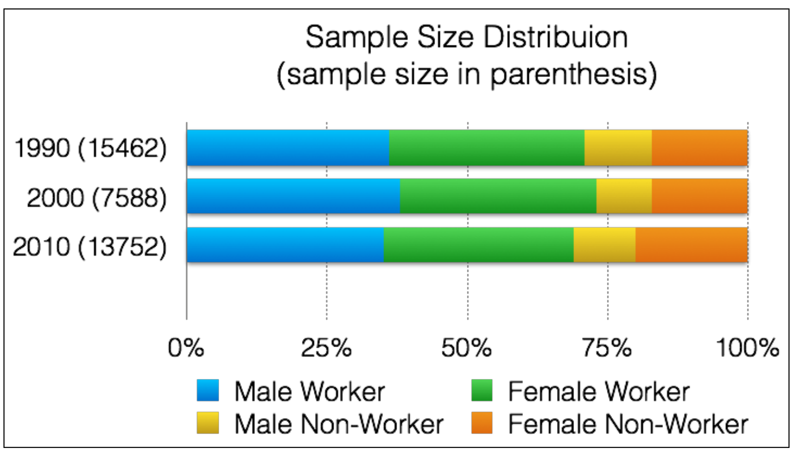

Figure 1.2: Sample Distribution

The Metropolitan Council divides the region into small areas called Transportation Analysis Zones (TAZs). These TAZs allow for a higher resolution of data than just municipality level statistics, especially for the large cities of Minneapolis and Saint Paul. Different TAZ systems were in use for the different surveys. For this analysis the year 2000 TAZ system is used to be consistent with the accessibility calculations that are used..

For all years, accessibilities were calculated based on a cumulative opportunities model, where the number of opportunities from a TAZ given a certain travel time threshold (in minutes) is calculated. Additional population and employment data were collected from the United States Census

Bureau. Accessibility measures for 2010 for both auto and transit were calculated by [27]. The Accessibilities for 1995 and 2000 were computed for auto [8] and transit [13]. In order to find the number of opportunities available within a certain travel time, the travel times needed to be estimated for arterial links. This was done by comparing various models of travel time models to find the most accurate [7]. Davis and Xiong recommended the Skarbardonis-Dowling model (shown below) [29], and this was the model used to estimate the travel costs for the accessibility measures.

$$TT = (\frac{L}{FFS} + 0.5NC(1 - \frac{g}{C})^2 PF)(1 + 0.05(\frac{v}{c})^{10})$$

where
TT = predicted mean travel time
FFS = free-flow travel speed
N = number of signals in the link
C = cycle length
g = effective green time
PF = progression adjustment factor
v = volume
c = capacity (adjusted by green time/cycle length ratio)

$PF = \frac{(1-P)f_{PA}}{1-\frac{g}{C}}$

where
PF = progression adjustment factor
P = proportion of vehicles arriving on green
g/C = proportion of green time available
f_{PA} = supplemental adjustment factor for platoon arriving during green (approximately =1)

When the link has only one signalized intersection at the downstream site, the model can be simplified to

$$TT \approx (\frac{L}{FFS} + 0.5(1 - P)(C - g))(1 + 0.05(\frac{v}{c})^{10})$$

1.4 Methods

The activity durations were calculated by linking the trips taken by each respondent and then subtracting the arrival time of the former trip from the departure time of the latter. The remaining time was calculated by adding the travel times for each trip to the calculated activity durations and subtracting the total from 1440 minutes. This time was cross-checked by subtracting the time of departure of the first trip from midnight and the last trips' arrival from midnight and adding the two. This remaining time was attributed to time at home due to the parameter that all respondents began and ended their travel days at home. Figure 1.3 illustrates this calculation process on an idealized data set.

Person ID	Origin	Destination	Trip departure time	Trip arrival time	Travel time	Activity Duration (min)	Total
1	Home	Shop	8:30	8:45	15	30	45
1	Shop	Work	9:15	9:30	15	360	420
1	Work	Dining	15:30	15:45	15	105	540
1	Dining	Shop	17:30	17:40	10	20	570
1	Shop	Home	18:00	18:20	10	850	1440
2	Home	Work	8:00	8:20	20		360

Figure 1.3: Activity Duration Calculation

Each activity's allocation of time was calculated by taking the mean of the activity durations for each gender/employment category, where the total sample size was the size of that gender/employment category. This equates to the average time that each respondent spent on that activity, including those who did not partake in that activity on the travel day. Thus, each gender/employment category represents a time budget of each activity to add to a total of 1440 minutes. The results from 2000 were compared to 1990 and 2010 were compared to both 1990 and 2000 using a t-test to determine if any changes were significant.

In order to analyze the effects of suburbanization in the region, the network distances to the central business district (CBD) were calculated. It is assumed that the density of development decreases, and the average velocities of vehicles increase as distance to the CBD increases. These factors are all intertwined with accessibility, but also looked at independently and in relation to accessibility. Due to the nature of the Minneapolis - Saint Paul region being the "Twin Cities" and essentially having two CBDs, the distances were calculated from both. All trips were then placed into categories based on their minimum distance to the CBDs (for example, if a trip origin was closer to Downtown Minneapolis than Downtown Saint Paul, its category was determined by its distance to Downtown Minneapolis.) Figure 1.4 shows the network distance map of the region illustrating this calculation.

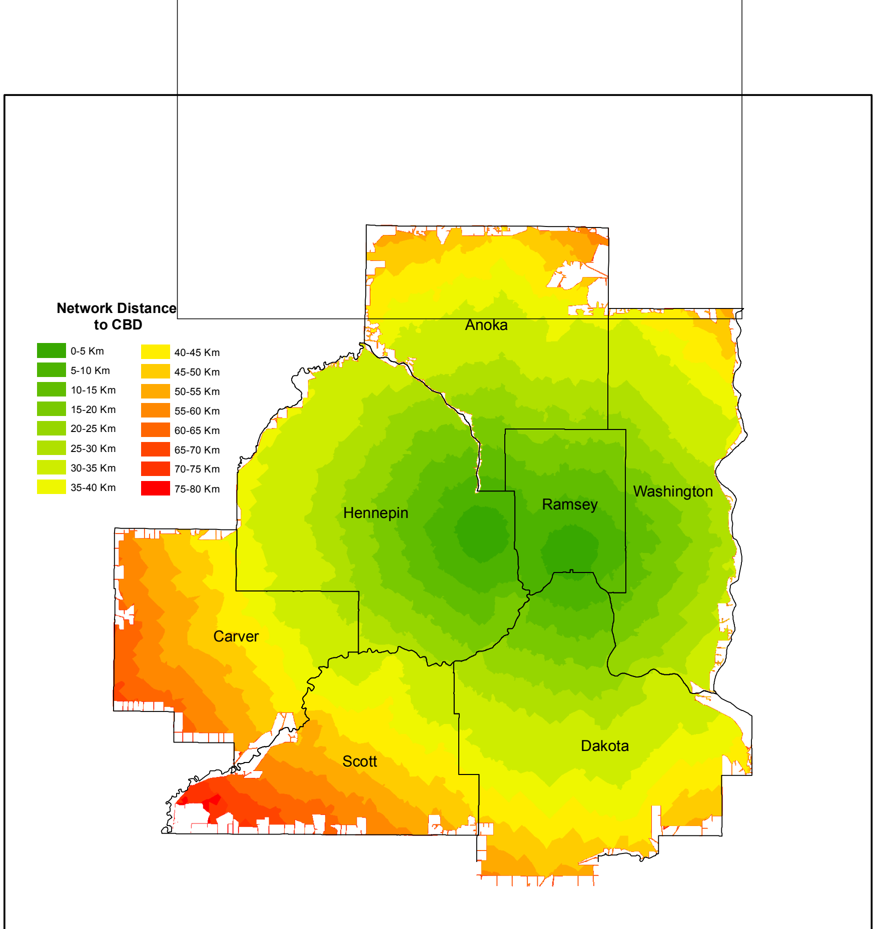

Figure 1.4: 2010 Network Distance to CBD

While the analysis ideally would enter separate cumulative accessibility values for 10 minutes, 20 minutes, ..., 60 minutes, this faces the problem of autocorrelation in that 10 minute accessibility is highly correlated with the 20 minute accessibility (as the 20 minute jobs accessibility number contains all of the 10 minute jobs). Even with the use of rings (looking at the number of jobs which are 10 to 20 minutes away, e.g., rather than 0 to 20 minutes) still shows correlations with the the 0 to 10 minute and 20 to 30 minute rings, as they are a function of the same process of urbanization. Thus, a composite weighted accessibility at each TAZ was calculated by using the equation

$$A_{TAZ} = \sum (A_x - A_{x-1})e^{cx}$$

where
A_x = accessibility within x minute threshold
A_{x-1} = accessibility within the previous minute threshold.
c = coefficent

The distance delay factor c was estimated to be -0.08 using data from the Washington DC region [16] for the first models tested. If c were zero, then people are indifferent to travel time. If c is very negative, people are very sensitive to travel time, and value close destinations much more highly than far-away destinations. This weighted accessibility calculation combines the multiple cumulative opportunities accessibility measures (the exact number of opportunities available within a certain travel cost) into a gravity-like model of accessibility, and maintains comparability with [14]. In order to test the validity of this model (specifically the coefficient of -0.08) for the

Twin Cities region, the regression analysis was tested using a variety of coefficients for 2010. The results of these regressions as well as adjusted R^2 and F values for each can be found in [3].

An OLS regression was performed for auto and transit users where the dependent variable was the commute duration. Using the same explanatory variables as previous studies allows for direct comparison to the DC results, with a few exceptions; the addition of workers aged 70+ to the age60 category, since there were none in 2010 and 1990, and very few in 2000, and the elimination of the ”female head of household” variable, since the TBI survey did not record that and it would be difficult to determine from the questions asked to the same confidence as the DC study. Additionally, the same analysis was run with the dependent variable as the time allocated to work for auto commuters. For these regressions, the data was organized by worker (based on the previously stated criteria) and an additional explanatory variable of the number of work trips made that day was added. Income as an explanatory variable was initially found to be insignificant, but was removed from the regression due to the multitude of problems with the income records in the TBI; the income is recorded for the household, not at the person level, it is self reported, and more than half of the survey respondents declined to answer the question, which greatly reduced the sample size and accuracy of the regressions.

Once the regressions most matching the DC study were conducted, several other models were tested on the 2010 auto commuter data; including using the accessibility from each TAZ as a separate model for both cumulative and non-cumulative measures, and using all non-cumulative TAZ accessibilities as explanatory variables (these regressions were done with the same independent variables as the non-collinear test). In addition, a log-linear GLM was tested for the weighted accessibility with a coefficient of -0.08, however the results were not very different from the OLS model and the Akaike information criterion suggested that the GLM was only slightly a better fit. The results of these regressions may be found in [3] (all regressions included the demographic variables, but due to their very similar results and relative unimportance to fit testing, their coefficients were omitted from some of these tables).

Regressions were also done for the work duration using only the accessibility variables (plus demographics), with commute duration substituting for accessibility, and with predicted commute duration from the best fit model as a substitute for accessibility.

In order to compare the models over the three surveys, the Z statistic was calculated using the following equation [6]

$$Z = \frac{\beta_1 - \beta_2}{\sqrt{SE_{\beta_1} + SE_{\beta_2}}}$$

Where β_x = coefficient of year x SE_{β_x} = standard error of the variable for year x.

1.5 Descriptive Analysis

Table 1.2 and 1.3 show the characteristics of trips taken in the region (speeds are in kph). Trip durations for workers has gone up for all activities from 2000 to 2010, but for non-workers it has gone down. This may be due to economic factors in that workers may have taken less desirable jobs based on distance from their homes, or caused people to move further from their workplace.

The latter may have had an effect on non-work trips as well. The travel time for female workers increased; however for non-workers and overall travel time is down. This matches other research that shows that less time is being spent traveling, as evidenced by a decrease in the total vehicle travel in the United States [2]. Interestingly, the average trip duration for 2000 and 2010 did not significantly change (18 minutes for 2000 and 19 minutes for 2010). This implies that the reductions are in the willingness to make a trip, but not based on the distance of said trip.

This decline in the amount of time spent traveling has been a topic recently in the transportation field. The rate of change in Total Vehicle Travel has been steadily decreasing, and the per capita total distance traveled has begun to decline. As technologies change, the attitude towards cars and car travel has also changed, with the car becoming a less desirable form of transportation to alternatives or simply not making a trip [22]. The term "Peak Travel" has been used to describe the idea that travel growth in the United States has ceased and may begin to decline [23]. The results of this study indicate that, while trip times remain somewhat steady, total travel is declining in the Twin Cities region.

Table 1.4 and 1.5 summarize the allocation of time over these three surveys. The time spent working for both genders and both work from home and work outside of home have decreased by a large amount. This is in part due to the economic recession of 2008, which caused a rise in the number of part-time laborers [1]. However there has also been a decade-long decline in labor force participation rates beginning just prior to the 2008 recession [26].

Total time spent shopping decreased for everyone except for non-working females, likely caused in part by an increase in online shopping. According to the United States Census Bureau, the percentage of households in the United States that had access to the Internet increased from 41.5% in 2000 to 71.7% in 2011 [9]. The Internet has provided electronic accessibility, much as the transportation network has in the material world. It helps to facilitate commerce, communication, education, and leisure. This may lead to a decreased need for people to travel, and account for more time spent at home. The recession of 2008 may have had an impact on shopping traveling habits as a reduction in the household budgets for luxuries such as eating out and shopping for unemployed persons, but also for those nervous about the potential of unemployment. Further, all other activities also declined from 2000 to 2010. These decreases meant a proportional increase in the amount of time spent at home.

Table 1.2: Average travel times (minutes) and travel distances (km) auto

			Worker						Non-Worker					
Destination		Year	Male	S.D.		Female	S.D.		Male	S.D.		Female	S.D.	
	Time	1990	23.1	16.8		20.2	14.9		–	–		–	–	
	Distance	1990	11.0	15.2		8.4	12.1		–	–		–	–	
	Speed	1990	28.6	–		25.0	–		–	–		–	–	
	Time	2000	22.8	16.9	†	19.8	15.3	†	–	–		–	–	
Work	Distance	2000	12.1	16.9	†	9.8	13.7		–	–		–	–	
	Speed	2000	31.8	–		29.7	–		–	–		–	–	
	Time	2010	23.9	16.8	†††	21.6	15.3	†††	–	–		–	–	
	Distance	2010	14.2	15.6	†††	12.3	13.2	††	–	–		–	–	
	Speed	2010	35.6	–		34.2	–		–	–		–	–	
	Time	1990	12.9	11.5		12.4	12.0		13.8	12.3		12.4	12.5	
	Distance	1990	7.2	6.4		6.3	6.4		7.3	11.2		7.2	10.9	
	Speed	1990	33.5	–		30.5	–		31.7	–		34.8	–	
	Time	2000	13.2	11.7		13.0	11.7		14.2	13.1	†	12.8	12.3	†
Shop	Distance	2000	7.6	12.1	†	6.8	11.5	†	7.4	12.3		7.3	12.6	
	Speed	2000	34.5	–		31.4	–		31.3	–		34.2	–	
	Time	2010	15.4	13.7	†††	14.1	12.1	†††	13.6	12.7	†	12.4	11.0	†
	Distance	2010	8.4	11.0	†††	7.1	9.6	††	7.0	10.8		6.5	9.5	†††
	Speed	2010	32.7	–		30.2	–		30.9	–		31.5	–	
	Time	1990	16.4	14.2		13.4	12.9		18.4	16.4		15.6	15.2	
	Distance	1990	7.8	12.9		7.8	12.2		10.2	13.4		8.0	10.9	
	Speed	1990	28.5	–		34.9	–		33.3	–		30.8	–	
	Time	2000	16.6	15.5		14.6	13.3		18.2	16.8		15.3	14.6	†
Other	Distance	2000	8.2	15.4		7.2	12.3		9.8	15.3		8.1	12.4	
	Speed	2000	29.6	–		29.6	–		32.3	–		31.8	–	
	Time	2010	16.6	14.6		15.5	13.1	†††	17.8	15.7	††	15.8	13.6	†
	Distance	2010	8.9	7.6		8.1	10.3		9.2	13.1	††	7.9	9.5	
	Speed	2010	32.2	–		31.4	–		31.0	–		30.0	–	

† Indicates statistically different from previous year
†† Indicates 2010 statistically different from 1990
†††Indicates statistically different from both previous years
$P < 0.5$

Table 1.3: Average travel times (minutes) and travel distances (km) transit

			Worker						Non-Worker					
Destination		Year	Male	S.D.		Female	S.D.		Male	S.D.		Female	S.D.	
Work	Time	1990	24.4	18.1		21.5	16.2		–	–		–	–	
	Distance	1990	9.9	16.3		7.3	13.2		–	–		–	–	
	Speed	1990	24.3	–		20.4	–		–	–		–	–	
	Time	2000	23.6	17.7	†	20.6	16.1	†	–	–		–	–	
	Distance	2000	11.4	17.6	†	9.1	14.4	†	–	–		–	–	
	Speed	2000	29.0	–		26.5	–		–	–		–	–	
	Time	2010	25.4	18.3	†††	23.1	16.8	†††	–	–		–	–	
	Distance	2010	12.7	17.1	†††	10.8	14.7	†††	–	–		–	–	
	Speed	2010	30.0	–		28.1	–		–	–		–	–	
Shop	Time	1990	14.2	12.8		13.7	13.3		15.1	13.6		13.7	13.8	
	Distance	1990	6.7	6.9		5.8	6.9		6.8	11.7		6.7	11.4	
	Speed	1990	28.3	–		25.4	–		27.0	–		29.3	–	
	Time	2000	13.8	12.3	†	13.6	12.3		14.8	13.7	†	13.4	12.9	
	Distance	2000	6.2	13.5		5.4	12.9	†	6.0	13.7	†	5.9	14.0	†
	Speed	2000	27.0	–		23.8	–		24.3	–		26.4	–	
	Time	2010	15.9	14.2	†††	14.6	12.6	†††	14.1	13.2	†††	12.9	11.5	†††
	Distance	2010	7.5	11.9	†††	6.2	10.5	††	6.1	11.7	††	5.6	10.4	††
	Speed	2010	28.3	–		25.5	–		26.0	–		26.0	–	
Other	Time	1990	17.1	14.9		14.1	13.6		19.1	17.1		16.3	15.9	
	Distance	1990	7.1	13.6		7.1	12.9		9.5	14.1		7.3	11.6	
	Speed	1990	24.9	–		30.2	–		29.8	–		26.9	–	
	Time	2000	18.1	17.0	†	16.1	14.8	†	19.7	18.3	†	16.8	16.1	
	Distance	2000	7.6	16.0		6.6	12.9	†	9.2	15.9		7.5	13.0	
	Speed	2000	25.2	–		24.6	–		28.0	–		26.8	–	
	Time	2010	17.1	15.1	†	16.0	13.6	††	18.3	16.2	†††	16.3	4.1	†
	Distance	2010	7.7	8.8		6.9	11.5	††	8.0	14.3	†††	6.7	10.7	†††
	Speed	2010	27.0	–		25.9	–		26.2	–		24.7	–	

† Indicates statistically different from previous year
†† Indicates 2010 statistically different from 1990
†††Indicates statistically different from both previous years
$P < 0.5$

Table 1.4: Activity durations auto (minutes)

		Workers				Non-Workers			
Activity	Year	Male	S.D.	Female	S.D.	Male	S.D.	Female	S.D.
Home	1990	777	286	816	302	1101	453	1172	482
	2000	778	340	809	349	1082	482	1140	485
	2010	787	340	825	351	1175	494	1175	486
Work	1990	514	206	477	198	–	–	–	–
	2000	502	237	471	205	–	–	–	–
	2010	495	218	470	202	–	–	–	–
Shop	1990	7	22	15	32	21	43	41	61
	2000	8	38	14	31	21	43	41	61
	2010	5	64	9	44	32	74	41	53
Other	1990	52	85	55	79	143	167	132	144
	2000	59	78	62	67	243	192	177	128
	2010	65	72	55	64	171	134	161	115
Travel	1990	88	22	77	20	79	21	80	20
	2000	93	17	84	15	82	16	81	14
	2010	87	17	81	15	73	15	74	14

Table 1.5: Activity durations transit (minutes)

		Workers				Non-Workers			
Activity	Year	Male	S.D.	Female	S.D.	Male	S.D.	Female	S.D.
Home	1990	765	291	803	306	1084	455	1154	484
	2000	772	346	803	355	1074	487	1131	490
	2010	784	346	822	359	1171	501	1171	493
Work	1990	512	211	475	206	–	–	–	–
	2000	497	243	466	212	–	–	–	–
	2010	489	220	464	207	–	–	–	–
Shop	1990	8	34	17	43	24	55	47	76
	2000	8	48	14	37	21	49	41	67
	2010	4	59	7	41	26	65	33	48
Other	1990	58	100	61	96	160	194	147	169
	2000	62	89	65	78	255	210	186	143
	2010	71	88	60	77	187	153	176	133
Travel	1990	97	29	83	30	173	54	92	31
	2000	101	25	92	25	90	27	82	23
	2010	92	23	87	24	57	20	61	20

1.6 Results

Table 1.6 and 1.11 show the results of the initial models tested. These models used the same parameters as the DC study (with a few modifications, see 1.4). This allows for a verification that the study methods are sound relative to the previous literature was well as a comparison between the different regions. For the most part, the relationships of the accessibility variables retain the same signs as the DC study (with the exception of resident accessibility in 2010 auto users). Additionally, in both transit and auto users, some of the other significant demographic variables differ in their signs. These differences may be related to different external factors that govern behavior for the different regions. Similarly, the magnitudes of the coefficients of the models differ due to both the slightly different parameters as well as the different urban structure between the two cities (among other factors such as culture and changing dynamics over time).

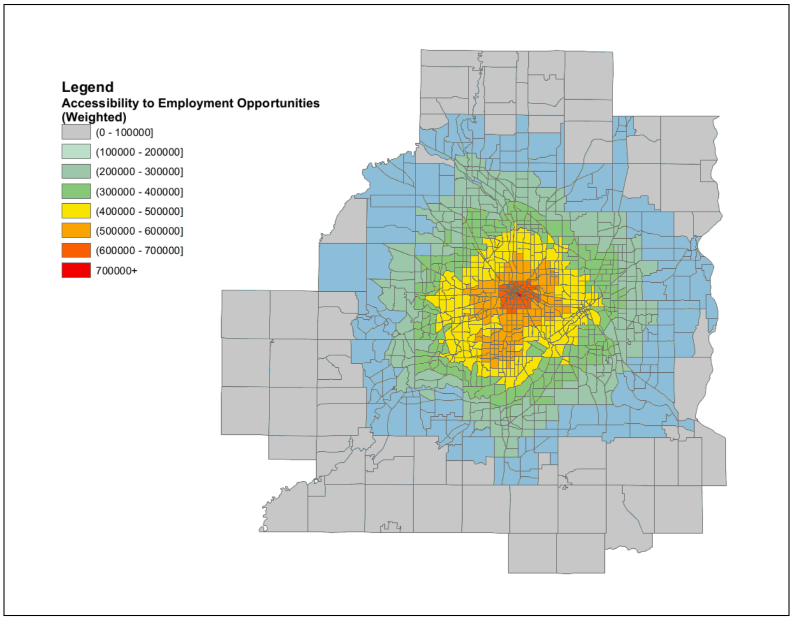

Figure 1.5: 2010 Employment Accessibility by Auto

Tables 1.7 and 1.12 show the results of the final model to predict commute duration selected; adjusting the weighting coefficient to 0.04 rather than 0.08. This coefficient was selected due to it having the highest R^2 value of all of the coefficients tested. The 20-minute interval and 0.04 weight models are very similar both in their results as well as their respective fits. This is expected because the two methods of calculating the accessibility are very similar. The reason for the difference in coefficient for the weighting equation from the DC study warrants further analysis, but was beyond the scope of this project. Although this model did not have the exact parameters as the DC study's model, the accessibility variables retain the same relationships as found in that study. Tables 1.8 and 1.13 show the z and p values for the coefficients calculated from the commute duration models. The relationships between the independent and dependent variables do not seem to be changing much over time.

Tables 1.9, and 1.14 show the results of the regressions to predict the time spent at work for auto and transit respectively. The results for both auto and transit are similar in both magnitude and sign. Tables 1.10 and 1.15 show the statistical differences of the allocation models. The relationships appear to be relatively stable for auto users but are changing slightly for transit users' time spent at work. This change may be due to the more rapid change of the transit system compared to the road network as well as economic changes that may affect transit users more heavily than auto users. Additionally, the high error rates of the data may account for the lack of statistical differences between the coefficients in the models.

Table 1.6: Regressions to predict commuting duration by auto DC study variables

Variable	DC		2010 MSP		2000 MSP		1990 MSP	
Age	Coefficient		Coefficient		Coefficient		Coefficient	
yr	(t-value)		(t-value)		(t-value)		(t-value)	
10	-5.85	***	-5.76	***	-6.92	***	-5.87	***
	(-2.75)		(-2.98)		(-3.26)		(-4.12)	
20	1.90	**	-1.38	**	-1.216	*	-0.28	***
	(1.96)		(-1.75)		(-1.42)		(-0.26)	
40	0.434		0.65		0.634		0.697	
	(0.50)		(1.12)		(2.31)		(1.25)	
50	-0.62		-1.04	**	-0.44		-0.35	
	(-0.62)		(-1.85)		(-0.61)		(-0.76)	
60	-0.77		-0.83		-0.52		-0.62	
	(-0.56)		(-1.19)		(-0.35)		(-0.42)	
Male	1.82	**	1.53	***	1.79	***	1.42	**
	(2.52)		(4.26)		(5.12)		(4.32)	
SFhome	0.16		-0.155		-0.78		-1.23	
	(0.18)		(-0.275)		(-0.41)		(-0.31)	
VPD	1.03		0.179	**	1.24	*	1.09	**
	(1.07)		(0.44)		(0.98)		(1.27)	
Children	0.936	*	-0.341		0.32		0.12	
	(1.72)		(-0.948)		(1.02)		(0.15)	
HHsize	0.0857		0.196		0.22		0.19	
	(0.24)		(0.909)		(1.05)		(1.03)	
A_{iEa}	-8.68E-05	***	-1.60E-05	**	-7.231E-06	***	-7.892E-06	***
	(-4.86)		(-1.97)		(-3.214)		(-2.923)	
A_{iRa}	1.18E-04	***	-1.14E-05		1.989E-05	***	2.003E-05	**
	(2.75)		(-0.869)		(2.43)		(2.63)	
A_{jEa}	7.13E-05	***	3.73E-05	***	3.68E-05	***	3.02E-05	***
	(4.21)		(5.04)		(4.29)		(5.02)	
A_{jRa}	-1.47E-04	***	-4.03E-05	***	-2.72E-05	***	-3.09E-05	***
	(-3.26)		(-3.17)		(-2.46)		(-3.02)	
D_{io}	0.63	***	2.75E-02	**	0.43	**	0.53	***
	(5.82)		(2.71)		(4.036)		(5.23)	
D_{jo}	-0.55	***	-5.21E-02	***	-0.32	**	-0.30	**
	(-3.77)		(-4.31)		(-2.29)		(-3.02)	
Constant	23.29	***	28.26	***	25.42	***	24.32	***
	(4.61)		(11.30)		(9.85)		(11.26)	
Sample Size	1950		5228		2978		6574	
Adj. R^2	0.17		0.1398		0.14		0.142	
F	22.79	***	52.94	***	42.21	***	44.26	

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table 1.7: Regressions to predict commute duration for auto users weight coefficient -0.04

	2010				2000				1990			
	Employment		Resident		Employment		Resident		Employment		Resident	
Variable	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient	
age	(t-value)		(t-value)		(t-value)		(t-value)		(t-value)		(t-value)	
10	-5.682	***	-5.764	***	-7.214	***	-7.358	***	-6.490	***	-6.407	***
	(-2.935)		(-2.968)		(-3.252)		(3.317)		(-4.872)		(-5.018)	
20	-1.401	*	-1.529	*	-1.321	**	-1.281	*	-1.263	**	-1.250	*
	(-1.78)		(-1.936)		(-1.455)		(-1.348)		(-1.352)		(-1.338)	
40	0.6102		0.5815		0.6211		0.634		0.689		0.717	
	(1.052)		(1.000)		(2.269)		(2.018)		(2.004)		(2.084)	
50	-1.029	*	-1.075	*	-0.523	*	-0.507	*	-1.307	*	-1.137	*
	(-1.837)		(-1.915)		(-0.684)		(-6.234)		(-2.17)		(-1.888)	
60	-0.8348		-0.9055		-0.762		-0.732		-0.650		-0.728	
	(-1.196)		(-1.294)		(-0.484)		(-0.416)		(-1.211)		(-1.465)	
Male	1.477	***	1.452	***	1.629	***	1.662	***	1.924	***	1.520	***
	(4.105)		(4.021)		(4.981)		(5.022)		(7.04)		(5.562)	
SFhome	-0.2046		-0.2178		-0.822		-0.797		-0.969		-0.978	
	(-0.362)		(-0.385)		(-0.463)		(-0.411)		(-0.367)		(-0.364)	
VPD	0.1644		0.1437		1.31		1.258		0.314		0.323	
	(0.404)		(0.352)		(1.001)		(0.973)		(0.413)		(0.411)	
Children	-0.317		-0.3125		0.281		0.284		-0.651		-0.622	
	(-0.882)		(-0.867)		(0.988)		(1.002)		(-1.38)		(-1.03)	
HHsize	0.2083		0.2273		0.1975		0.199		0.216		0.182	
	(0.965)		(1.051)		(1.021)		(1.024)		(0.942)		(1.245)	
A_{iEa}, A_{iRa}	-1.095E-05	***	7.441E-06	***	-1.031E-06	***	1.05E-06	***	-1.15E-05	***	2.88E-05	***
	(-24.243)		(23.892)		(-22.41)		(23.02)		(-22.45)		(23.17)	
A_{jEa}, A_{jRa}	1.022E-05	***	-6.991E-06	***	2.013E-05	***	-1.93E-05	***	3.15E-05	***	-2.67E-05	***
	(21.233)		(-20.451)		(19.821)		(-19.224)		(25.31)		(-27.67)	
Constant	21.19	***	21.3	***	19.8	***	19.998	***	20.76	***	25.17	***
	(16.759)		(16.023)		(15.798)		(15.82)		(18.76)		(20.52)	
Sample Size	5228		5228		2978		2978		6574		6574	
Adj. R^2	0.1355		0.1303		0.1378		0.1325		0.1257		0.1231	
F	69.26	***	66.25	***	40.21	***	41.57	***	45.78	***	42.68	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table 1.8: Statistical differences between years in predicted commute duration for auto users weight coefficent -0.04

	Employment			Resident		
Variable	2010-2000	2000-1990	2010-1990	2010-2000	2000-1990	2010-1990
age	Z-value	Z-value	Z-value	Z-value	Z-value	Z-value
	p-value	p-value	p-value	p-value	p-value	p-value
10	-0.752	0.384	-0.447	-0.781	0.509	-0.358
	0.226	0.650	0.327	0.217	0.695	0.360
20	0.061	0.043	0.105	0.188	0.023	0.212
	0.524	0.517	0.542	0.575	0.509	0.584
40	-0.012	-0.086	-0.082	-0.055	-0.102	-0.141
	0.495	0.466	0.467	0.478	0.459	0.444
50	0.440	-0.671	-0.258	0.709	-0.762	-0.057
	0.670	0.251	0.398	0.761	0.223	0.477
60	0.048	0.077	0.166	0.111	0.003	0.162
	0.519	0.531	0.566	0.544	0.501	0.564
Male	-0.183	-0.381	-0.562	-0.252	0.183	-0.085
	0.427	0.352	0.287	0.400	0.572	0.466
SFhome	-0.404	-0.070	-0.427	-0.366	-0.084	-0.422
	0.343	0.472	0.335	0.357	0.466	0.337
VPD	-0.875	0.692	-0.138	-0.854	0.648	-0.164
	0.191	0.756	0.445	0.196	0.742	0.435
Children	0.045	-0.425	-0.366	0.036	-0.359	-0.315
	0.518	0.335	0.357	0.514	0.360	0.376
HHsize	0.017	-0.028	-0.012	0.044	0.029	0.075
	0.507	0.489	0.495	0.518	0.512	0.530
A_{iEa}, A_{iRa}	1.41E-02	-1.40E-02	-5.60E-04	1.07E-02	-2.44E-02	-1.71E-02
	0.506	0.494	0.500	0.504	0.490	0.493
A_{jEa}, A_{jRa}	-8.10E-03	-7.56E-03	-0.016	-1.06E-02	-5.27E-03	-1.72E-02
	0.497	0.497	0.494	0.496	0.498	0.493
Constant	0.876	-0.625	0.279	0.808	-3.277 ***	-2.421 ***
	0.809	0.266	0.610	0.791	0.001	0.008

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table 1.9: Regressions to predict time at work for auto users using predicted travel times

Variable	2010		2000		1990	
Age	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
10	-64.8	**	-57.77	**	-48.32	**
	(-2.14)		(-1.90)		(-1.59)	
20	-10.7		-12.278		-13.066	
	(-0.982)		(-1.12)		(-1.19)	
40	1.74		1.818		2.077	
	(0.252)		(0.26)		(0.3)	
50	14.8	**	13.745	**	13.523	**
	(1.975)		(1.83)		(1.8)	
60	-8.74		-10.191		-9.351	
	(-1.053)		(-1.22)		(-1.12)	
Male	25	***	4.184		4.284	
	(4.78)		(0.63)		(0.64)	
SFhome	-3.94		-3.959		-3.487	
	(-0.587)		(-0.58)		(-0.51)	
VPD	11.3	**	12.377	**	10.185	**
	(2.367)		(2.59)		(2.13)	
Children	-10.4	**	-12.197	**	-13.067	**
	(-2.432)		(-2.85)		(-3.05)	
HHsize	-0.455		-0.38		-0.41	
	(-0.178)		(-0.14)		(-0.16)	
Number of Work trips	-150 (-43.759)	***	-146.634 (-42.77)	***	-123.232 (-35.9)	***
PredictedCommute Duration	10.5 (3.001)	***	9.15 (2.61)	***	8.55 (2.44)	***
Constant	772	***	266.388	*	251.157	*
	(21.43)		(2.13)		(2.01)	
Sample size	5228		2978		6574	
Adj. R^2	0.274		0.2987		0.2964	
F	165.4	***	162.1	***	164.5	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table 1.10: Statistical differences between years in predicted time spent at work for auto users weight coefficient -0.04

Variable	2010-2000	2000-1990	2010-1990
age	Z-value	Z-value	Z-value
	p-value	p-value	p-value
10	0.902	1.212	2.116
	0.817	0.887	0.983
20	-0.338	-0.168	-0.506
	0.368	0.433	0.306
40	-0.021	-0.069	-0.091
	0.492	0.472	0.464
50	0.272	0.057	0.330
	0.607	0.523	0.629
60	-0.356	0.206	-0.150
	0.361	0.581	0.440
Male	6.042	-0.027	5.999
	1.000	0.489	1.000
SFhome	-0.005	0.128	0.123
	0.498	0.551	0.549
VPD	-0.348	0.709	0.361
	0.364	0.761	0.641
Children	-0.614	-0.297	-0.912
	0.269	0.383	0.181
HHsize	0.033	-0.013	0.020
	0.513	0.495	0.508
A_{iEa}, A_{iRa}	1.285	8.934	10.220
	0.901	1.000	1.000
A_{jEa}, A_{jRa}	0.510	0.227	0.737
	0.695	0.590	0.769
Constant	39.837	0.963	41.051
	1.000	0.832	1.000

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table 1.11: Regressions to predict commuting duration by Transit DC study variables

Variable	DC		2010 MSP		2000 MSP		1990 MSP	
Age	Coefficient		Coefficient		Coefficient		Coefficient	
yr	(t-value)		(t-value)		(t-value)		(t-value)	
10	-9.83	*	22.75	***	12.35	*	20.13	**
	(-1.82)		(2.91)		(1.23)		(2.68)	
20	0.58		-1.07		-0.63		-0.98	
	(0.28)		(-0.41)		(-0.32)		(-0.45)	
40	3.39		-2.22		1.06		-0.84	
	(1.82)		(-0.99)		(0.35)		(-0.84)	
50	-1.08		-3.733		-1.29		-2.42	
	(-0.40)		(-1.73)		(-0.93)		(-3.21)	
60	7.26	**	-2.084		5.06		-1.05	
	(2.04)		(-0.71)		(1.92)		(-2.34)	
70	16.96	*	-11.3		-9.84		-10.2	
	(1.79)		(-1.45)		(-1.94)		(-3.62)	
Male	-0.33		0.94		0.84		0.95	
	(-0.18)		(0.62)		(0.51)		(0.86)	
SFhome	-3.78	**	-0.86		-0.57		-0.92	
	(-2.04)		(-1.55)		(-0.84)		(1.24)	
VPD	-2.30		-2.01		-2.56		-2.87	
	(-1.13)		(-0.89)		(-1.43)		(-1.94)	
Children	-2.80	**	-1.88		-2.41		-2.81	
	(-2.09)		(-1.11)		(-1.58)		(-3.21)	
HHsize	1.83	**	1.88		1.94		2.02	
	(2.04)		(1.05)		(1.10)		(1.24)	
A_{iEt}	-1.15E-03	**	-4.314E-05	*	-4.105E-05	*	-4.204E-05	**
	(-2.27)		(-1.257)		(-1.426)		(-1.072)	
A_{iRt}	1.12E-03		3.79E-05		2.49E-05		2.21E-05	
	(0.85)		(0.59)		(0.92)		(1.46)	
A_{jEt}	-1.14E-03	**	-3.655E-05	**	-4.026E-05	*	-3.84E-05	*
	(-2.56)		(-1.301)		(-1.02)		(-1.24)	
A_{jRt}	1.05E-03		2.04E-06		9.842E-07		8.612E-07	
	(0.75)		(0.89)		(0.57)		(0.14)	
D_{io}	1.71	***	0.92	***	1.21	***	1.31	**
	(9.71)		(3.081)		(4.091)		(5.012)	
D_{jo}	-1.67	***	-1.57	**	-1.27	*	-1.02	*
	(-5.63)		(0.112)		(0.101)		(0.312)	
Constant	44.12	***	38.95	***	40.21	***	39.26	***
	(9.21)		(6.415)		(7.691)		(5.292)	
Sample Size	409		124		106		164	
Adj. R^2	0.038		0.114		0.095		0.137	
F	12.96	***	4.501	***	6.02	***	5.06	

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table 1.12: Regressions to predict commute duration for transit users weight coefficient -0.04

	2010				2000				1990			
	Employment		Resident		Employment		Resident		Employment		Resident	
Variable	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient	
age	(t-value)		(t-value)		(t-value)		(t-value)		(t-value)		(t-value)	
10	21.74	**	18.70	***	13.89	**	13.276	**	19.24	**	16.747	**
	(2.780)		(2.391)		(1.383)		(1.322)		(2.562)		(2.229)	
20	-0.95		-0.82		-0.68		-0.564		-0.81		-0.670	
	(-0.362)		(-0.313)		(-0.345)		(-0.286)		(-0.373)		(-0.307)	
40	-2.65		-2.24		0.91		0.748		-0.69		-0.791	
	(-1.180)		(-0.999)		(0.299)		(0.247)		(-0.618)		(-0.706)	
50	-3.19		-2.91		-1.41		-1.210		-2.08		-1.911	
	(-1.480)		(-1.348)		(-1.016)		(-0.872)		(-2.755)		(-2.534)	
60	-2.11		-2.00		5.36		5.694		-1.12		-1.094	
	(-0.720)		(-0.682)		(2.032)		(2.160)		(-2.488)		(-2.437)	
Male	1.01		1.03		0.72		0.846		1.12		1.202	
	(0.669)		(0.681)		(0.436)		(0.513)		(1.012)		(1.088)	
SFhome	-0.90	*	-0.77	*	-0.48	*	-0.447	*	-0.85	**	-0.691	*
	(-1.627)		(-1.382)		(-0.712)		(-0.659)		(1.146)		(0.930)	
VPD	-1.76		-1.64		-2.40		-2.586		-3.09		-3.432	
	(-0.781)		(-0.724)		(-1.342)		(-1.444)		(-2.087)		(-2.319)	
Children	-1.99	**	-2.33	*	-2.77	**	-2.964	**	-3.00	**	-3.447	**
	(-1.176)		(-1.377)		(-1.817)		(-1.943)		(-3.432)		(-3.937)	
HHsize	1.75		1.64		2.24		2.370		2.14		2.308	
	(0.977)		(0.915)		(1.268)		(1.343)		(1.313)		(1.417)	
A_{iEt}, A_{iRt}	-4.22E-05	***	3.65E-05	***	-4.03E-05	**	3.89E-05	***	-4.12E-05	***	4.02E-05	***
	(-1.21)		(0.63)		(-1.01)		(0.85)		(-1.13)		(0.82)	
A_{jEt}, A_{jRt}	-3.24E-05	**	1.95E-06	**	-3.12E-05	*	2.03E-06	**	-2.86E-05	**	2.89E-06	**
	(-1.26)		(0.85)		(-1.13)		(0.89)		(-1.01)		(0.78)	
Constant	32.68		26.80		33.06		28.540		33.89		31.244	
	(5.382)		(4.413)		(6.323)		(5.458)		(4.568)		(4.211)	
Sample Size	124		124		106		106		164		164	
Adj. R^2	0.102		0.125		0.123		0.122		0.105		0.112	
F	5.23	***	4.32	***	4.52	***	4.44	***	4.25	***	5.02	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table 1.13: Statistical differences between years in predicted commute duration for transit users weight coefficient -0.04

	Employment			Resident		
Variable	2010-2000	2000-1990	2010-1990	2010-2000	2000-1990	2010-1990
age	Z-value	Z-value	Z-value	Z-value	Z-value	Z-value
	p-value	p-value	p-value	p-value	p-value	p-value
10	1.857	-1.277	0.639	1.283	-0.828	0.499
	0.968	0.101	0.738	0.900	0.204	0.691
20	0.126	-0.064	0.064	0.119	-0.052	0.068
	0.550	0.475	0.525	0.548	0.479	0.527
40	0.757	0.108	1.069	0.650	-0.021	0.790
	0.775	0.543	0.857	0.742	0.492	0.785
50	0.946	-0.458	0.651	0.903	-0.479	0.585
	0.828	0.324	0.742	0.817	0.316	0.721
60	-1.377 *	2.413	0.538	-1.565 *	2.619	0.493
	0.084	0.992	0.705	0.059	0.996	0.689
Male	0.163	-0.241	-0.068	0.103	-0.215	-0.106
	0.565	0.405	0.473	0.541	0.415	0.458
SFhome	0.379	-0.311	0.044	0.291	-0.205	0.069
	0.648	0.378	0.518	0.614	0.419	0.528
VPD	-0.143	-0.157	-0.688	-0.470	-0.468	-0.926
	0.443	0.438	0.246	0.319	0.320	0.177
Children	-0.435	-0.149	-0.630	-0.353	-0.312	-0.697
	0.332	0.441	0.264	0.362	0.378	0.243
HHsize	-0.260	0.054	-0.211	-0.387	0.034	-0.361
	0.398	0.522	0.417	0.349	0.513	0.359
A_{iEt}, A_{iRt}	2.20E-04	-1.03E-04	1.18E-04	-2.36E-04	-1.34E-04	-3.58E-04
	0.500	0.500	0.500	0.500	0.500	0.500
A_{jEt}, A_{jRt}	1.64E-04	3.48E-04	0.001	-3.74E-05	-3.52E-04	-3.84E-04
	0.500	0.500	0.500	0.500	0.500	0.500
Constant	-0.113	-0.233	-0.329	-0.518	-0.760	-1.210
	0.455	0.408	0.371	0.302	0.224	0.113

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table 1.14: Regressions to predict time at work for transit users using predicted travel times

Variable	2010		2000		1990	
Age	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
10	-228.3 (-9.61)	***	-300.77 (-12.66)	***	-134.11 (-5.65)	***
20	-26.98 (-2.82)		-60.47 (-6.33)	**	-52.97 (-5.54)	**
40	0.74 (0.1)		1.24 (0.17)		0.68 (0.09)	
50	-1.7 (-0.25)		-2.03 (-0.3)		-1 (-0.15)	
60	-12.8 (-1.09)		-29.44 (-2.5)		-15.96 (-1.36)	
Male	4.05 (7.63)	*	3.79 (7.13)	**	5.58 (10.51)	**
SFhome	-7.54 (-1.12)		-8.78 (-1.3)		-6.85 (-1.02)	
VPD	7.6 (1.43)		13.74 (2.58)		8.87 (1.67)	
Children	-16.4 (-4.28)	**	-19.08 (-4.98)	**	-18.49 (-4.83)	**
HHsize	-0.6 (-0.21)		-1.11 (-0.39)		-1.25 (-0.44)	
Number of Work trips	-15.2 (-5.26)	**	-20 (-6.93)	**	-7.33 (-2.54)	**
Predicted/Reported Commute Duration	8.3 (2.4)	***	4.56 (1.32)	***	8.84 (2.56)	***
Constant	508.2 (31.534)	***	241.88 (15.008)	***	560.15 (34.76)	***
Sample size	124		106		164	
Adj. R^2	0.201		0.214		0.194	
F	146.3	***	162.3	***	162.3	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table 1.15: Statistical differences between years in predicted time spent at work for transit users weight coefficient -0.04

Variable	2010-2000		2000-1990		2010-1990	
age	Z-value		Z-value		Z-value	
	p-value		p-value		p-value	
10	-10.514	***	24.183		13.668	
	3.74E-26		1.000		1.000	
20	-7.659	***	1.715		-5.942	***
	9.37E-15		0.957		1.40E-09	
40	-0.130		0.145		0.016	
	0.448		0.558		0.506	
50	-0.090		0.281		0.191	
	0.464		0.611		0.576	
60	-3.431	***	2.780		-0.652	
	3.00E-04		0.997		0.257	
Male	0.252		-1.737	**	-1.485	*
	0.600		0.041		0.069	
SFhome	-0.338		0.526		0.188	
	0.368		0.701		0.575	
VPD	-1.882	**	1.493		-0.390	
	0.030		0.932		0.348	
Children	-0.968		0.213		-0.755	
	0.166		0.584		0.225	
HHsize	-0.214		-0.059		-0.272	
	0.415		0.477		0.393	
A_{iEa}, A_{iRa}	-1.997	**	5.274		3.275	
	0.023		1.000		0.999	
A_{jEa}, A_{jRa}	1.422		-1.628	*	-0.205	
	0.923		0.052		0.419	
Constant	46.909		-56.060	***	-9.151	***
	1.000		0		2.83E-20	

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

1.7 Discussion

It is apparent that there are many factors that affect time budgets, as discussed previously and as found in the results. The results of this study show that accessibility is a significant factor in determining not only travel behavior, but overall time budgeting in general. However, simply looking at the coefficients of the models is somewhat uninformative.

Although the values of the coefficients of the models for the accessibility variables are very small, when multiplied up by the total accessibility indices and then across the entire region, the time saved/lost due to changes in accessibility are quite noticeable. For instance, in 2010, many TAZs in the suburbs had weighted employment accessibility indices for auto of around 200,000, while the indices in downtown Minneapolis were over 700,000, a difference of 500,000 (see figure 1.5). The commute duration coefficient for employment accessibility at the origin for the final weighted model is -1.095×10^{-5} (see Table 1.7), this means that if an individual moved from one of those outer suburbs to downtown Minneapolis, their commute duration, according to the model, would decrease by 5.475 minutes. See Table 1.16 for the results of this calculation for all years, modes, and accessibilities.

Table 1.16: Minute change in commute duration for every 500,000 additional jobs/ residences

		2010		2000		1990	
Auto	A_{iEa}, A_{iRa}	-5.475	3.7205	-0.5155	0.525	-5.75	14.4
	A_{jEa}, A_{jRa}	5.11	-3.495	10.065	-9.65	15.75	-13.35
Transit	A_{iEt}, A_{iRt}	-21.1	18.25	-20.15	19.45	-20.6	20.1
	A_{jEt}, A_{jRt}	-16.2	0.975	-15.6	1.015	-14.3	1.445

Additionally, if a TAZ that has 10,000 people living in it was able to increase its accessibility index through either transportation infrastructure improvements or through land-use changes, even by a relatively small amount of 10000 for an individual commute cost savings of 0.1095 minutes, the total system savings for that TAZ would be 18 hours, 15 minutes a day.

The models here are also useful for planners or engineers as these methods can be easily adapted to other data from other cities or for other activities besides work. This gives a tool that can be used to gauge the impact of a transportation or other large project from an accessibility standpoint and how that project will translate into time allocation.

1.8 Conclusion

The results of this analysis show a measurable decline in the time people spend outside of their homes as well as the amount of time people spend in travel over the past decade. The rise of the Internet and mobile telecommunications and changes in the economy between 2000 and 2010, along with changing demographics and new modes of work may be among the factors causing people to reconsider the necessity of travel. Although distances per trip are not getting any shorter, the willingness to make those trips is declining, and as a result fewer kilometers are being traveled and less time on average is being allocated to travel.

This study corroborates previous studies showing that accessibility is a significant factor in commute durations. Though commutes do not make up the majority of travel, they are the most important and regular trips made by most working-age people. This study shows that the structure of a city affects average commute durations and time spent at work. Even as travel patterns change, the relationship between accessibility and commute duration remains relatively stable. This means that adjusting land-use patterns to increase the number of workers living in job-rich areas and the number of jobs in labor-rich areas is a reliable way of reducing auto commute durations.

In addition, this study shows a correlation between commute duration and the amount of time spent at work. Further analysis into the cause of this may be warranted, though it is most likely due to a blending of the work and home environments when one lives very close to where one works. The main factors looked at that affect time spent at work are age, the number of work (destination) trips and commute duration. Age plays a large role, especially in the younger brackets due to younger workers being more likely to work part-time shifts, with people in their 20s to 40s spending the most time at work. The number of work trips was expected to have an effect because of the way the data were recorded. If a person left for a lunch break or on an errand during the work day on personal business, that would likely show up as multiple work trips, whereas someone who ate his or her lunch at the workplace would have that lunch time included in his or her time at work. Interestingly, the number of children one has, while a significant factor statistically, did not decrease the time spent at work by a large amount. The predicted commute durations resulted in very similar models both to each other and to the actual recorded commute durations for both auto and transit. This is further evidence to the validation of the commute time models. In addition, the relationships between demographics and accessibility and travel behavior appear to be relatively stable, especially for auto users; however, there are a few changes among transit users. These changes may be due to the changing nature of the transit system in the Twin Cities (with a light rail system being constructed between 2000 and 2010), as well as changes in the economy, which may have disproportionately affected transit users. There were some limitations to this study, such as the lack of a day-to-day comparison and the relative simplicity of the models. Using different data sources to analyze these relationships more in-depth could be an area for future study. Despite the limitations, these findings show that the transportation network and urban structure have significant impacts on day-to-day life beyond simply traveling. It would follow that similar relationships would exist with other activities besides work. Each person has to decide how he or she will use his or her allotted time each day, and many of those decisions are directly related to the transportation systems in place. It is important to understand how transportation and urban form affect social behavior so that informed decisions can be made regarding policy and design.

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Nomenclature

Table 1.17: Variables used in regressions

Demographic and socio-economic variables	
Age 10[0,1]	1 if individual aged 10-20. 0 otherwise
Age 20[0,1]	1 if individual aged 20-30, 0 otherwise
Age 30[0,1]	1 if individual aged 30-40, 0 otherwise
Age 40[0,1]	1 if individual aged 40-50, 0 otherwise
Age 50[0,1]	1 if individual aged 50-60, 0 otherwise
Age 60[0,1]	1 if individual aged 60+, 0 otherwise
Children	Number of children 0 - I6 in the household
HHsize	Number of persons in household
Male[0,1]	1 if individual is male, 0 otherwise
SFhome[0,1]	1 if individual lives in single family home, 0 otherwise
VPD	Number of vehicles per licensed driver
Accessibility variables	
A_{iEa}, A_{iEt}	Origin (home-end) accessibility to employment, by auto, transit
A_{iRa}, A_{iRt}	Origin (home-end) accessibility to population (housing for DC), by auto, transit
A_{jEa}, A_{jEt}	Destination (work-end) accessibility to employment, by auto, transit
A_{jRa}, A_{jRt}	Destination (work-end) accessibility to population (housing for DC), by auto, transit
D_{io}	Distance (Km) between origin (home-end) and IDS Tower (miles, White House)
D_{jo}	Distance (Km) between destination (workplace) and IDS Tower (miles, White House)
T_W	Time spent at work
T_E	Travel time to work
WT	Number of work trips (a trip that had work or work-related as its destination)

Chapter 2: Telecommuting and its Relationships with Travel and Residential Choices: Exploration of the 2000 and 2010 Regional Travel Surveys in the Twin Cities

2.1 Introduction

It is well perceived that information and communication technologies (ICTs) have had pervasive impacts on modern society - they are changing how and where we work, shop, and in other ways live our lives. Conceptual and empirical studies in the field of ICT and transportation suggest that telecommuting may interact with travel behavior in four ways: substitution, complementarity, modification, and neutrality (Mokhtarian, 1990; Salomon, 1986). *Substitution* denotes that an individual works at home instead of making a physical trip to her workplace. *Complementarity* means that telecommuting generates new demands for other non-work trips. *Modification* denotes that telecommuting does not affect the total amount of physical travel but changes the characteristics of trips such as mode choice, timing, and chaining. *Neutrality* means that telecommuting has no impacts on travel behavior. Among the four ways, planners are the most interested in substitution because it has the potential mitigate traffic congestion during peak hours.

The relationships between telecommuting and travel behavior vary based on the measures of travel behavior. For example, an individual replaces a commute trip by working at home, but she makes another nonwork trip because of time savings from not making the commute trip. In this case, the former represents a substitution effect and the latter is a complementary effect. The net effect of telecommuting on total travel is dependent on the characteristics of the commute and nonwork trips. If the nonwork trip is longer than the commute trip, the net effect is complementarity. If the nonwork trip is shorter than the commute trip, the net effect is substitution. If the two trips have the same length but take place at different times (such as peak vs. non-peak hours), the net effect can be classified as modification.

Significant research has been conducted to understand the impact of ICTs on where work is done and how this affects travel. Not surprisingly, previous studies offer mixed results. Pendyala et al. (1991) found that telecommuters not only reduced commute trips, but also chose non-work destinations close to their home. By contrast, Gould and Golob (1997) found that telecommuters generated new non-work trips, which offset the benefits of saved commute trips. Using aggregate data from the U.S. Consumer Expenditure Survey, Choo et al. (2007) found that ICTs substituted transportation but also complemented it.

Endogeneity issue has recently complicated the relationships between telecommuting and travel behavior. Several studies have found that telecommuting is positively associated with commute distance (Mokhtarian et al., 1995; Zhu, 2012). Because researchers are unsure about which comes first, telecommuting or residential location, the association may result from two potential causal mechanisms. One is that individuals choose to telecommute because they want to reduce the cost associated with their long commute distance and the rival is that individuals choose to live farther away from their workplaces because they are able to telecommute (Ory and Mokhtarian, 2006). The endogeneity arises because the direction of influence is unknown. Using the 2001 and 2009 National Household Travel Survey (NHTS), Zhu (2012) explored the impacts of telecommuting on travel behavior. He addressed the endogeneity issue using the instrument variable approach. Specifically, he used the use of the Internet as an instrument to predict the probability of telecommuting, and then used the predicted probability of telecommuting to explain travel behavior. He found that telecommuting has positive associations with the following behavioral variables: one-way commute distance, one-way commute duration, total work-trip distance, total work-trip duration, total work-trip frequency, total non-work-trip distance, total non-work-trip duration, and total non-work-trip frequency. Overall, he concluded that telecommuting increases travel, rather than reduces travel.

Telecommuting not only affects telecommuters' travel behavior but also has the potential to impact other household members' travel (Zhu, 2013). The ability of telecommuting may motivate a household to move closer to the workplace of non-telecommuting household members and hence reduce their commute distance. On the other hand, to meet a household's preference for other amenities (such as school quality), the ability of telecommuting may incentivize the household to move farther away from the workplace of non-telecommuting household members and hence increase their commute distance. Using the 2001 and 2009 NHTS, Zhu (2013) found that although for two-worker households, telecommuting households tended to have longer total commute distance and time than non-telecommuting households, the ability of telecommuting of one household member did not affect the commute distance of the other household member. The impacts of telecommuting on total work trips and total trips are not addressed in this study.

This study adapts the approaches of (Zhu, 2012, 2013) to examine the impacts of telecommuting on travel behavior in the Minneapolis-St. Paul metropolitan area (Twin Cities). Using the 2000 and 2010 Travel Behavior Inventory (TBI), it aims to addressing the following research questions: (1) How do telecommuters and non-telecommuters differ from each other in terms of demographic and land use characteristics? (2) To what extent does telecommuting replace or complement auto use? (3) How does telecommuting affect residential location choice (commute distance)? (4) How have the relationships evolved between 2000 and 2010?

2.2 Data and Variables

The data used in the study come from the 2000 and 2010 TBIs, which are regional travel surveys conducted by the Metropolitan Council (the Metropolitan Planning Organization in the Twin Cities). Travel behavior variables include one-way commute distance, vehicle kilometer traveled (VKT), and vehicle hour traveled (VHT). VHT was derived based on the self-reported duration in travel diaries. Commute distance and VKT were based on the shortest path from trip origin to destination in the road network. Both surveys include samples from the seven core counties collar counties of the Twin Cities. Because the quality of road network data outside of the Twin Cities are inferior to that in the Twin Cities, this study considers only the households that live and work within the seven-county area. To explore the impact of telecommuting on other household members, we divide the whole sample into two subsamples:

one-worker households and multiple-worker household. In this study, a worker is defined as someone who is identified as a worker in the person table (self-reported). It differs from the definition in Task 3: someone who made a work or work-related trip on travel day. The number of workers in this study is much larger than that in Task 3. The results are not directly comparable.

Table 2.1 describes the differences in travel behavior variables between the two TBIs. For the one-worker households, commute distance, workers' average VKT and household average VKT in 2010 are lower than those in 2000; that is, travel distances decrease. However, both of the travel durations have increased from 2000 to 2010. For the two (or more)-worker households, both of the travel durations have also increased over the period. Commute distance in 2000 is also higher than that in 2010. However, there are no significant differences in workers' average VKT and household average VKT. Overall, from 2000 to 2010, travel durations have increased whereas distance-based travel behavior measures have either decreased or remained unchanged.

Both the 2000 and 2010 TBIs include two questions related to telecommuting. Specifically, respondents were asked to indicate whether they have ever worked from home instead of traveling to their usual workplace and how often they have done so. Table 2.2 illustrates telecommuting frequencies in the 2000 and 2010 TBIs. Consistent with the literature, telecommuters in this study are defined as those who work from home instead to traveling to their workplace for at least once a week. For the one-worker households, the share of telecommuting households has increased from 13.1 percent in 2000 to 15.1 percent in 2010. The difference is statistically significant (with a p-value of 0.024). Other telecommuting frequency categories also show increases over the 10-year period. The two (or more)-worker households share the same patterns as the one-worker households.

Table 2.1. Description of key travel behavior variables

Travel Behavior	**One-worker Households**			**Multiple-worker Households**		
	2000	2010	P-value	2000	2010	P-value
Commute distance (km)	17.3	16.4	0.091	19.0	17.9	0.008
Number of observations	1414	4109		2076	4491	
Workers' average VKT	50.2	45.8	0.000	43.4	42.0	0.105
Number of observations	1950	3986		2615	4689	
Workers' average VHT	1.51	1.59	0.030	1.39	1.54	0.000
Number of observations	2038	4133		2653	4761	
Household average VKT	41.3	37.7	0.001	37.7	37.52	0.553
Number of observations	2058	4194		2624	4703	

Household average VHT	1.28	1.36	0.007	1.22	1.38	0.000
Number of observations	2090	4273		2655	4770	

Notes: workers' average VKT (or VHT) = daily VKT (or VHT) of all workers / the number of workers; household average VKT (or VHT) = daily VKT (or VHT) of all household members / the number of all members.

Table 2.2. Telecommuting frequencies

	One-worker Households				Multiple-worker Households			
	2000		2010		2000		2010	
Telecommuting frequency	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Telecommuters								
4-5 days per week	166	6.9	262	5.8	281	10.0	369	7.6
Once per week or more	153	6.3	423	9.3	294	10.5	756	15.6
Non-telecommuters								
Once per month or more	155	6.4	488	10.7	285	10.2	947	19.6
A few times per year or more	82	3.4	288	6.3	143	5.1	488	10.1
Once a year	15	0.6	11	0.2	29	1.0	22	0.5
Never	1864	76.6	3079	67.7	1769	63.2	2261	46.7
Total	2435	100	4551	100	2801	100	4843	100

It is worth noting that the shares of telecommuters in the 2000 and 2010 TBIs are much higher than national average. Telecommuters account for 4.6 percent of workers in the 2001 and 2009 NHTS (Zhu, 2013). The American Community Survey shows that the share of telecommuters is 4.4 percent in 2012. The overrepresentation of telecommuters in the TBIs is partly because the data include a disproportional share of highly educated workers. For the one-worker households, the proportion of workers with college degrees or higher is about 50 percent in both 2000 and 2010.

The data include a list of demographic variables including household income, household size, the number of children (under 6 years old) in the household, car ownership per licensed driver, age, education, gender, being disabled, being a student, having a driver's license, having multiple jobs, and working hours for primary job.

We also developed two land use variables: the number of jobs per worker within a 10-mile buffer (job-worker ratio) and population density within a half-mile buffer (population density). We assume that they will affect worker's decisions to telecommute and use private automobiles.

2.3 Results

2.3.1 Who are telecommuters?

Binary logit models were developed to illustrate demographic and build environment characteristics of telecommuters. I tested all of the demographic characteristics (household income, household size, the number of children (under 6 years old) in the household, car ownership per licensed driver, age, education, gender, being disabled, being a student, having a driver's license, having multiple jobs, and working hours for primary job) described in Section 2, as well as job-worker ratio and population density. The variables significant at the 0.10 level were kept to obtain a parsimonious model. For the one-worker households (Table 2.3), telecommuters tend to have a higher income and a higher education, are older, and are more likely to have multiple jobs than non-telecommuters in both 2000 and 2010. In 2010, telecommuters are positively associated with three more variables: household size, having a driver's license, and having a disability. However, neither of the built environment variables is significant in the 2000 and 2010 models. The impacts of built environment characteristics on hardcore telecommuters (who telecommute 4-5 days per week) were also tested. However, neither of the variables is significant.

Table 2.3. Binary logit models of being telecommuters for one-worker households

	2000		2010	
Variables	**Coefficients**	**P-value**	**Coefficients**	**P-value**
Constant	-4.610	0.000	-6.018	0.000
Income	0.103	0.000	0.059	0.002
Education	0.318	0.000	0.125	0.002
Age	0.011	0.049	0.019	0.000
Having multiple jobs	0.549	0.008	0.729	0.000
Household size			0.172	0.002
Having a driver's license			1.630	0.026
Being disabled			1.069	0.014
Number of observations	2073		2611	
Pseudo R^2	0.047		0.035	

For the multiple-worker households, build environment characteristics and household-level demographics (including household income, household size, the number of children (under 6 years old) in the household, and car ownership per licensed driver) were tested. Income and household size are positively associated with telecommuting in both 2000 and 2010 (Table 2.4). Job-worker ratio has a positive association with telecommuting in both 2000 and 2010. Other variables are insignificant in the models. Overall, workers living in multiple-worker households and job-rich areas are more likely to telecommute than others.

Table 2.4. Binary logit models of being telecommuters for multiple-worker households

	2000		2010	
Variables	**Coefficients**	**P-value**	**Coefficients**	**P-value**
Constant	-2.788	0.000	-2.385	0.000
Income	0.068	0.010	0.048	0.006
Household size	0.133	0.008	0.113	0.003
Job-worker ratio	0.040	0.015	0.030	0.001
Number of observations	1936		3506	
Pseudo R^2	0.010		0.007	

2.3.2 How does telecommuting influence travel behavior?

We first conducted ANOVA with Bonferroni tests. We found that those who telecommute once a week or more (or telecommute four-five days per week) are indifferent from others in terms of travel behavior variables in both years.

We developed regression models to examine the differences in travel behavior between telecommuters and non-telecommuters. For the one-worker households (Table 2.5), telecommuters appear to have larger values for all four travel behavior variables in both years than non-telecommuters. However, in three of the eight models, telecommuting is insignificant at the 0.10 level and their p-values are between 0.1 and 0.2. Specifically, they ae household average VHT in 2010, worker's average VKT in 2000, and workers' average VHT in 2010. In general, telecommuting tends to have a complementary effect on VKT and VHT in both years. The complementary relationships are consistent with Zhu (2012). A further examination shows that there are no differences in home-based work-related travel behavior measures. Therefore, the complementary effect is due to the increase in non-work travel. All of the control variables (if significant) are consistent with my expectation. In particular, car ownership, income, having multiple jobs, and driver's license are positively associated with travel behavior variables whereas household size, women, job-worker ratio, and population density have negative associations with travel behavior variables. Age is negatively associated with travel distance but positively associated with travel time.

However, when it comes to multiple-worker households (Table 2.6), one of the eight variables is has a p-value of 0.06 and other variables are insignificant. In particular, in 2000, telecommuting households tend to have a shorter vehicular distance than non-telecommuting households. Furthermore, car ownership and income are positively associated with travel behavior variables. Household size (if significant) is negatively associated with household travel behavior variables but positively associated with workers' travel behavior variables. Overall, telecommuting has few significant connections with travel behavior variables for multiple-worker households.

Table 2.5. Differences in travel behavior for one-worker households

	Household average VKT				Household average VHT				Workers' average VKT				Workers' average VHT			
	2010		2000		2010		2000		2010		2000		2010		2000	
	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P
Constant	49.67	0.00	58.72	0.00	1.23	0.00	1.24	0.00	31.31	0.00	60.28	0.00	1.23	0.00	1.24	0.00
Telecommuter	2.80	0.05	4.85	0.08	0.09	0.16	0.14	0.04	3.12	0.08	4.99	0.13	0.09	0.16	0.14	0.04
# cars per driver	4.18	0.00			0.18	0.00	0.11	0.01	4.06	0.00			0.18	0.00	0.11	0.01
Household size	-5.62	0.00	-6.38	0.00	-0.19	0.00	-0.17	0.00					-0.19	0.00	-0.17	0.00
Income	0.73	0.00	1.18	0.00	0.02	0.00	0.02	0.00	0.50	0.01	1.21	0.00	0.02	0.00	0.02	0.00
Female			-4.51	0.03			-0.11	0.03	-3.65	0.00	-7.07	0.00			-0.11	0.03
Age	-0.09	0.04					0.00	0.02							0.00	0.02
Driver's license									19.16	0.04						
Having multiple jobs	4.35	0.01			0.17	0.03							0.17	0.03		
Job-worker ratio	-0.95	0.00	-1.88	0.00			-0.02	0.00	-1.34	0.00	-2.59	0.00			-0.02	0.00
Population density	-0.82	0.00	-0.80	0.00					-0.97	0.00	-0.79	0.00				
# observations	0.094		0.087		0.029		0.073		0.089		0.089		0.029		0.073	
Adjusted R2	2956		1508		3436		1477		2844		1444		3436		1477	

Table 2.6. Differences in travel behavior for multiple-worker households

	Household average VKT				Household average VHT				Workers' average VKT				Workers' average VHT			
	2010		2000		2010		2000		2010		2000		2010		2000	
	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P
Constant	28.76	0.00	18.49	0.00	1.06	0.00	0.77	0.00	13.78	0.00	17.90	0.00	0.65	0.00	0.80	0.00
Telecommuter	0.03	0.98	-3.15	0.06	0.05	0.27	-0.02	0.57	-0.09	0.93	-1.37	0.45	0.04	0.42	0.05	0.20
Car ownership	8.36	0.00	9.81	0.00	0.22	0.00	0.15	0.00	10.97	0.00	12.26	0.00	0.26	0.00	0.18	0.00
Household size	-3.86	0.00			-0.10	0.00			1.00	0.03			0.07	0.00		
Income	0.76	0.00	0.79	0.01	0.03	0.00	0.02	0.00	0.96	0.00	1.07	0.00	0.03	0.00	0.03	0.00
# observations	0.045		0.015		0.018		0.009		0.029		0.02		0.012		0.015	
Adjusted R2	3991		2370		4048		2397		3982		2364		4044		2396	

How does telecommuting affect residential location?

In the short run, long commute may motivate workers to choose telecommuting to reduce their commute burden. In the long run, the ability to telecommute may incentivize workers to move farther away from their workplace to enjoy other amenities. If true, telecommuters in one-worker households may have a longer commute than non-telecommuters, all else equal. For multiple worker households, average commute distance between telecommuting households and non-telecommuting households vary. Here, we developed negative binomial models to explore the relationship between telecommuting and commute distance, while controlling for the influence of all of the demographic and built environment variables. Although all demographic and land use variables were tested, the variables significant at the 0.10 level were kept in the final model.

Table 2.7 shows the model for the one-worker households. First, in both 2000 and 2010, telecommuting is not significantly associated with commute distance. In other words, telecommuting has no impact on residential location choice. A list of demographic and land use variables are significant in the model. In both 2000 and 2010, women tend to have a shorter commute distance than men. Affluent workers are more likely to have a long commute than poor workers. Working hours are positively associated with commute distance. In 2000, students tend to have a shorter commute distance than others. In 2010, having a driver's license and the number of children under six years old have positive associations with commute distance. Finally, job-worker ratio and population density are negatively associated with commute distance in 2000 and 2010. The impacts of land use variables on commute distance are consistent with the literature. For the multiple-worker households (Table 2.8), the associations of income, job-worker ratio, and population density with commute distance are the same as those for the one-worker households, respectively. Car ownership is positively associated with average commute distance in 2010. More importantly, telecommuting households tend to have a shorter average commute distance than non-telecommuting households in 2010. If job-worker ratio and population density were manually removed from the 2000 model, the coefficient for telecommuting household would have been significant and negative. The insignificance of telecommuting household in the 2000 final does not mean the gap between telecommuting and non-telecommuting households is getting smaller, the model explains why it is getting smaller. Overall, the results suggest that telecommuting facilitates the coordination of residential location choice in multiple-worker households.

Table 2.7. Negative binomial regression for commute distance for one-worker households

	2000		2010	
Variables	**Coefficients**	**P-value**	**Coefficients**	**P-value**
Constant	3.012	0.000	2.609	0.000
Telecommuter	0.049	0.517	-0.023	0.603
Income	0.020	0.007	0.011	0.028
Number of kids under 6			0.061	0.085
Having a driver's license			0.282	0.006
Being a student	-0.225	0.003		
Women	-0.094	0.027	-0.096	0.002
Primary job working hours	0.005	0.053	0.005	0.000
Job-worker ratio	-0.071	0.000	-0.040	0.000
Population density	-0.031	0.000	-0.028	0.000
Alpha	0.369	0.000	0.553	0.000
Number of observations	1056		2804	

Table 2.8. Negative binomial regression for average commute distance for multiple-worker households

	2000		2010	
Variables	**Coefficients**	**P-value**	**Coefficients**	**P-value**
Constant	3.032	0.000	2.735	0.000
Telecommuting household	-0.033	0.427	-0.076	0.002
Income	0.024	0.003	0.029	0.000
cars per driver			0.087	0.003
Job-worker ratio	-0.057	0.000	-0.038	0.000
Population density	-0.039	0.000	-0.031	0.000
Alpha	0.346	0.000	0.288	0.000
Number of observations	1506		3253	

2.4 Conclusions

This study uses the 2000 and 2010 travel behavior inventories to examine telecommuting and its connections with travel behavior and residential choice. One-worker households and multiple-worker households were differentiated to study the interactions among employed household members. Here travel behavior is measured as workers' average VKT and VHT and household average VKT and VHT. Residential choice is measured as average commute distance.

First, the data show that the share of telecommuters has increased from 2000 to 2010 whereas workers' and household average travel times have increased during the same period. Workers' and household average VKT has decreased for the one-worker households but remained unchanged for the multiple-worker households.

For the one-worker households, telecommuters tend to be more affluent, more highly educated, older, and more likely to have multiple jobs than non-telecommuters in both 2000 and 2010. For the multiple-worker households, telecommuting households tend to be more affluent and have more household members than non-telecommuting households in both years. Furthermore, telecommuters in multiple-worker households tend to live in job-rich areas (within a 10-mile buffer from their residence) than non-telecommuters.

In general, telecommuting has limited impacts on travel behavior of multiple-worker households. However, for one-worker households, telecommuting is positively associated with most travel behavior variables in 2000 and 2010. Therefore, telecommuting tends to complement travel and the increase is mainly due to non-work travel.

Telecommuting has no influences on commute distance for the one-worker households but has a negative association with average commute distances for the multiple-worker households. This suggests that the ability of one worker to telecommute may motivate the household to seek a location closer to the workplace of other household members and hence leads to a decrease in average commute distance.

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Chapter 3

Transit Service Quality and Transit Use

3.1 Introduction

The Twin Cities transit system changed dramatically between 2000 and 2010. One major driver of these changes is a desire on the part of the Metropolitan Council and local governments in the region for transit to carry an increasing share of trips. Service improvements such as the implementation of Light Rail Transit (LRT) and the creation of the Hi-Frequency Network of bus-routes with all-day frequent service aim to further this end by attracting increased ridership—assuming (not without reason) a direct proportionality between transit service and transit use. Is that relationship stable, though, or can it change if some tipping-point service level is reached? The task described in this chapter explores that question both at the trip level and at the person level. In both cases, we employ logistic regression to explain the probability of a traveler using transit as a function of transit service (as well as built environment, social, economic and demographic factors) in both 2000 and 2010. At the trip level, our model estimates the probability of a one-way trip including a transit leg. The corresponding models at the person level estimate the probability of a person using transit at least once during their travel day.

We measure “transit service” not in terms of daily runs or raw travel times, but in terms of cumulative opportunity accessibility to jobs *within* 30 minutes’ travel time. This approach considers what can be achieved through a certain amount of transit travel rather than simply how much transit travel can be achieved in a certain amount of time (Cervero, 1997). It is important to note that this approach considers both the speed of travel and the density of destinations. As a result, increasing one key determinant of accessibility tends to decrease another. However, a recent analysis of 52 metropolitan regions throughout the United States found that proximity to destinations advances the cause of accessibility in practice more so than high travel speeds (Levine, Grengs, Shen, & Shen, 2012). Accessibility by various modes strongly predicts mode choice—even in the absence of traditionally included social and demographic variables (A. Owen & Levinson, 2013). In fact, in a region with significant variation of transit accessibility levels, strong, automobile-dominated suburban employment centers and a growing suburbanization of poverty, social and demographic factors may be insufficient to predict transit use: no matter how poor one may be, one cannot commute by transit if there is no service connecting one’s home and workplace (Fan, 2012; Glaeser, Kahn, & Rappaport, 2008). Inconsistent transit job accessibility by residential location and socioeconomic status is a particular problem in American metropolises (Shen, 2006), which tends to constrain non-automotive travel options and employment opportunities for those without access to a car (Grengs, 2010). The use of accessibility as a measure of service also fits with transit improvements implemented in the Twin Cities region between the 2000 and 2010 TBIs. Research specifically focused on the Metro Blue Line found significant regional accessibility improvements associated with light rail implementation and associated bus service changes—improvements shared across income groups. Accessibility improvement also accrued primarily from the changes in transit service, not from any shift in regional employment patterns (Fan, Guthrie, & Levinson, 2012). Research on the accessibility and social equity implications of improvements to the Toronto transit system reaches broadly similar findings of improving regional accessibility, with particular gains for disadvantaged areas (Foth, Manaugh, & El-Geneidy, 2013). Although accessibility does not exclusively measure transit service *quantity*, it offers a measure of transit service *quality* that more closely corresponds with the utility of transit travel, and can be expected to reflect service improvements.

The following sections describe the study areas and universe of trips and people considered, provide cross tabulations and descriptive statistics on the trips and people included in the analysis, as well as the results of the estimated regression models. The chapter concludes with discussion of the implications modeling results.

3.2 Trip-Level Model

At its most basic level, the region's transit use can be broken down into a pattern of individual trips, or, more precisely, individual trips involving a transit leg. The first model we consider predicts the probability of transit use at the trip level; the response variable is binary, with a value of 1 if transit is the mode of at least one leg of a trip, and a value of 0 otherwise. This model provides the finest scale possible, with the impacts of individual trip purposes and origins/destinations included. It also implicitly assumes that an individual's mode choices throughout the day are independent of each other.

3.2.1 Study Area and Trips Considered

Transit differs from other modes in that it is only available in part of the region. It would not be appropriate to include trips which could not reasonably be made using transit in a model predicting mode choice—in such cases, whether to use transit is not a choice. Park-and-ride lots can extend the effective transit-served area, but represent an option unavailable to travelers without a motor vehicle. In addition, according to the Metropolitan Council's 2030 Park-and-Ride Plan, "Over 70% of park-and-ride users reside within the transit taxing district (TTD)." (*2030 Park-and-Ride Plan*2010), indicating that relatively few park-and-ride trips originate at extreme distances from transit stops. Also, of all trips in the TBI including a transit leg, a relatively small proportion has non-motorized access and egress modes in both years (96 of 734 in 2000 and 312 of 2,378 in 2010). The trip model does not exclude park-and-ride trips, but focuses primarily on trips that *could* be made with non-motorized access and egress modes. For these reasons, we focus on trips with origin *and* destination points within 800M (0.5mi) network distance of a transit stop.

Table 3.1 shows the total number of trips in the TBI dataset, with origins and destinations in the seven-county metro area, with O/D points in the study area, along with the portion of the trips which included a transit leg for 2000 and 2010. It also includes the total number of observations and transit trips participating in our model. In both years, a majority of metro trips fall within the study area. In both years, a small share of transit trips has origin and destination points outside the defined service area. Despite the presence of these trips, the model's focus on trips beginning and ending in areas with relatively high densities of transit trip origins and destinations maximizes our ability to effectively the transit mode.

Table 3.1: Trips in Study Area

Year	Total	7-County	Used Transit, All	Used Transit, Outside Svc. Area	Transit Served*	Served, used transit	In trip model	In trip model, used transit
2000	56,811	34,593	734	240	23,435	494	20,321	438
2010	115,821	94,645	2,378	569	55,203	1,809	45,940	1,541

*O & D within 800M (0.5mi) of transit

3.2.2 Traveler and Trip Characteristics

Figure 3.1 shows the distribution of trips that used transit by transit accessibility at origin and destination in both years. In all cases, we use the cumulative opportunity approach, with a 30-minute cutoff time; the number reported represents the total number of jobs reachable by a walk-ride transit user in 30 minutes or less total travel time. Accessibility offers a direct measure of the potential utility of transit in a given location, and serves as our transit service measure. It is important to bear in mind the fact that the large “0-10,000” bar in each graph is partly a consequence of express routes which run on the freeway system for more than 30 minutes without stopping. By definition, these routes have zero 30-minute accessibility. Regarding the remainder of the graphs, transit trip origins are less likely to have very high accessibility than destinations. The pattern differs markedly for 2010, with origins’ and destinations’ accessibility much more similar, and an apparent trend towards greater percentages of trips occurring between locations with high transit accessibility. (It is important to note that this shift could indicate transit users adjusting their travel to the transit system, the transit system adjusting to travel patterns, or some combination of both.)

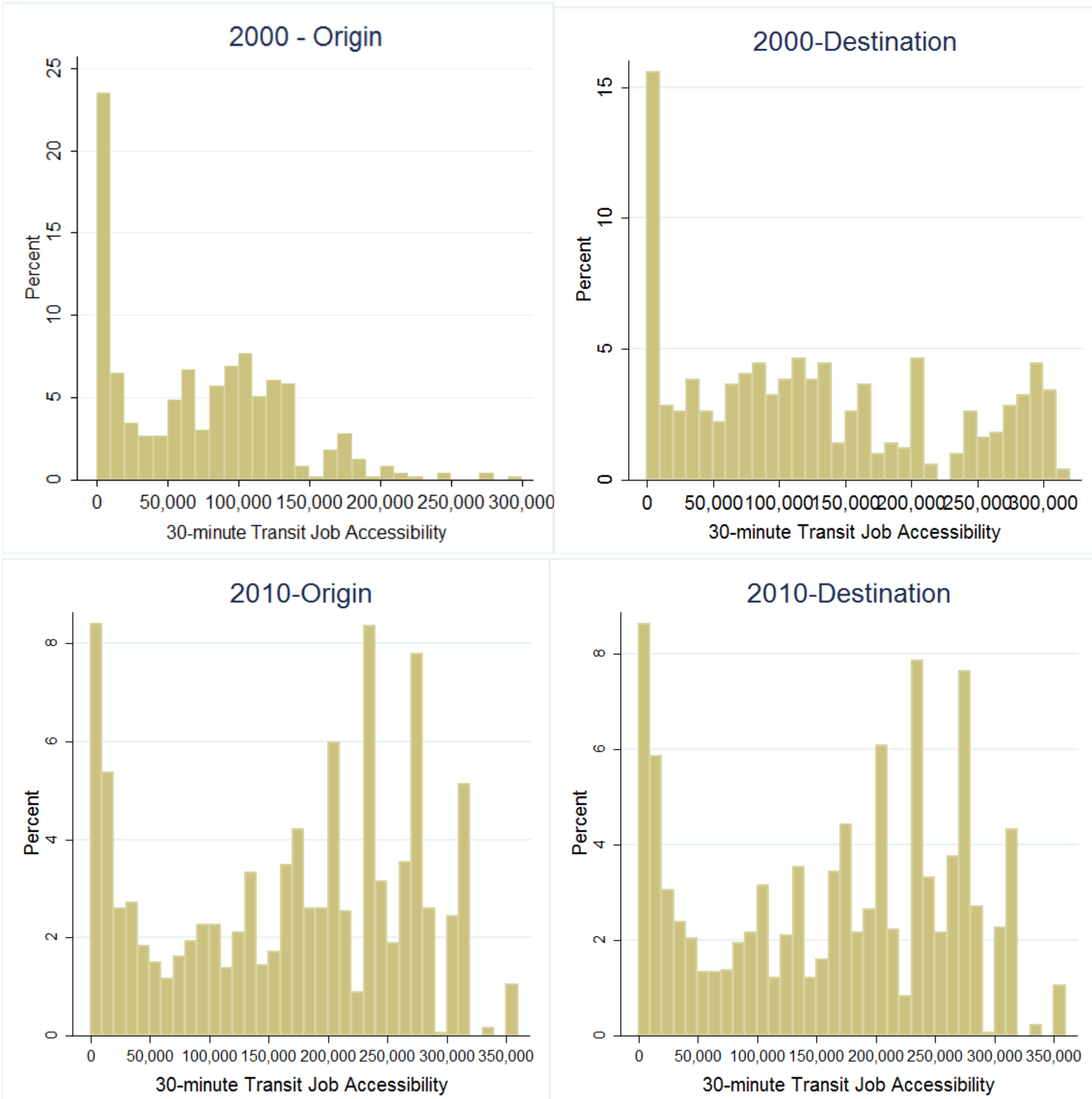

Figure 3.1: Transit Trips by Origin/Destination Accessibility

Table 3.2 shows transit use rates by traveler and trip characteristics in both study years. In addition to the overall trend of transit use rates increasing in general, trips and travelers with certain specific characteristics show particular increases in their probability of using transit between 2000 and 2010. Travelers ages 18-39 use transit for 6% of their trips, and 14% of trips with origins or destinations in either central business district include a transit leg in 2010, compared with 3% and 7%, respectively in 2000. Travelers in lower and moderate-income household categories also show significant gains in transit use, though high-income travelers and licensed drivers show increased transit use as well. Longer (in terms of shortest-path network distance) trips are also more likely to use transit in 2010.

Table 3.2: Cross tabulation of Transit Use and Trip/Traveler Characteristics

		2000			2010		
		Used Transit		Total Number	Used Transit		Total Number
		No	Yes		No	Yes	
	<18 yrs old	99%	1%	4,445	99%	1%	6,114
	18-39 yrs old	97%	3%	7,043	94%	6%	10,840
	40-64 yrs old	98%	2%	9,725	97%	3%	27,325
	65+ years old	98%	2%	2,222	98%	2%	10,924
	Licensed driver	98%	2%	19,550	97%	3%	48,162
	Not licensed driver	96%	4%	3,287	94%	6%	7,103
	AM peak departure	96%	4%	4,057	94%	6%	9,816
	Mid-day departure	99%	1%	7,885	98%	2%	19,450
	PM peak departure	97%	3%	6,971	96%	4%	16,684
	Evening departure	100%	0%	4,165	99%	1%	8,635
	CBD origin	93%	7%	233	86%	14%	3,549
	Non CBD origin	98%	2%	23,202	97%	3%	51,654
	CBD destination	93%	7%	2,133	86%	14%	3,550
	Non CBD destination	98%	2%	21,302	97%	3%	51,653
	Network distance <= 800M (0.5mi)	99%	1%	4,300	99%	1%	7,840
	Network distance >800M (0.5mi), <=3.2kM (2mi)	98%	2%	5,454	98%	2%	14,707
	Network distance >3.2kM (2mi), <=16.1kM	97%	3%	10,442	96%	4%	26,120
	Network distance >16.1kM (10mi)	98%	2%	3,239	95%	5%	6,536
	Worker	97%	3%	15,815	96%	4%	30,540
	Non worker	99%	1%	7,125	98%	2%	24,663
	Student	98%	2%	4,289	97%	3%	9,435
	Non student	98%	2%	18,503	97%	3%	45,768
	Female	98%	2%	12,674	97%	3%	30,545
	Male	98%	2%	10,761	97%	3%	24,617
	Cars in household >= drivers	99%	1%	20,012	98%	2%	46,808
	Drivers in household > cars	93%	7%	3,423	90%	10%	8,395
Household Income	< $5,000	96%	4%	107	81%	19%	383
	$5,000 - $10,000	83%	17%	144	84%	16%	403
	$10,000 - $15,000	92%	8%	311	87%	13%	757
	$15,000 - $20,000	96%	4%	615	91%	9%	905
	$20,000 - $25,000	95%	5%	945	94%	6%	1,245
	$25,000 - $30,000	97%	3%	763	96%	4%	1,473
	$30,000 - $35,000	96%	4%	860	95%	5%	1,202
	$35,000 - $40,000	98%	2%	745	96%	4%	1,237
	$40,000 - $45,000	97%	3%	791	94%	6%	1,283
	$45,000 - $50,000	99%	1%	1,453	97%	3%	2,008
	$50,000 - $60,000	98%	2%	3,258	97%	3%	3,661
	$60,000 - $75,000	99%	1%	3,546	98%	2%	6,011
	$75,000 - $100,000	98%	2%	3,803	97%	3%	9,404
	$100,000 - $150,000	99%	1%	2,491	98%	2%	10,272
	>= $150,000	99%	1%	1,252	98%	2%	5,796

3.2.3 Regression Analysis

In the next phase of the research task, we estimated a pooled logistic regression model to explain the probability of a given trip including a transit leg as a function of transit accessibility, trip characteristics, traveler characteristics and the built environment at origin and destination. The pooled regression approach allows for the use of Chow tests to identify structural breaks in the data—statistically significant changes in the relationship between the probability of transit use and various explanatory variables between 2000 and 2010. The response variable is Used Transit—a binary variable with a value of 1 if at least one segment of the trip used transit, and a value of 0 otherwise. The logistic regression employed uses the following explanatory variables to predict the probability that Used Transit will have a value of 1 under each of their possible values.

<18 years old, 40-64 years old, 65+ years old—Binary variables identifying travelers' ages. Included due to potential generational differences in transit use. Negative coefficients expected. (Note: 18-39 is omitted as the reference; the preceding variables compare a member of their age group to an 18-39 year old.)
Licensed driver — Binary variable identifying travelers with a driver's license. Included as a measure of access to a private vehicle. Negative coefficients expected.
Population density at origin, Population density at destination —The density of population, in people per square kilometer in census blocks within 800M (0.5mi) of the trip origin and destination. Included to account for normally higher transit use and service levels in dense areas. Positive coefficients expected.
Average temperature on travel day—The average temperature on the day of travel, in degrees Fahrenheit. Included to account for the Minnesota climate. Positive coefficients expected.
Precipitation—Binary variable identifying travel days with precipitation. Included to account for possible losses of choice riders in inclement weather. Negative coefficients expected.
30-minute transit accessibility at origin, 30-minute transit accessibility at destination —The 30-minute, cumulative opportunity jobs accessibility at the trip origin/destination, in units of ten thousand jobs. Included as a measure of transit service. Positive coefficients expected.
Origin/Destination within 800M (0.5mi) of express route/limited stop route/light rail/ commuter rail—Set of non-exclusive binary variables identifying trips with origins and/or destinations within one half mile network distance of the type of premium transit service in question. Included as measures of the attractiveness of transit. Positive coefficients expected.
% Retail area at origin, % Retail area at destination, % Office/Institutional area at origin, % Office/Institutional area at destination—The percentage of the area of the block group containing each origin/destination occupied by retail and office or institutional land uses. Included as a measure of land use mix. Positive coefficients expected.
School destination activity, Utilitarian personal destination activity, Non-utilitarian personal destination activity, Home destination activity—Binary variables identifying the travelers' reported activity at the trip destination. Included as a measure of trip purpose, with work omitted as the reference. Negative coefficients expected.
Female—Binary variable identifying a female traveler. Included due to historically high rates of transit use among women in the Twin Cities. Positive coefficients expected.
Mid-day departure, PM peak departure, Evening departure—Binary variables included to identify the time of day at which the trip was made. Included to account for changing transit service levels. AM peak is excluded as the reference. Negative coefficients expected.

Household income—Ordinal variable for traveler's household income (A. Owen, Schoner, & Levinson, 2013, p. 30). Included due to higher rates of transit use among low-income people. Negative coefficients expected.

Origin stop distance, Destination stop distance—The shortest path network distance, in meters, from the trip origin/destination to the nearest transit stop. Included as a measure of transit service. Negative coefficients expected.

One-person household, Children under 6 in household, Children 6-17 in household—Binary variables identifying household type. Included due to differing travel patterns of different types of households. Positive coefficients expected for the former, negative for the latter two.

Worker, Student—Binary variables identifying workers and students. Included due to high rates of transit use for regular work/school commutes. Positive coefficients expected.

Household vehicles/household drivers—The ratio of motor vehicles to drivers in the traveler's household. Included as a measure of access to a private vehicle. Negative coefficients expected.

Network distance <= 800M (0.5mi), Network distance > 800M (0.5mi), <= 3.2kM (2mi)—Binary variables identifying short trips for which non-motorized modes may compete with transit. Trips longer than 2 miles are excluded as the reference. Negative coefficients expected.

Home-based trip—Binary variable identifying trips with a home origin activity. Included due to higher popularity of transit for simple rather than complex trip patterns. Positive coefficients expected.

Descriptive Statistics

Table 3.3 shows descriptive statistics for the variables and observations included in the model. Mean transit accessibility increases between 2000 and 2010 for both origins and destinations. Mean stop distance declines slightly for origins, but increases slightly for destinations. The two measures of automobile access, licensed driver and household vehicles/household drivers, show very little change. The rate of employment shows a predictable decline, likely due to the recession. Measures of the built environment, such as land uses and trip network distances show little change, as do surrounding population characteristics. Other than growth in the rate of transit use, trip characteristics change relatively little as well, with mid-day and pm peak departures slightly more common in 2010, at the expense of evening departures. In 2010, travelers also experienced lower average temperatures, along with fewer days with rainfall and more with snowfall.

Table 3.3: Descriptive Statistics

	2000		2010	
Variable	**Mean/%**	**Std. Dev.**	**Mean/%**	**Std. Dev.**
Used Transit	2.16%	14.52%	3.35%	18.01%
Origin Stop Distance (m)	262.5888	201.4468	209.6527	199.8378
Destination Stop Distance (m)	140.7875	164.9225	210.7790	203.6994
Origin Job Accessibility (‘0,000)	3.3995	4.6101	8.4678	8.7778
Destination Job Accessibility (‘0,000)	5.6882	7.2524	8.4403	8.7734
Origin Hi-Frequency Served	17.56%	38.05%	26.54%	44.15%
Dest. Hi-Frequency Served	27.98%	44.89%	26.41%	44.09%
Origin Express Served	58.72%	49.23%	57.49%	49.44%
Dest. Express Served	68.06%	46.63%	57.45%	49.44%
Origin Ltd-Stop Served	19.04%	39.27%	39.20%	48.82%
Dest. Ltd-Stop Served	29.43%	45.58%	39.11%	48.80%
Origin LRT Served	1.24%	11.07%	5.84%	23.45%
Destination LRT Served	8.39%	27.72%	5.86%	23.49%
Origin CR Served	0.19%	4.38%	0.99%	9.88%
Destination CR Served	1.27%	11.20%	1.01%	10.01%
Origin Population Density	7.1508	4.7089	7.0864	5.0894
Dest. Population Density	6.2369	4.9354	7.0611	5.0837
Origin % Retail Use	5.09%	8.31%	10.56%	14.67%
Destination % Retail Use	13.60%	16.98%	10.63%	14.70%
Origin % Office/Institutional Use	6.03%	8.66%	10.68%	12.52%
Dest. % Office/Institutional Use	12.35%	15.17%	10.63%	12.43%
Kids Under 6 in Household	10.97%	31.25%	11.97%	32.46%
Kids 6-17 in Household	32.98%	47.01%	33.21%	47.10%
One-Person Household	19.60%	39.70%	19.02%	39.24%
Licensed Driver	84.86%	35.85%	86.77%	33.89%
Cars/Drivers	104.74%	42.77%	103.17%	44.10%
Student	18.55%	38.87%	17.75%	38.21%
Worker	70.36%	45.67%	56.45%	49.58%
Household Income	9.8286	3.1685	10.6834	3.2568
Female	53.53%	49.88%	55.15%	49.73%
Age Under 18	16.01%	36.67%	11.71%	32.16%
Age 40-64	43.07%	49.52%	50.07%	50.00%
Age 65 and Over	8.41%	27.75%	17.93%	38.36%
Average Temperature	69.4753	10.9061	49.6140	22.6442
Precipitation	10.32%	29.15%	7.92%	24.54%
School Destination	1.81%	13.32%	3.98%	19.54%
Utilitarian Personal Dest.	33.22%	47.10%	30.48%	46.03%
Non-Utilitarian Pers. Dest.	14.80%	35.51%	15.60%	36.29%
Home Destination	32.18%	46.72%	30.30%	45.95%
Mid-Day Departure	33.03%	47.03%	34.60%	47.57%
Pm-Peak Departure	29.90%	45.78%	30.46%	46.03%
Evening Departure	18.13%	38.53%	15.79%	36.47%
Trip <= 800M (0.5mi)	18.26%	38.63%	14.28%	34.98%
Trip > 800M (0.5mi), <= 3.2kM (2mi)	23.26%	42.25%	26.67%	44.23%
Home-based Trip	64.69%	47.79%	60.84%	48.81%

Table 3.4: Binary Logistic Regression Models of Probability a Trip uses Transit —Modes and Built Environment

	2000		2010	
	Observations	20,321	Observations	45,940
	Pseudo R2	0.3061	Pseudo R2	0.335
	Coefficient	***Odds Ratio***	***Coefficient***	***Odds Ratio***
Origin Stop Dist.	-8.95e-4***	0.9995	-9.75e-4***	0.9995
Destination Stop Dist.	-8.25e-4*	0.9995	-7.15e-4***	0.9996
Origin Hi-Frequency Served	0.1059	1.1117	0.3712***	1.4495
Dest. Hi-Frequency Served	0.0894	1.0936	0.2985***	1.3479
Origin Express Served	-0.3910***	0.6764	0.0578	1.0595
Dest. Express Served	0.3304**	1.3916	-0.0776	0.9253
Origin Ltd-Stop Served	0.2443*	1.2767	0.2376***	1.2682
Dest. Ltd-Stop Served	0.4265***	1.5319	0.1801**	1.1973
Origin LRT Served	0.9857***	2.6796	1.0251***	2.7873
Destination LRT Served	0.3225*	1.3806	0.9733***	2.6467
Origin CR Served	0.0957	1.1004	0.1671	1.1819
Destination CR Served	-0.3322	0.7173	0.0790	1.0822
Origin Population Density	0.0315***	1.0320	0.0159**	1.0161
Dest. Population Density	0.0390***	1.0397	0.0162***	1.0164
Origin % Retail Use	-1.1004*	0.3328	1.1904***	3.2885
Destination % Retail Use	0.8339**	2.3024	1.0031***	2.7267
Origin % Office/Institutional Use	0.6359	1.8887	1.3311***	3.7852
Dest. % Office/Institutional Use	-0.9096**	0.4027	1.1470***	3.1487
Kids Under 6 in Household	-1.0916***	0.3357	-0.1358	0.8730
Kids 6-17 in Household	-0.2541	0.7756	0.0219	1.0221
One-Person Household	0.2577*	1.2940	0.0686	1.0710
Licensed Driver	-1.6286***	0.1962	-1.5064***	0.2217
Cars/Drivers	-2.1155***	0.1206	-1.2429***	0.2885
Student	0.0141	1.0142	0.5096***	1.6647
Worker	0.4884**	1.6298	0.1762**	1.1927
Household Income	-0.0275	0.9728	-0.0984***	0.9063
Female	0.1145	1.1213	0.0037	1.0037
Age Under 18	-1.1069***	0.3306	-2.3213***	0.0981
Age 40-64	-0.1244	0.8830	0.0101	1.0101
Age 65 and Over	-0.1576	0.8542	-0.5218***	0.5934
Average Temperature	0.0105**	1.0105	-0.0034**	0.9966
Precipitation	0.0630	1.0650	0.4509***	1.5698
School Destination	-0.0849	0.9186	0.0699	1.0724
Utilitarian Personal Dest.	-0.2299	0.7946	-0.7641***	0.4658
Non-Utilitarian Pers. Dest.	-1.0758***	0.3410	-0.7914***	0.4532
Home Destination	0.2651	1.3036	-0.1546	0.8568
Mid-Day Departure	-1.1265***	0.3242	-0.6508***	0.5216
Pm-Peak Departure	-0.5271***	0.5903	-0.2523**	0.7770
Evening Departure	-2.4634***	0.0851	-1.2300***	0.2923
Trip <= 800M (0.5mi)	-1.4738***	0.2290	-3.4175***	0.0328
Trip > 800M (0.5mi), <= 3.2kM	-1.0043***	0.3663	-1.3930***	0.2483
Home-based Trip	-0.0750	0.9277	0.3737***	1.4531
Constant	-0.8032		-0.2638	

Legend: *p<0.1; **p<0.05; ***p<0.01

Regression Model

Tables 3.4 and 3.5 show the results of the regression models. The relationship of transit use to both overall levels of transit service (measured here in terms of accessibility) and specifics of transit modes and surrounding built environment characteristics are of potential interest for future transit planning in the region; however, transit accessibility, transit mode and surrounding built environment characteristics are strongly correlated. As a result, we present two trip-level models: one considering modes and the built environment and one considering accessibility. Logistic regression results are most easily interpreted through the use of odds ratios. Odds ratios measure the difference in the probability of the response variable having a value of 1 associated with one unit of change in each explanatory variable. For example: Origin within 800M (0.5mi) of LRT station in the 2010 modes/built environment model has an odds ratio of roughly 2.6—meaning that, all else equal, a trip with an origin in a light rail station area is 2.6 times as likely to use transit as a trip from a non-station area origin. Odds ratios are always positive; values less than one indicate a negative coefficient. For example—a non-utilitarian personal destination activity in both 2000 models has an odds ratio of roughly 0.34, meaning that, all else equal, a trip with such a destination activity is just over *one-third* as likely to use transit as a trip with the reference destination activity, work.

Except for the inclusion of either origin/destination transit modes and built environment characteristics or origin/destination accessibility, the model results are striking in their similarity. Of the variables that participate in both models, few show any material change in either significance or coefficients between the two modeling approaches. The modes/built environment model produces a slightly higher pseudo R^2 in 2000, while the accessibility model's goodness of fit is better in 2010.

Origin and destination accessibility are significant and positive in both years for the accessibility model. With means ranging from 33,000 to 85,000 jobs and a unit of 10,000 jobs, the potential range of variation in predicted transit use is large. Stop distance is significant and negative in all cases except for trip origins in the 2000 accessibility model. Trip origins and destinations within 800M (0.5mi) network distance of a light rail station are significant and positive in both years for the modes/built environment model. (In 2000, this variable measures presence in what would become a station area following light rail implementation.)

Licensed driver and household vehicles/household drivers are both significant and negative in both years and models, but less negative in 2010 than in 2000. For instance, a trip made by a member of a household with twice as many drivers as cars in 2000 would be roughly eight times as likely to use transit as a trip made by a member of a household with equal numbers of drivers and cars. In 2010, the trip from the former household would be roughly four times as likely to use transit as the trip from the latter household.

In the modes/built environment model, origin and destination retail area are significant and positive in both years. Office/institutional area at origin is significant (and positive) for 2010 only. Office/institutional area at destination is significant in both years, but switches from a negative to a positive coefficient. The <= 800M (0.5mi) and > 800M (0.5mi), <= 3.2kM (2mi) trip binary variables are both significant and negative in both years and both models, but they become more strongly negative in 2010.

Regarding social characteristics: in both the modes/built environment and accessibility models, Children Under 6 in Household is significant and negative (as expected) in 2000, but becomes insignificant by 2010. In addition, Student is significant and positive, but only in 2010—showing a trip made by a current student (though not necessarily a school-related trip) is roughly 1.5 to 1.7 times as likely to involve transit as a trip made by a non-student. In 2010, all age variables except 40-64 are significant and negative, underscoring the propensity of 18-39 year-old travelers to use transit. The lack of significance for the Age 40-64 variable also indicates there is no statistically significant difference between this age group the 18-39 year-old reference group.

Table 3.5: Binary Logistic Regression Models of Probability a Trip uses Transit —Accessibility

	2000		2010	
	Observations	20,321	Observations	45,940
	Pseudo R2	0.2961	Pseudo R2	0.37
	Coefficient	*Odds Ratio*	*Coefficient*	*Odds Ratio*
Origin Stop Dist.	-0.7247	0.4845	-2.0715***	0.1260
Destination Stop Dist.	-1.3593*	0.2568	-1.5282***	0.2169
Origin Accessibility (‘0,000)	0.0650***	1.0672	0.0664***	1.0686
Destination Accessibility (‘0,000)	0.0559***	1.0575	0.0527***	1.0542
Kids Under 6 in Household	-1.0992***	0.3331	-0.1709	0.8429
Kids 6-17 in Household	-0.2249	0.7986	0.0294	1.0298
One-Person Household	0.2299*	1.2585	0.1801**	1.1973
Licensed Driver	-1.6403***	0.1939	-1.4679***	0.2304
Cars/Drivers	-1.9881***	0.1370	-1.2699***	0.2809
Student	0.0470	1.0481	0.4227***	1.5261
Worker	0.5309***	1.7004	0.2072***	1.2303
Household Income	-0.0499***	0.9514	-0.0771***	0.9258
Female	0.1375	1.1474	-0.0237	0.9766
Age Under 18	-1.0724***	0.3422	-2.4126***	0.0896
Age 40-64	-0.0903	0.9136	-0.0273	0.9731
Age 65 and Over	-0.1997	0.8190	-0.5169***	0.5964
Average Temperature	0.0093*	1.0093	-0.0043***	0.9957
Precipitation	0.0421	1.0430	0.3757***	1.4560
School Destination	-0.1189	0.8879	0.0381	1.0389
Utilitarian Personal Dest.	-0.2045	0.8150	-0.8145***	0.4429
Non-Utilitarian Pers. Dest.	-1.0676***	0.3438	-0.8856***	0.4124
Home Destination	0.2661	1.3048	-0.1175	0.8892
Mid-Day Departure	-1.1362***	0.3211	-0.7099***	0.4917
Pm-Peak Departure	-0.5172***	0.5962	-0.2664***	0.7661
Evening Departure	-2.4795***	0.0838	-1.3345***	0.2633
Trip <= 800M (0.5mi)	-1.5052***	0.2220	-2.7652***	0.0630
Trip > 800M (0.5mi), <= 3.2kM (2mi)	-0.9889***	0.3720	-1.3132***	0.2689
Home-based Trip	-0.0557	0.9458	0.0723	1.0750
Constant	-0.6052		0.0951	

Legend: *p<0.1; **p<0.05; ***p<0.01

Table 3.6: Chow Test Results—Modes and Built Environment

	Prob > chi2	
Origin Stop Distance	0.6490	
Destination Stop Dist.	0.4155	
Origin Hi-Frequency Served	0.1072	
Dest. Hi-Frequency Served	0.6361	
Origin Express Served	0.0015	**
Dest. Express Served	0.0205	**
Origin Ltd-Stop Served	0.6928	
Dest. Ltd-Stop Served	0.3418	
Origin LRT Served	0.9816	
Destination LRT Served	0.0022	**
Origin Pop. Density	0.0423	**
Destination Pop. Density	0.3669	
Origin % Retail Use	0.0001	***
Dest. % Retail Use	0.7265	
Origin % Office/Institutional Use	0.4031	
Dest. % Office/Institutional Use	0.0000	***
Children Under 6 in Household	0.0131	**
One-Person Household	0.2086	
Licensed Driver	0.3111	
Cars/Drivers	0.0000	***
Student	0.0378	
Worker	0.1972	
Household Income	0.0000	***
Age Under 18	0.0096	***
Age 65 and Over	0.2872	
Average Temperature	0.0176	**
Precipitation	0.0243	**
Utilitarian Personal Dest.	0.0019	***
Non-Utilitarian Personal Dest.	0.6432	
Mid-Day Departure	0.0373	*
Pm-Peak Departure	0.1622	
Evening Departure	0.0001	***
Trip <= 800M (0.5mi)	0.0000	***
Trip > 800M (0.5mi), <= 3.2kM (2mi)	0.0246	**
Home-Based Trip	0.0090	***

Chow Tests

Tables 3.6 and 3.7 show the results of Chow tests for variables significant in at least one year for each modeling approach. The Chow test tests the null hypothesis that the coefficients produced for a given variable significant in 2000 and/or 2010 are actually equal. If the test statistic is less than a critical value of 0.1, or preferably 0.05, we reject the null hypothesis and conclude that there is a structural break in the data—a genuine change in the relationship between explanatory variable and transit use between the two observations. Once again, the result of the modes/built environment and accessibility approaches are quite similar. In the modes/built environment models (above) LRT served destination produces a significant structural break, indicating light rail implementation led to a statistically significant difference in the relationship between station area locations and the probability of transit use. Notably, for the accessibility models, the test statistics for both origin and destination accessibility variables fail to achieve significance. As a result, we fail to reject the null hypothesis, and cannot conclude there is a structural break in the data. In addition to the accessibility variables, we also include Chow tests for the two automobile access variables, due to their striking apparent change between 2000 and 2010. While the licensed driver variable fails to produce a significant test statistic, Household vehicles/household drivers—arguably a more direct measure of access to an actual vehicle—is significant. According to our model, access to a motor vehicle (not surprisingly) is negatively related to the probably of using transit for any given trip in both 2000 and 2010, but that relationship significantly weakened between the two years.

Under 18 years old, Origin/destination within 800M (0.5mi) of an express bus stop, Retail area at origin, Office/institutional area at destination, Evening departure and Household income (in both sets of models) also show structural breaks. Trips shorter than 800M (0.5mi) are even less likely to use transit in 2010 than in 2000. Regardless of the modeling approach, mid-day and evening departure show a similar pattern to Vehicles/drivers: negative in both years, but significantly less so in 2010.

Household income becomes slightly more strongly negative in 2010. The presence of children in the household is a significant negative predictor of transit use in 2000, but not in 2010.

Table 3.7: Chow Test Results—Accessibility

	Prob > chi2	
Origin Stop Distance	0.0401	**
Destination Stop Dist.	0.7286	
Origin Job Accessibility	0.5383	
Destination Job Accessibility	0.5737	
Children Under 6 in Household	0.0178	**
One-Person Household	0.3968	
Licensed Driver	0.1834	
Cars/Drivers	0.0000	***
Student	0.2168	
Worker	0.2105	
Household Income	0.0000	***
Age Under 18	0.0056	*
Age 65 and Over	0.2492	
Average Temperature	0.0214	**
Precipitation	0.1086	
Utilitarian Personal Dest.	0.0003	***
Non-Utilitarian Personal Dest.	0.9457	
Mid-Day Departure	0.0669	*
Pm-Peak Departure	0.1672	
Evening Departure	0.0002	***
Trip <= 800M (0.5mi)	0.0000	***
Trip > 800M (0.5mi), <= 3.2kM (2mi)	0.0310	**

3.3 Person-Level Model

In addition to the trip-level model described above, we also considered two person-level models, which estimate the probability of an individual using transit at some point in their travel day. These models consider the travel behavior implications of transit service improvements in terms of the total number residents of the Twin Cities whose daily lives they touch, rather than in terms of their implications for individual trips. This is a valuable perspective from which to explore transit use, as even "transit-dependent" people generally make a significant portion of their trips by modes other than transit. The response variable is binary, with a value of 1 if the person in question used transit for at least one leg of one trip during the travel day. In the person-level approach, we separate "walk-and-ride" and "park-and-ride" transit users. One model focuses on walk-and-ride trips, with the response variable counting only transit trips with non-motorized access *and* egress modes; the other model focuses on park-and-ride trips, with the response variable counting only transit trips with an automotive access *or* egress mode. These definitions are not mutually exclusive, and an individual can be a transit user in both models. For example, a park-and-ride commuter might make a walk-and-ride trip at lunch.

3.3.1 Study Areas

Spatial analysis for the person model focuses on TBI participants' home locations. This allows the model to consider the impacts of residential location and neighborhood characteristics on travel behavior; the model also implicitly considers dependency between individuals' mode choices throughout the day. The walk-and-ride model includes TBI participants who live within 800 m (one half-mile) network distance of a transit stop and who made at least one trip *either* an origin *or* a destination within 800 m (one half-mile) network distance of a transit stop. The individuals included thus have the spatial capability to access transit, and made one or more trips that conceivably could be made using transit.

Table 3.8: People

	2000	2010
In TBI	14,671	30,286
In 7-County metro	11,771	28,137
Within walk & ride catchment area…	8,399	18,114
Used walk & ride transit—Total	355	1,109
Used walk & ride transit— > 800M (0.5mi) from stop	124	317
In walk & ride person model	4,915	12,690
In walk & ride person model, Used transit	*231 (4.72%)*	*792 (6.85%)*
Used (Park & Ride) Transit	67	181
Used park & ride transit— > 9.7kM (6mi) from park & ride	35	55
Within park & ride catchment area…	9,565	25,630
In park & ride person model	5,101	16,490
In park & ride person model, Used transit	*32 (0.63%)*	*126 (0.76%)*

The park-and-ride model includes individuals who live within 9.7kM (6mi) network distance (Over 90% of park-and-ride users live within 9.7kM (6mi) of the park-and-ride facility they patronize.) of a park-and-ride facility and who made at least one trip with either an origin or a destination within one half-mile network distance of a transit stop. We require such an origin or destination as park-and-ride trips because even park-and-ride trips generally have a non-motorized access/egress leg at one end. This arrangement means the participants included in the park-and-ride model also have the spatial capability to reasonably access transit and made one or more trips that conceivably could be made using transit.

Table 3.8 shows the numbers of people included in the TBI, the seven-county metro area, within the walk-and-ride and park-and-ride, who made trips with transit-served origin or destination points and who actually made transit trips in 2000 and 2010. In both years, the percentage of *people* in the walk-and-ride population who made transit trips is more than double the percentage of *trips* in the trip model population that include a transit leg. This pattern reflects the fact that even habitual transit users generally make some trips by other modes. Percentages of park-and-ride trips—even with the population constrained by distance from park-and-ride facilities and the theoretical potential to make use of transit—are quite low, less than 1% in both years. Comfortable majorites of transit users are captured within the service areas defined for both walk-and-ride and park-and-ride trips, with the exception of park-and-ride users in 2000—a group which suffers from a very small sample size.

3.3.2 Regression Analysis

Walk-and-Ride

The walk-and-ride models employ a pooled, binary logistic regression which estimates the probability of a TBI participant using transit or not as a function of the following variables:

30-minute transit accessibility at home —The 30-minute, cumulative opportunity jobs accessibility at the participant's home, in tens of thousands of jobs. Included as a measure of transit service. Positive coefficients expected.

Network distance to nearest transit stop—The cumulative distance along the street network from the participant's home to the nearest transit stop, in meters. Included as a measure of the convenience of transit. Negative coefficients expected.

Express route, limited stop route, light rail and commuter rail within 800M (0.5mi) of home—A set of non-exclusive binary variables describing whether the participant's home is within 800M (0.5mi) network distance of each type of premium transit service operating in the Twin Cities during the study period. (Light rail and commuter rail are only included in 2010.) Included as a measure of the attractiveness of nearby transit service. Positive coefficients expected.

% Retail area and % Office/Institutional area at home—The percentage of the area within one half mile network distance of the participant's home occupied by retail and office or institutional land uses. Included as a measure of land use mix. Positive coefficients expected.

Children under 6 in household, Children 6-17 in household, One-person household—Binary variables identifying household type. Included due to differing travel patterns of different types of households. Negative coefficients expected for the former, positive for the latter.

Household income—Ordinal variable for traveler's household income(A. Owen, Schoner, & Levinson, 2013, p. 30). Included due to higher rates of transit use among low-income people. Negative coefficients expected.

Household vehicles<household drivers—Binary variable identifying participants living in households where drivers outnumber cars. Included as a measure of access to a private vehicle. Negative coefficients expected.

Licensed driver—Binary variable identifying travelers with a driver's license. Included as a measure of access to a private vehicle. Negative coefficients expected.

Student/Worker—Binary variables identifying workers and students. Included due to high rates of transit use for regular work/school commutes. Positive coefficients expected.

Female—Binary variable identifying a female traveler. Included due to historically high rates of transit use among women in the Twin Cities. Positive coefficients expected.
<18 years old, 40-64 years old, 65+ years old—Binary variables identifying travelers' ages. Included due to potential generational differences in transit use. Negative coefficients expected. (Note: 18-39 is omitted as the reference; the preceding variables compare a member of their age group to an 18-39 year old.)

Descriptive Statistics

The variables included mirror the trip model with the exception of focusing spatial variables on the participant's home location and omitting variables pertaining to individual trips. Table 3.7 presents descriptive statistics of the variables included in the walk-and-ride model. Both percentages of transit use and average transit accessibility increased from 2000 to 2010. Interestingly, the percentage of participants living within 800 m (one-half mile) of stops on express routes declines, while the percentage of participants living within 800 m of limited stop routes increases. The percentage of workers decreases, reflecting the downturn in the economy between 2000 and 2010. The percentage of white residents in the areas surrounding participants' homes decreases, while percentages of residents in the two oldest age groups increase, both reflecting general demographic trends. Other variables show little change between the two years.

Table 3.9: Descriptive Statistics, Person-Level Walk-and-Ride Model

	2000		2010	
Variable	**Mean/%**	**Std. Dev.**	**Mean/%**	**Std. Dev.**
Used Transit	4.70%	21.17%	6.24%	24.19%
Stop Distance	270.7058	204.0931	376.3801	317.3152
Job Accessibility	3.1012	4.4187	3.7756	6.2067
Served by Hi-Frequency Bus	15.91%	36.58%	18.75%	39.04%
Served by Express Bus	59.59%	49.08%	44.83%	49.73%
Served by Limited-Stop Bus	18.05%	38.46%	29.20%	45.47%
Served by Light Rail	1.22%	10.98%	1.62%	12.64%
Served by Commuter Rail	0.26%	5.14%	0.32%	5.61%
Population Density	6.8575	4.6302	7.0294	4.6842
% Retail Land Use	4.71%	7.73%	4.57%	7.56%
% Office/Institutional Land Use	5.68%	7.98%	6.60%	9.03%
Children Under 6 in Household	11.25%	31.60%	11.21%	31.55%
Children 6-17 in Household	31.45%	46.44%	33.09%	47.06%
One-Person Household	18.64%	38.94%	18.01%	38.43%
Fewer Cars than Drivers	13.04%	33.68%	14.37%	35.08%
Licensed Driver	81.55%	38.80%	83.20%	37.39%
Student	19.94%	39.96%	20.68%	40.50%
Worker	68.26%	46.55%	54.91%	49.76%
Household Income	9.8065	3.1837	10.6551	3.2515
Female	51.78%	49.97%	53.06%	49.91%
Age Under 18	17.25%	37.79%	14.67%	35.38%
Age 40-64	40.61%	49.12%	47.68%	49.95%
Age 65 and Over	8.52%	27.93%	18.00%	38.42%

Regression Model

Tables 3.10 and 3.11 present the results of the walk-and-ride regression model. As with the trip-level analysis, we present separate models to explore the impacts of transit modes and the built environment on the one hand (Table 3.10), and transit accessibility on the other (Table 3.11). Once again, both modeling approaches produce generally similar results (at least for the variables included in both), as well as similar goodness of fit. In the modes/built environment models, home location in a light rail station area is significant—and positive—in both 2000 and 2010; location in a commuter rail station is only significant (and positive) in 2010. As expected, employment accessibility is significant with a positive coefficient in both years of its model. Its odds ratios of 1.0949 and 1.0334 indicate a 9% and 3% (respectively) increase in the probability of transit use for every additional 10,000 jobs reachable within 30 minutes' transit travel from an individual's home, holding all else equal. In both years, for both modeling approaches, the constant term of the model becomes much less negative in 2010, reflecting the overall increase in transit use rates. (This pattern may reflect less accessible areas "catching up" somewhat to more accessible area, as overall levels of both transit service and transit use rise.) Distance to the nearest transit stop is significant, with the expected negative coefficient, with the exception of the 2000 accessibility model.

Among the household characteristics variables, the presence of young children in the household is significant (with a strongly negative coefficient) in 2000, predicting a 77% decrease in the probability of transit use for both modeling approaches. In both cases for 2010, however, the variable is insignificant.

The variable indicating one-person household is significant and positive in both years, though with a weaker coefficient in 2010 than in 2000. Household income is significant and negative in 2010 only, and a household in which drivers outnumber cars is significant and positive in both yearsIn both years, the model predicts a person from such a household is roughly 4.5 times as likely to use transit at some point in their travel day than a person from a household with at least as many cars as drivers.

Whether or not the participant is a licensed driver is significant and negative in both years, but the relationship is weaker in 2010. While both modeling approaches predict a 95% decrease in the probability of using transit from having a driver's license in 2000, they predicts an 89% decrease in 2010. Worker is significant and positive in both years, while student is significant and positive in 2010 only. Female is significant and positive in 2000Participants under age 18 (in both years) and age 65 and over (in 2010) are significant, with the expected negative coefficients.

Table 3.10: Person-Level Walk & Ride Binary Logistic Regression—Modes and Built Environment

	2000		2010	
	Observations	4,915	Observations	12,690
	Pseudo R2	0.2303	Pseudo R2	0.2059
	Coefficient	***Odds Ratio***	***Coefficient***	***Odds Ratio***
Meters to Nearest Stop	-0.0011**	0.9989	-0.0012***	0.9988
Served by Hi-Frequency Bus	-0.1549	0.8565	0.1362	1.1460
Served by Express Bus	-0.4775***	0.6203	-0.3233***	0.7237
Served by Limited-Stop Bus	0.4544**	1.5752	0.1037	1.1093
Served by Light Rail	0.9338**	2.5441	0.8025***	2.2311
Served by Commuter Rail	0.2276	1.2556	1.2406***	3.4577
Population Density	0.0647***	1.0668	0.0296***	1.0301
% Retail Land Use	-1.4154	0.2428	-0.1775	0.8373
% Office/Institutional Land Use	0.1606	1.1742	-0.6066	0.5452
Children Under 6 in Household	-1.4698***	0.2300	0.1169	1.1240
Children 6-17 in Household	0.0464	1.0475	-0.1790	0.8361
One-Person Household	0.8537***	2.3483	0.6875***	1.9888
Fewer Cars than Drivers	1.6107***	5.0065	1.5498***	4.7107
Licensed Driver	-3.0902***	0.0455	-2.2000***	0.1108
Student	0.0173	1.0174	0.2963**	1.3449
Worker	0.7883***	2.1996	0.6309***	1.8794
Household Income	-0.0136	0.9865	-0.0670***	0.9352
Female	0.3006**	1.3506	-0.0517	0.9496
Age Under 18	-2.8495***	0.0579	-2.6526***	0.0705
Age 40-64	-0.1363	0.8725	-0.0991	0.9056
Age 65 and Over	-0.3294	0.7194	-0.9109***	0.4022
Constant	-1.3237***		-0.5410**	

Legend: *p<0.1; **p<0.05; ***p<0.01

Table 3.11: Person-Level Walk & Ride Binary Logistic Regression—Accessibility

	2000		2010	
	Observations	4,915	Observations	12,690

	Coefficient	Odds Ratio	Coefficient	Odds Ratio
	Pseudo R2	0.2205	Pseudo R2	0.1984
Meters to Nearest Stop	-0.0006	0.9994	-0.0011***	0.9989
30 min Job Accessibility ('0,000)	0.0907***	1.0949	0.0328***	1.0334
Children Under 6 in Household	-1.4784***	0.2280	0.1084	1.1145
Children 6-17 in Household	0.1090	1.1152	-0.1543	0.8570
One-Person Household	0.8431***	2.3235	0.7011***	2.0160
Fewer Cars than Drivers	1.5656***	4.7855	1.5648***	4.7819
Licensed Driver	-2.9544***	0.0521	-2.2345***	0.1070
Student	0.0391	1.0399	0.2400*	1.2712
Worker	0.7832***	2.1884	0.6553***	1.9258
Household Income	-0.0216	0.9786	-0.0654***	0.9367
Female	0.3115**	1.3655	-0.0529	0.9485
Age Under 18	-2.7263***	0.0655	-2.6076***	0.0737
Age 40-64	-0.1598	0.8524	-0.0935	0.9108
Age 65 and Over	-0.4321	0.6492	-0.9032***	0.4053
Constant	-1.5677***		-0.5771***	

Legend: *p<0.1; **p<0.05; ***p<0.01

Chow Tests

Tables 3.12 and 3.13 show the results of Chow tests performed on the walk-and-ride person model results for variables that were significant in at least one year. In the modes/built environment approach, none of the transit modes produce significant structural breaks. In the accessibility approach, the test statistics indicate a significant structural break between 2000 and 2010 for transit job accessibility, which is significant and positive in both years, but less so in 2010. In addition, for both modeling approaches, significant structural breaks appear for the presence of children under 6 (which goes from significant and negative to insignificant) and being a licensed driver (which is negative in both years, but less strongly in 2010.)

Table 3.12: Chow Test Statistics, Person-Level Walk-and-Ride Model—Modes & Built Environment

	Prob > chi2	
Meters to Nearest Stop	0.8892	
Express Served	0.4069	
Ltd-Stop Served	0.1402	
LRT Served	0.9741	
Commuter Rail Served	0.4599	
Population Density	0.0767	*
Children Under 6 in Household	0.0024	***
Single Person Household	0.4633	
Cars<Drivers	0.7700	
Licensed Driver	0.0013	***
Student	0.3058	
Worker	0.5817	
Household Income	0.0518	*
Female	0.0419	**
Age Under 18	0.6996	
Age 65 and Over	0.1351	
Constant	0.1095	

Table 3.13: Chow Test Statistics, Person-Level Walk-and-Ride Model—Accessibility

	Prob > chi2	
Meters to Nearest Stop	0.1356	
30 min Job Accessibility (‘0,000)	0.0000	***
Children Under 6 in Household	0.0015	***
Single Person Household	0.9849	
Cars<Drivers	0.6383	
Licensed Driver	0.0166	**
Student	0.8566	
Worker	0.6967	
Household Income	0.1557	
Female	0.0139	**
Age Under 18	0.9161	
Age 65 and Over	0.1291	
Constant	0.0192	**

3.3.3 Park-and-Ride Model

Due to the small number of observations including a trip including both transit and automotive modes, we are only able to report a park-and-ride model for 2010. Early model runs showed very little statistical power for 2000, as one would expect with only 32 “yes” observations. Figure 3.2 shows the general home locations of park-and-ride users in both data years. (Precise locations are obscured to protect participants’ privacy.) The distribution is heavily suburban in both years, but much less concentrated in the West metro suburbs in 2010 than in 2000.

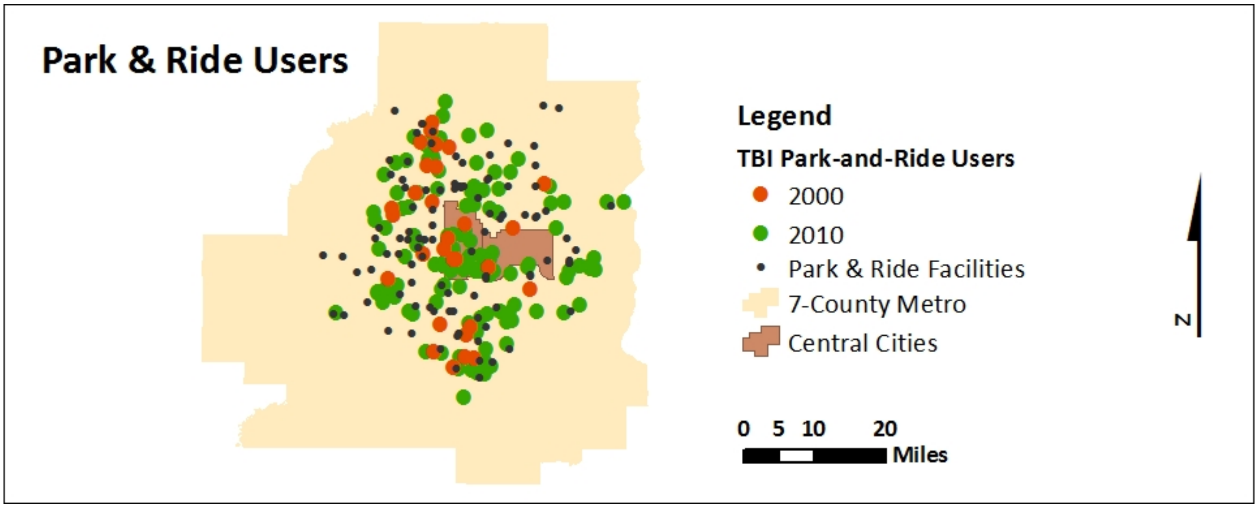

Figure 3.2: TBI Park-and-Ride Users' Household Locations

The 2010 model allows for comparison with the walk-and-ride model and is specified to parallel it as closely as possible. Network distance to the nearest park-and-ride facility is substituted for distance to the nearest transit stop, and a binary variable identifying whether that facility is served by rail is substituted for the modal binary variables in the walk-and-ride model. (Bus service types are not included, as express routes serve the overwhelming majority of park-and-ride facilities. Otherwise, the variables included are the same as in the walk-and-ride model.

Table 3.14 shows descriptive statistics for the park-and-ride model. As one would expect of a more suburban group of TBI participants, average transit accessibility at home locations is significantly lower than for the walk-and-ride model. Average surrounding population density is significantly lower as well, though percentages of white residents are quite similar.

Table 3.14: Descriptive Statistics, Person-Level Park-and-Ride Model

Variable	Mean	Std. Dev.
Used Transit	0.77%	8.73%
kM to Nearest Park & Ride	4.3577	3.3238
Job Accessibility	2.7864	5.5588
Nearest Park & Ride Rail Served	11.21%	31.56%
Population Density	5.8237	4.5619
% Retail Land Use	3.83%	6.79%
% Office/Institutional Land Use	5.59%	8.24%
Children Under 6 in Household	11.81%	32.27%
Children 6-17 in Household	36.45%	48.13%
One-Person Household	15.06%	35.77%
Fewer Cars than Drivers	12.59%	33.17%
Licensed Driver	83.76%	36.88%
Student	21.01%	40.74%
Worker	56.35%	49.60%
Household Income	11.0027	3.0753
Female	52.52%	49.94%
Age Under 18	15.04%	35.75%
Age 40-64	49.25%	50.00%
Age 65 and Over	16.24%	36.88%

Tables 15 and 16 present the results of the mode/built environment and accessibility (respectively) binary logistic models estimated to explain 2010 park-and-ride use. In the modes/built environment approach, neither rail-served nearest park-and-ride nor population density is significant. Transit employment accessibility at the participant's home location is significant and negative. Distance to the nearest park-and-ride is not significant in either model. In the modes/built environment model, office and institutional uses near the participant's home are marginally significant and negative.

In contrast to the 2010 walk-and-ride model, the presence of young children in the participant's household is significant and negative in both models, reducing the probability of transit use by more than half. Household income is significant and positive with both modeling approaches.

Worker is positive in both models, with the expected positive coefficient. All categories are significant, with the expected negative coefficients.

Table 3.15: Binary Logistic Regression, Person-Level Park-and-Ride Model—Modes & Built Environment

	Observations	17,326
	Pseudo R2	0.1847

	Coefficient	*Odds Ratio*
kM to Nearest Park & Ride	-0.0490	0.9522
Nearest Park & Ride Rail Served	-0.1732	0.8410
Population Density	0.0087	1.0088
% Retail Land Use	-0.3022	0.7392
% Office/Institutional Land Use	-3.1834**	0.0414
Children Under 6 in Household	-0.7466**	0.4740
Children 6-17 in Household	0.3839**	1.4681
One-Person Household	0.4627	1.5884
Fewer Cars than Drivers	0.2993	1.3489
Licensed Driver	-0.0605	0.9413
Student	0.3825	1.4660
Worker	0.9097***	2.4835
Household Income	0.1571***	1.1701
Female	0.2521	1.2867
Age Under 18	-2.5888***	0.0751
Age 40-64	-0.5469***	0.5787
Age 65 and Over	-3.0550***	0.0471
Constant	-6.6798***	

Legend: *p<0.1; **p<0.05; ***p<0.01

Table 3.16: Binary Logistic Regression, Person-Level Park-and-Ride Model—Accessibility

	Observations		17,326
	Pseudo R2		0.0806
	Coefficient		*Odds Ratio*
kM to Nearest Park & Ride	-0.0437		0.9573
30 min Job Accessibility (‘0,000)	-0.0408	*	0.9600
Children Under 6 in Household	-0.7385	**	0.4778
Children 6-17 in Household	0.3781	*	1.4596
One-Person Household	0.5025	*	1.6529
Fewer Cars than Drivers	0.3606		1.4341
Licensed Driver	-0.1014		0.9035
Student	0.3726		1.4515
Worker	0.9146	***	2.4957
Household Income	0.1528	***	1.1651
Female	0.2517		1.2862
Age Under 18	-2.6234	***	0.0726
Age 40-64	-0.5626	***	0.5697
Age 65 and Over	-3.1011	***	0.0450
Constant	-6.6490	***	

Legend: *p<0.1; **p<0.05; ***p<0.01

3.4 Discussion

Based on our findings, the question “has there been a basic shift in the relationship between transit service levels and transit use at the trip level between 2000 and 2010?” yields mixed results. On the one hand, we find no difference in the relationship between the transit accessibility of the origin and destination of an individual *trip* and the probability of that trip including a transit leg. On the other hand, we find that the transit accessibility of a person’s home actually declined in importance as a predictor of transit use with non-motorized access and egress modes between 2000 and 2010. We must here reiterate that the overall probability of transit use—measured either in terms of trips or of persons—increased notably between TBI years. In other words, while transit accessibility is as strongly related to transit use at the *trip* level as before, differences in transit use between individuals with more and less accessible homes have lessened, all in the broader context of an increasing probability of transit use.

This is not to say that the significant transit service expansions undertaken in the region between those two years have not yielded a return of increased transit use. Within the transit-served area of the region (which itself expanded), residents of the Twin Cities were significantly more likely to use transit in 2010 as compared with 2000—either for a particular trip or at any point during the day. At the trip level, the rate of transit use has increased, transit service has increased, and higher service levels are related to higher use rates—they simply appear to have the same relationship in both years. This result indicates that Twin Cities transit improvements have not reached a point of diminishing ridership returns. At the individual level, both service and use also increased between 2000 and 2010. Within the confines of a 800m (half-mile) network distance from transit stops, however, the relationship between the two weakens in the latter observation. Again, the *overall* probability of a person using transit increased significantly between 2000 and 2010; there is merely less difference in that probability based on home accessibility. It is also important to bear in mind that the increase in average accessibility between the two years means that many “less accessible” household locations in 2010 are actually more accessible than they were in 2000.

Both rail service variables are positive and highly significant in the 2010 person-level model, and both origin and destination light rail variables are positive and significant in the 2010 trip-level model considering modes and built environment. The Metro Blue Line and the Northstar commuter rail line did improve employment accessibility in their station areas, but they also provide comfort and reliability benefits as well. Any such comfort or reliability (schedule adherence) impacts would not be captured in accessibility analysis, which considers the schedules and the destinations served. The finding of a significant, positive coefficient for light rail station areas in 2000—four years before light rail service began—may seem counter-intuitive at first, but these areas had a relatively high level of bus service before rail implementation, and are also central city areas being compared to the rest of the metro area. Previous research also finds that the greatest accessibility benefits of the Blue Line in terms of population served actually accrue from bus connections, and extend far beyond immediate station areas. Such a pattern is entirely consistent with our finding of increasing probability of transit use overall and a lessening of the difference in transit use between areas surrounding high level of service corridors and their surroundings. In addition, the trip model finds a significant, dramatic strengthening of trip destinations in light rail station areas as a positive predictor of transit use.

In addition, the unexpected structural break we found for access to an automobile in all four models that included both years (though by different measures), is compelling. True, easier access to a car makes one considerably less likely to use transit for a particular trip in both 2000 and 2010, however, the effect is moderated enough in the latter year to have significant practical implications in terms of attracting choice riders. It also speaks to the potential for policies aimed at encouraging car shedding and car-lite lifestyles hold significant potential to encourage transit use. Given the trip model’s finding of a significant structural break on the ratio of cars to drivers, that potential appears to exist even among members of households with at least one car. This finding may indicate some broadening of the appeal of transit between the two years studied—a conclusion supported by the disappearance of Children in the household as a negative predictor of transit use. This result, found again by all four models considering both 2000 and 2010, suggests the change in the relationship between the presence of children and transit use may be greatest in urban areas, where walk-and-ride trips are most common. It also points to a high level of importance for ensuring an adequate supply of family housing in transit served area as the region continues to grow, and that transit may be better able to hold onto its market share better than before as currently young cohorts age.

Chapter 3 References

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Chapter 4

Cohort Analysis of Travel Behavior

4.1 Introduction

In October 2013 the Metropolitan Council released a report highlighting some of the findings from its most recent household travel survey, the Travel Behavior Inventory (TBI). While the report documented some modest shifts toward increased use of public transit, bicycling and walking, one of the most striking findings was marked decline in trip rates per household, from 11.1 in 2000 to 8.8 in 2010 [13]. While this can partially be explained by the long-term trend toward declining household size, several other competing hypotheses relating to events of the last decade may also help explain this decline. These include rising fuel prices, the effects of the 2007-2008 recession on employment levels and incomes, and the impact of demographic transitions.

It is the latter of these that is of greatest interest in the present study. The aging of the population is beginning to have to profound effects on the demand for travel. Not only is a greater proportion of the population shifting into older age groups which traditionally have lower rates of vehicle ownership and trip-making, but this shift has also corresponded in recent years to a decline in labor force participation, thus reducing the amount of work-related travel. In addition to these age group effects, there may also be *cohort effects* reflecting varying preferences toward vehicle ownership and travel among different segments of the population based on their life experience. As different cohorts work their way through the population, they may have residual effects on the demand for travel at various points in time. Cohort effects have begun to take on increasing significance in policy debates, as speculation about the location and travel preferences of the so-called "Millennial Generation" informs proposals for various types of urban development and transportation policy.

In this study we examine the effects of age cohorts on travel demand and vehicle ownership using pooled data from the TBI. We first introduce the concept of cohort analysis in more detail and discuss its application to travel demand analysis. We then operationalize the concept of cohort analysis by specifying models of trip rates and vehicle ownership which account for both age group effects and birth cohort effects. Following a discussion of the empirical results, we conclude by offering some suggestions about further research directions and opportunities to incorporate cohort analysis into planning practice.

4.2 Cohort Analysis and Travel Behavior

Cohorts can be more broadly defined as groups of people who share a common experience. While cohort studies are more common in fields such as epidemiology, they have also found useful applications in other fields such as marketing where companies may tailor their product offerings to specific market segments based on observed age or birth cohorts [18]. Experience with cohort analysis in transportation is still somewhat limited, though there are a few subjects to which it has been successfully applied, such as car ownership [1, 2, 8, 9, 12], various dimensions of travel demand [4, 10, 17, 20], and travel behavior of specific groups such as the elderly [7]. Applications in transportation tend to focus specifically on birth cohorts (groupings of subjects by birth year) and follow them over time, often through the use of repeated cross-sectional surveys.

Cohort analysis is typically designed to disaggregate the different components of demographic transition and identify their unique effects on travel. By examining cohorts through repeated cross-sectional surveys, it is possible to identify at least three types of effects [7]:

- A *period effect*, which refers to effects limited to a specific period of time and which applies to all cohorts
- An *age effect*, which refers to any effects associated with a particular age group. This component essentially captures the effects of various life cycle stages, and
- A *cohort effect* which reflects any effects associated with being born at a specific time in history

The interpretation of the cohort effect suggests that there are unique experiences or socialization processes associated with a particular birth cohort that follow its members forward and shape their behavior. One interpretation of this effect is that the age of a person during the intense motorization of his or her environment will have lasting effects on their perceptions, habits, and expectations toward transportation during their lifetime [10]. For example, someone who grew up during or lived through periods in intense scarcity, such as the Great Depression, gasoline rationing during World War II, or the Arab oil embargoes of the 1970s, might be more inclined to conserve fuel and other resources, and hence make fewer or shorter trips on average.

There does not appear to be a single, dominant methodological approach when it comes to operationalizing cohort analysis. Several cohort studies simply compare age or gender-specific dimensions of motorization or travel behavior over time in repeat cross-sectional travel surveys, identifying the cohort effects in terms of age-specific differences in means or frequencies between survey years [4, 7, 17]. There are also attempts to incorporate cohort effects directly into empirical models of car ownership. For example, Jansson [9] modeled the entry and exit propensities of men and women toward car ownership, specifying the entry/exit decision as a function of incomes, prices, and gender differences. Age and cohort effects were accounted for by including an age variable along with separate birth year variable. A more complex method for modeling car ownership was employed by Dargay and Vythoulkas [3], who used repeated annual cross-sectional surveys to model cohort effects via a "pseudo-panel" approach. This method refers to the fact that birth cohorts are treated similarly to individual-specific fixed effects in a panel data econometric model. Typically, this method requires a larger number of cross-sections in order to properly implement.

The variety of methodological approaches to cohort analysis of travel behavior suggests that there is some flexibility in terms of designing a framework to capture cohort effects from travel surveys. In the next section, we will present some summaries of data on trip rates, licensure rates for drivers among the population, vehicle ownership and trip distance, and describe an empirical approach to cohort analysis using the TBI data that allows for the disaggregation of the three components described above.

4.3 Analysis of TBI Data

4.3.1 Trip Rates

Summary Data on Trip Rates

A good way to visualize the effects of birth cohorts on some dimension of travel behavior is to plot summary data for all cohorts on the same chart, as is done in Figure 4.1 which shows data on trip rates by cohort. Each 10-year birth cohort is represented by a separate trend line on the chart, and each contains three observations representing the three separate surveys from which the data were extracted. The exceptions are the two most recent cohorts (1974 to 1983 and 1984 to 1993), for which there are no observations of adults 18 years or older from the 1990 survey.

As the figure indicates, older birth cohorts tend to have lower overall trip rates, and the downward slope of the trend line seems to indicate that these rates have been falling over time. Part of this can be explained simply as an age effect, as respondents would fall in older age categories during more recent surveys. Nonetheless, there seems to be a broader trend of declining trip rates across most cohorts during the past two survey years. Also of note, more recent cohorts (1964 to 1973 and more recent) seem to have lower trip rates across virtually all survey years.

The data on trip rates by cohort can be further examined by disaggregating them by gender, as is done in Figure 4.2 which displays trip rates separately for men and women. The data suggest that trip rates are higher for men among the older age cohorts (1924-1933 and before 1924), while they also seem to be higher for women in the younger, more recent cohorts. For both men and women trip rates seem to have plateaued around 4.5 to 5 person trips per day. Also, with the exception of the most recent cohorts, there seems to be evidence of broadly lower trips rates across the population in 2010 relative to 2000.

Empirical Framework for Modeling Trip Generation

In the previous section it was noted that several birth cohort studies in the transportation literature have identified multiple components of cohorts, each with a distinct effect. It follows that an empirical framework designed to identify cohort effects should explicitly account for each of these components. In this section we outline such an empirical approach with an application to modeling trip rates by adult individuals.

Trip generation models have been extensively studied due to their many transportation planning applications, though most often through the use of single cross-sectional survey data sets. In

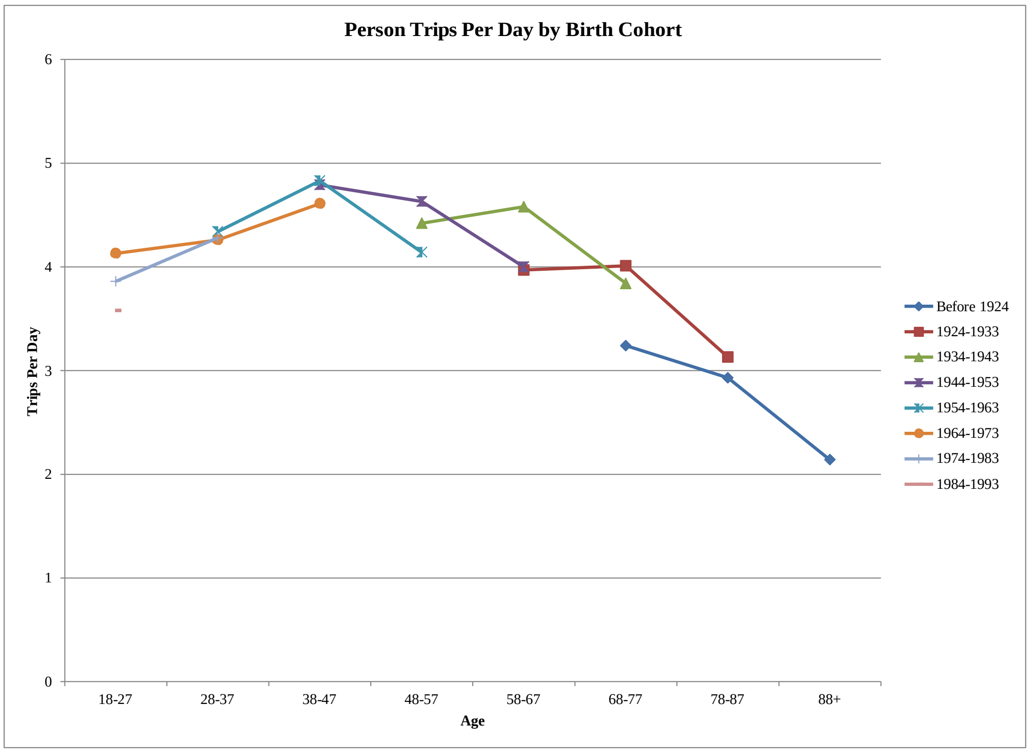
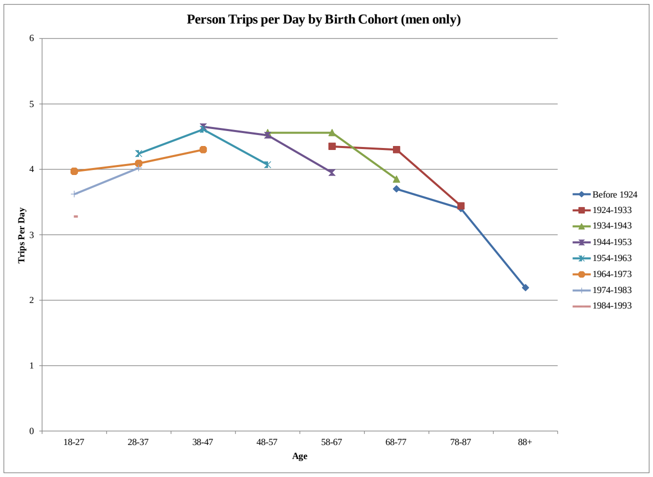
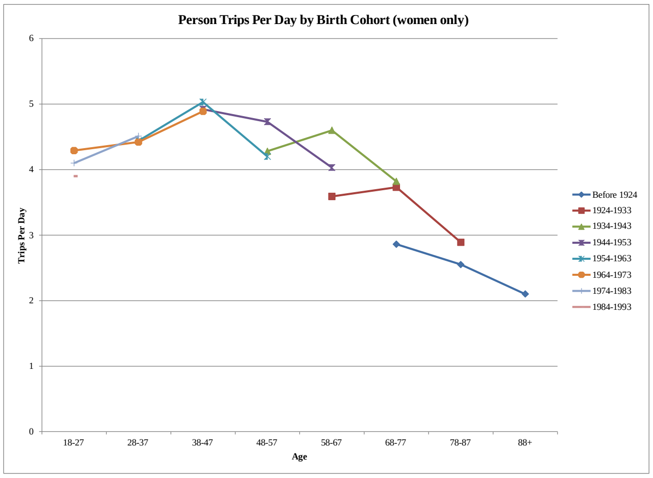


Figure 4.1: Summary of trip rates by birth cohort for 1990, 2001, and 2011 surveys



[men]



[women]

Figure 4.2: Trip rates by birth cohort for men and women in the 1990, 2001 and 2011 surveys

Table 4.1: List of variables in trip generation model

Variable Name	Description
Number of trips	Number of (daily) trips made by person i
Car availability	Number of cars per licensed driver in individual's household
Household size	Number of persons in household
Kids under 18	Number of children under age 18 in household
Female	Dummy variable indicating female gender
Student	Dummy variable indicating current student status
Employed	Dummy variable indicating whether an individual is currently employed
Disability	Dummy variable indicating an individual with a serious disability
Telecommute	Dummy variable indicating an individual who only works from home
$Income_j$	Dummy variable indicating household income in interval j
Population density	Population density per square mile of individual's neighborhood
Fuel price	Monthly fuel price observed in Minnesota during month of trip record
Year 2011	Dummy variable for records from the 2011 TBI survey
Age_i	Dummy variable for age in i^{th} age interval
$Cohort_{t,(t+10)}$	Dummy variable for birth cohort between time t and $t+10$

principle trip generation can be analyzed at either the household or person level, but we choose the latter due to its relevance to the cohort effects we wish to examine in greater depth. Let y_i represent the total number of trips made by person i on a given day. We can then specify a model for trip generation as follows:

$$y_i = \alpha + \mathbf{X_i}\beta_i + \mathbf{Z}\zeta + \sum_C \theta c_{t,(t+10)} + \lambda d_{2011} + \epsilon_i$$

where:

X_i is a set of variables describing person i, Z is a set of variables describing person i's household, as well as certain economic and location factors, $c_{t,(t+5)}$ is the birth cohort of person i, covering the period from time t to $t+5$, d_{2011} is a dummy variable identifying observations from the 2011 TBI, ϵ_i is an error term, and α, θ, λ, β_i, and ζ are sets of parameters to be estimated.

The model includes person-specific as well as household-specific variables thought to influence an individual's level of trip making, along with contextual factors capturing effects of residential location and economic constraints (price and income). The variables relating to cohort analysis include age, which is disaggregated into a set of dummy variables for age groups, a dummy variable for observations in the 2011 TBI (the "period" effect), and a set of birth cohort variables. The birth cohort variables (c) define cohorts in terms of 5-year intervals, with a separate dummy for each cohort to allow for time-varying effects and nonlinearities. The full list of variables and their descriptions are provided in Table 4.1. The next section discusses the results of the trip generation model fitted to the TBI data.

Results of Trip Generation Model

The model of trip generation with cohort effects is estimated using pooled data from the two most recent surveys conducted as part of the TBI in 2001 and 2011. Data from the 1990 survey is available but is not as complete as the more recent surveys and so was not considered compatible enough to include in this analysis. Nonetheless, person-level records from the two surveys produced over 22,000 trip records among them. Records were removed for children under the age of 18 as the focus of the analysis is on adult individuals, and for instances of key variables such as age and income missing from the data. The resulting data set retained over 22,000 records, with the bulk of them – about two-thirds – derived from the 2011 survey. Descriptive statistics for the variables in the data set are provided in Table 4.2. Statistics are provided for both survey years due to the fairly large variation in means between years for certain variables such as trip rates and fuel prices.

Table 4.3 shows the parameters of the trip generation model obtained via ordinary least squares (OLS) estimation. Two models are fitted to the data – one with the birth cohort variables included and one without. This allows us to test the joint significance (via an F-test) of the birth cohort variables to see if they collectively add explanatory power to the model. The adjusted-R^2 value for both models is around 0.04, an indication of the high level of heterogeneity in trip rates across individuals in the cross-sectional surveys, though many of the variables included in the models show up as individually statistically significant.

As expected, the household-related variables are mostly positively and significantly related to trip rates, with car availability and the presence of children under the age of 18 in the house all positively correlated with the number of trips. Household size does not appear to contribute additionally to trip rates by individuals, once other relevant covariates describing household structure and income have been included. The household income variable, which is split into a series of dummies representing various income intervals, seems to follow the expected trend, with higher incomes being associated with more person trips. The omitted income category in each model is the lowest income category, normalized to a value of less than $25,000 per year in 2011 dollars. At the highest income level, representing incomes of greater than $150,000 per year, individuals make nearly 0.5 more trips per day than those at the lowest income levels, a difference of about 10 percent in daily trip rates from individuals in the lowest income category.

Both models seem to indicate that females make more trips than their male counterparts, all else equal. In contrast, the dummy variable for employed persons has a statistically significantly negative effect on trip generation. It is possible that much of the effect of being employed on trip-making propensity is masked by the effect of income levels. The variable indicating status as a current student appears as both positive in both models, though only at a marginal level of statistical significance. The variable identifying individuals as regular telecommuters, namely those who only work from home, has a fairly large impact on trip rates. The coefficient for this variable indicates that those who telecommute exclusively make nearly one fewer trip per day than those who do not, thus providing some support for the notion of telecommuting as a more of a substitute for, as opposed to a complement to, physical trip-making.

Fuel price appears to have had a significant effect on trip generation also. Its coefficient of around -0.23 in both models suggests that for every one dollar increase in fuel prices, person trip decline by about 0.23 per day at the sample mean. The mean values for fuel prices in Table 4.2 indicate a large increase of around $2 per gallon in prices between the two survey years in the sample, a change large enough to account for a decline of around 0.5 trips per person per

Table 4.2: Descriptive statistics for model variables

	2001		2011	
Variable	Mean	S.D.	Mean	S.D
Number of trips	5.130	2.929	4.619	2.412
Car availability	1.090	0.444	1.110	0.483
Household size	2.716	1.288	2.506	1.182
Kids under 18	0.399	0.793	0.452	0.853
Female	0.517		0.524	
Student	0.088		0.066	
Employed	0.815		0.672	
Disability	0.016		0.027	
Telecommute	0.012		0.004	
Income (<25K)	0.026		0.045	
Income (25K-50K)	0.141		0.133	
Income (50K-75K)	0.143		0.122	
Income (75K-100K)	0.323		0.364	
Income (100K-150K)	0.128		0.199	
Income (>150K)	0.166		0.208	
Population density	3776.976	2973.034	3771.980	2927.473
Fuel price	1.604	0.140	3.603	0.240
Year 2011	0		1	
Age_{18-24}	0.081		0.055	
Age_{25-34}	0.197		0.099	
Age_{35-44}	0.264		0.173	
Age_{45-54}	0.244		0.246	
Age_{55-64}	0.116		0.246	
Age_{65-74}	0.066		0.123	
Age_{75-84}	0.029		0.050	
Age_{85+}	0.002		0.007	
$Cohort_{<1924}$	0.019		0.004	
$Cohort_{1924-33}$	0.053		0.035	
$Cohort_{1934-43}$	0.101		0.101	
$Cohort_{1944-53}$	0.206		0.217	
$Cohort_{1954-63}$	0.267		0.252	
$Cohort_{1964-73}$	0.226		0.195	
$Cohort_{1974-83}$	0.127		0.121	
$Cohort_{1984-93}$	0		0.073	
N	7,239		15,160	

day, or roughly the equivalent of moving from the highest income category in the data set to the lowest. Some of the fuel price variable's effect might also be interacting with the dummy variable representing the 2010-2011 survey year, which shows up negative but not significant both models, indicating a secular trend toward declining travel across all age groups and cohorts.

The age group dummy variables present evidence of different trip-making propensities at different age intervals controlling for other relevant factors. The omitted category is the 35-44 age group. The first model shows the familiar age-related pattern, with higher trip rates in the middle age categories and declining rates among young adults and more elderly residents. The coefficients in the second model, which controls for cohort effects, show broadly similar results.

Finally, the series of dummy variables identifying birth cohorts all appear to be highly significant. A joint F-test of the collective significance of these variables yields a test statistic of around 2.54, just outside the critical value for a one percent level of significance. The overall fit of the model seems to be relatively unaffected with the inclusion of the cohort effects, with most of the cohort indicators falling below conventional levels of statistical significance, though the trend in the magnitude of the coefficients looks fairly stable and seems to replicate the results shown in Figure 4.1, which contains the cohort trip rate summaries. Also of note, the last cohort in the sample, representing those born between 1984 and 1993, is the only cohort in the sample reflect- ing the group now commonly referred to as the "Millennial" generation. Contrary to conventional wisdom, there does not appear to be a large drop off in trip rates in this cohort, after controlling for age group and other relevant covariates.

4.4 Licensure Rates

A precursor to motorization and the higher rates of trip making that often accompany it is the ability to obtain a driver's license. Thus, any attempt to forecast future volumes of travel must necessarily take into account the universality of licensure rates and vehicle ownership among the population. Figure 4.3 shows the proportion of the population holding a valid driver's license among the various birth cohorts. Rates are noticeably lower among the oldest cohort, those born before 1924. Once again, this is probably at least partly an age effect, as some older residents may have physical limitations that prevent them from obtaining a valid license. However, most other cohorts seem to indicate near-universal rates of licensure, with many above 95 percent in all survey years. The exception seems to be most recent cohort (1984-1993), associated with the Millennial generation, which has rates a few percentage points lower than preceding cohorts. However, it is difficult to determine whether this represents a nascent trend, as there is only one survey year with valid observations of them.

A comparison of rates of licensure by cohort among men and women in the sample (Figure 4.4) indicates that among most birth cohorts licensure rates are broadly similar and follow the a similar trajectory. The exceptions seem to be the two oldest cohorts, where women have significantly lower rates than men. These results may reflect differing household roles among the older household in the surveys, with some women having never entered the labor force and thus possibly not needed to obtain a license in order to meet their daily travel needs.

Table 4.3: Coefficient estimates for trip generation model

Variable	Coeff.	S.E.	Sig.	Coeff.	S.E.	Sig.
Car availability	0.002	0.037		-0.003	0.037	
Household size	-0.184	0.023	***	-0.191	0.023	***
Kids under 18	0.525	0.033	***	0.521	0.033	***
Female	0.283	0.035	***	0.282	0.035	***
Student	0.112	0.075		0.113	0.075	
Employed	-0.422	0.047	***	-0.431	0.046	***
Disability	-0.644	0.124	***	-0.649	0.124	***
Telecommute	-0.953	0.210	***	-0.949	0.210	***
Income (25K-50K)	0.134	0.105		0.141	0.105	
Income (50K-75K)	0.133	0.106		0.142	0.106	
Income (75K-100K)	0.299	0.104	***	0.307	0.104	***
Income (100K-150K)	0.313	0.102	***	0.321	0.102	***
Income (>150K)	0.481	0.105	***	0.489	0.105	***
Population density	-4.23e-06	5.83e-06		-4.54e-06	5.83e-06	
Fuel price	-0.239	0.062	***	-0.226	0.062	***
Year 2010	-0.129	0.131		-0.173	0.125	
Age_{18-24}	-0.593	0.153	***	-0.483	0.088	***
Age_{25-34}	-0.199	0.106	*	-0.165	0.061	***
Age_{35-44}	0.146	0.068	**	0.114	0.052	**
Age_{55-64}	-0.106	0.069		-0.006	0.054	
Age_{65-74}	-0.181	0.111		-0.007	0.072	
Age_{75-84}	-0.516	0.167	***	-0.393	0.099	***
Age_{85+}	-1.008	0.309	***	-0.951	0.248	***
$Cohort_{1924-33}$	0.086	0.217				
$Cohort_{1934-43}$	0.237	0.229				
$Cohort_{1944-53}$	0.133	0.248				
$Cohort_{1954-63}$	-0.021	0.264				
$Cohort_{1964-73}$	-0.067	0.282				
$Cohort_{1974-83}$	0.139	0.304				
$Cohort_{1984-93}$	0.136	0.339				
Constant	5.799	0.301	***	2.246	0.635	***
Adjusted R^2	0.039			0.039		
N = 22,163						

Notes:
Dependent variable is the number of person trips
** = variable is statistically significant at $p < 0.1$ level
*** = variable is statistically significant at $p < 0.05$ level
**** = variable is statistically significant at $p < 0.01$ level

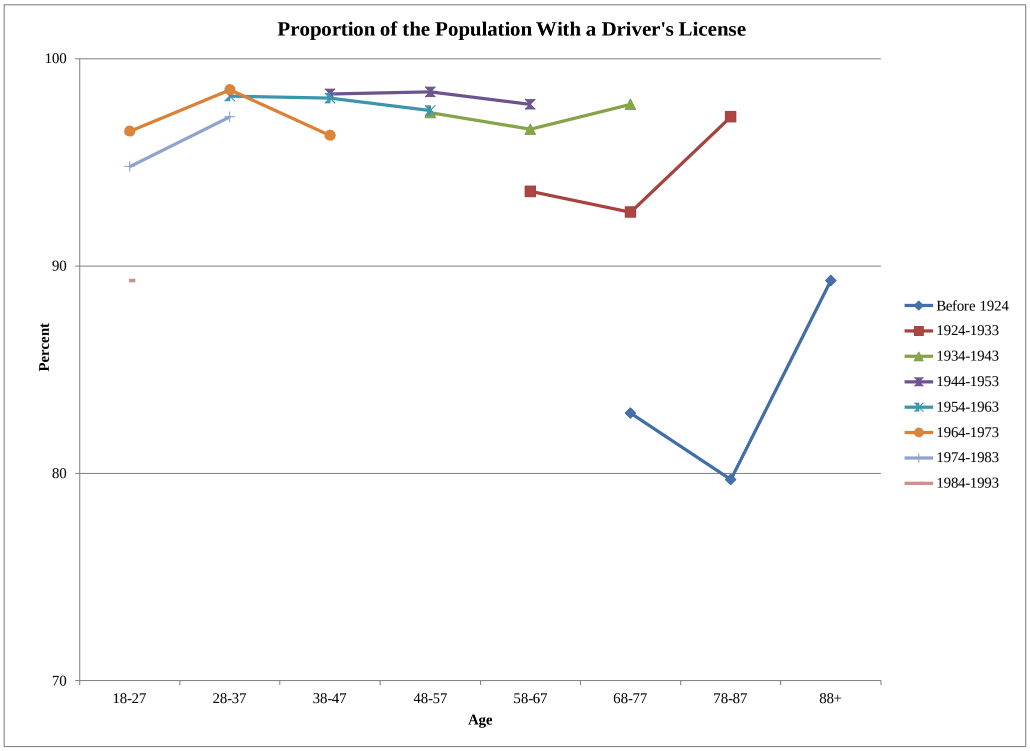


Figure 4.3: Summary of licensure rates by birth cohort for 1990, 2001, and 2011 surveys

Vehicle Ownership

Summary Data on Vehicle Ownership

Closely related to the proportion of the population holding a driver's license is the rate of vehicle ownership in a typical household. Figure 4.5 plots vehicle ownership rates for households in each of the travel surveys by cohort. Unlike the driver's license and trip rate summaries, the vehicle ownership rate is not disaggregated any further as it relies on data from the household records of the TBI, rather than person or trip records. However, the household records were linked to individual person records in order to obtain information about the age of adult household members and construct the birth cohorts to examine differences among them. In households with multiple adults, only one was retained in the sample in order to obtain birth year information. Other household members were ignored. This method was chosen since many adults in households with multiple adults, regardless of whether or not they are related or married, are similar in age, and thus likely to fall within the same cohort.

The summary in Figure 4.5 indicates that the older cohorts have significantly lower rates of vehicle ownership than other cohorts, and that ownership levels seem to have saturated at around

2 vehicles per household. The lower ownership levels among older cohorts likely reflect their different labor force and life cycle status (mostly the absence of dependent children), and thus a lesser need for the higher level of mobility afforded by the ownership of multiple vehicles.

Empirical Analysis of Car Ownership

Similar to the analysis of trip rate presented earlier, we expand upon the summary data on car ownership to probe more deeply the factors affecting car ownership beyond the age and birth cohort characteristics in Figure 4.5. The analysis focuses on car ownership at the household level, but includes the person-level characteristics related to age and birth cohort. This is done by focusing the analysis on the demographic characteristics of the household member who was chosen to respond to the TBI household survey. While decisions about vehicle ownership are typically made at the household level, it is not uncommon for models of vehicle ownership, especially those examining cohort effects, to include demographic characteristics of a household member, such as a designated "head of household" [2].

A model of car ownership, similar to the trip model in section 3.1, is specified using most of the same variables, but excluding the person-level factors except for age and birth cohort. The sample is again drawn from the 2001 and 2011 survey years to ensure a higher level of comparability across surveys. The total sample size is 13,068 with about 30 percent of the observations drawn from the 2001 survey and 70 percent from the 2011 survey. In the model, car ownership is specified as a function of household characteristics, such as household size, number of workers, number of children under age 18, and population density at the home location, along with respondent age and birth cohort. Again, there are controls for the price of fuel, set to the month of the individual's report travel, and a dummy for observations from the 2011 TBI, capturing the period effect component of the cohort analysis. Descriptive statistics for each of the variables are included in Table 4.4.

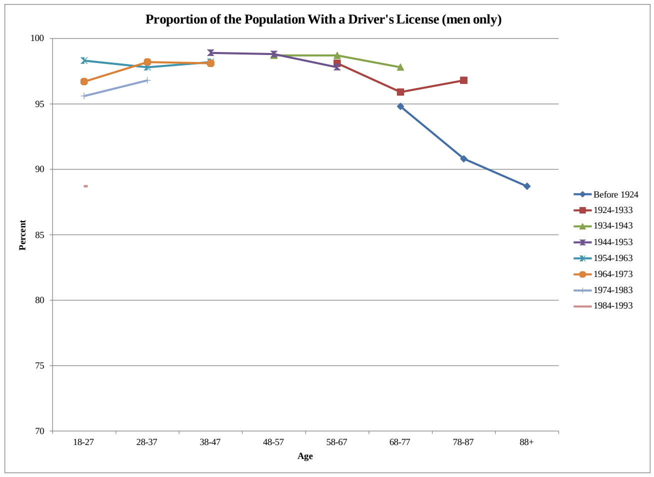
Further, because of the shifting nature of households, with an increasing number of households being composed of non-traditional household types, such as groups of unrelated individuals and parents with adult children living at home, we have estimated two sets of models. The first uses the traditional measure of the number of household vehicles as the dependent variable. The second uses the number of vehicles per licensed driver, a measure of vehicle intensity, as the dependent variable. This latter definition allows some flexibility to handle situations where there are more adults in a household than a traditional nuclear family, and where the adults may have more autonomy over vehicle ownership decisions than in a traditional household setting.

Results of Car Ownership Models

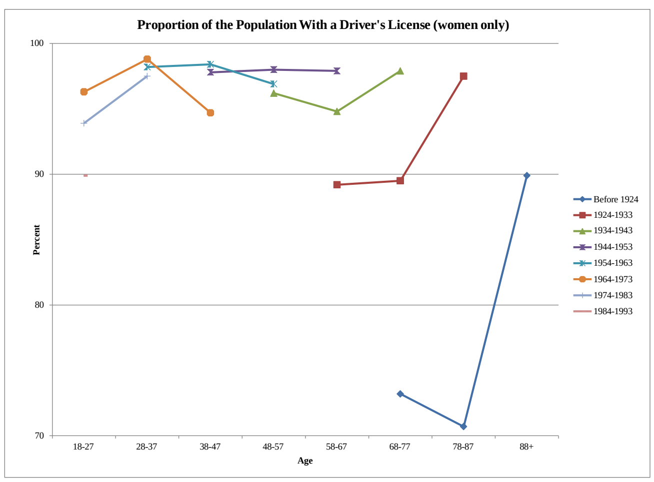
The first set of results relate to the car ownership models where the number of household vehicles is specified as the measure of ownership. Three variations of this model are estimated, again via OLS, and the coefficient estimates are presented in Table 4.5. The three models represent general to more specific specifications of the car ownership equation. Model 1 includes all variables, including those related to age group and birth cohort. The second model excludes the birth cohort variables but retains all others. The third only includes household, economic, and location factors, excluding the age-related characteristics of the respondent. As the fit of the three models suggests, there does not appear to be a great deal of difference among the three specifications.

Table 4.4: Descriptive statistics for vehicle ownership model variables

	2001		2011	
Variable	Mean	S.D.	Mean	S.D
Household vehicles	1.878	0.943	1.894	0.982
Car availability	1.108	0.502	1.080	0.484
Household size	2.716	1.288	2.506	1.182
Kids under 18	0.330	0.738	0.357	0.774
Workers	1.434	0.849	1.127	0.901
Population density	3900.534	3027.629	3895.514	3059.975
Fuel price	1.605	0.141	3.603	0.244
Year 2011	0		1	
Income (<25K)	0.037		0.067	
Income (25K-50K)	0.181		0.176	
Income (50K-75K)	0.156		0.138	
Income (75K-100K)	0.305		0.312	
Income (100K-150K)	0.129		0.166	
Income (>150K)	0.154		0.178	
Age_{18-24}	0.064		0.047	
Age_{25-34}	0.205		0.092	
Age_{35-44}	0.264		0.154	
Age_{45-54}	0.241		0.209	
Age_{55-64}	0.115		0.247	
Age_{65-74}	0.068		0.153	
Age_{75-84}	0.036		0.078	
Age_{85+}	0.006		0.020	
$Cohort_{<1924}$	0.027		0.009	
$Cohort_{1924-33}$	0.058		0.058	
$Cohort_{1934-43}$	0.097		0.128	
$Cohort_{1944-53}$	0.211		0.235	
$Cohort_{1954-63}$	0.261		0.224	
$Cohort_{1964-73}$	0.230		0.170	
$Cohort_{1974-83}$	0.114		0.111	
$Cohort_{1984-93}$	0		0.065	
N	3,932		9,136	



[men]



[women]

Figure 4.4: Licensure rates by birth cohort for men and women in the 1990, 2001 and 2011 surveys

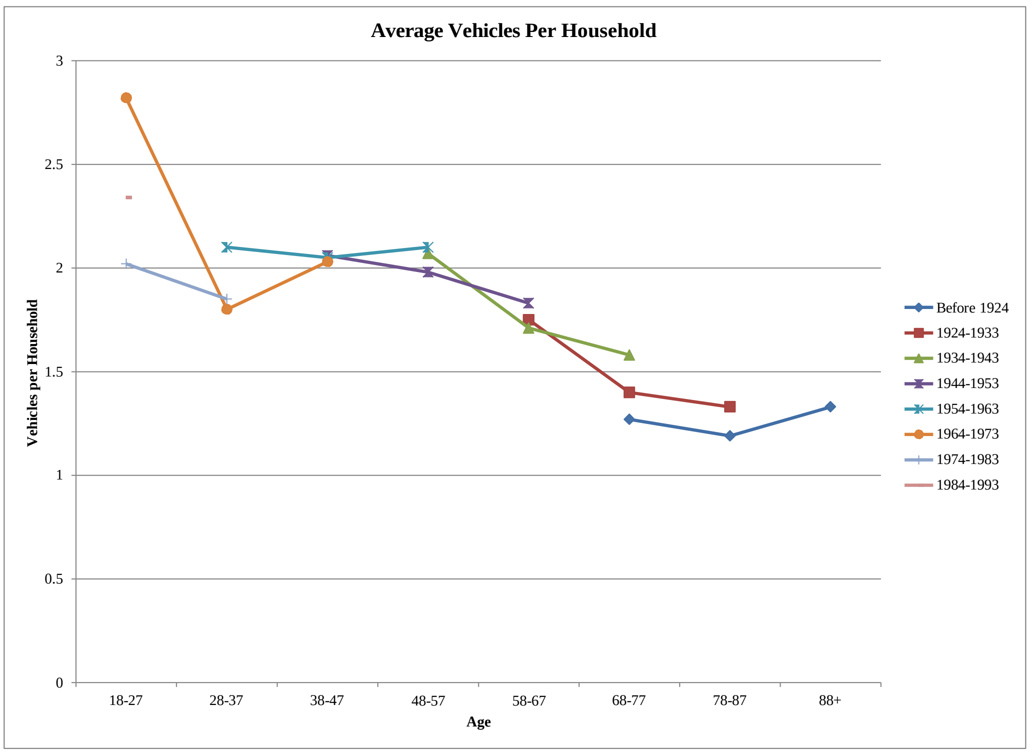


Figure 4.5: Summary of household vehicle ownership rates by birth cohort for 1990, 2001, and 2011 surveys

Table 4.5: Estimated coefficients for vehicle ownership model (dependent variable: number of household vehicles)

	Model 1			Model 2			Model 3		
Variable	Coeff.	S.E.	Sig.	Coeff.	S.E.	Sig.	Coeff.	S.E.	Sig.
Household size	0.495	0.009	***	0.498	0.009	***	0.496	0.009	***
Workers	0.143	0.011	***	0.139	0.011	***	0.156	0.010	***
Kids under 18	-0.410	0.014	***	-0.419	0.014	***	-0.430	0.013	***
Population density	-4.64e-05	2.24e-06	***	-4.67e-05	2.24e-06	***	-4.75e-05	2.22e-06	***
Fuel price	-0.029	0.030		-0.032	0.030		-0.046	0.030	
Year 2011	-0.023	0.065		0.003	0.063		0.039	0.063	
Income									
Income (25K-50K)	0.165	0.032	***	0.170	0.031	***	0.159	0.032	***
Income (50K-75K)	0.304	0.033	***	0.312	0.033	***	0.308	0.033	***
Income (75K-100K)	0.379	0.033	***	0.372	0.033	***	0.383	0.033	***
Income (100K-150K)	0.536	0.032	***	0.521	0.032	***	0.542	0.032	***
Income (>150K)	0.596	0.034	***	0.582	0.034	***	0.607	0.034	***
Age									
Age_{18-24}	0.055	0.067		0.014	0.046				
Age_{25-34}	-0.219	0.041	***	-0.257	0.023	***			
Age_{35-44}	-0.200	0.027	***	-0.228	0.020	***			
Age_{55-64}	-0.015	0.026		-0.042	0.020	**			
Age_{65-74}	-0.034	0.041		-0.112	0.025	***			
Age_{75-84}	-0.083	0.060		-0.237	0.032	***			
Age_{85+}	-0.122	0.094		-0.344	0.066	***			
Cohorts									
$Cohort_{1924-33}$	0.132	0.074	*						
$Cohort_{1934-43}$	0.223	0.082	***						
$Cohort_{1944-53}$	0.260	0.089	***						
$Cohort_{1954-63}$	0.329	0.095	***						
$Cohort_{1964-73}$	0.224	0.102	**						
$Cohort_{1974-83}$	0.293	0.110	***						
$Cohort_{1984-93}$	0.184	0.128							
Constant	0.536	0.106	***	0.820	0.062	***	0.718	0.062	***
Adjusted R^2	0.415			0.414			0.403		
N	13,068			13,068			13,068		

Household size, structure, and incomes appear to have the greatest effect on car ownership levels. Household size has a large, positive influence on car ownership, with the number of household workers having an additional positive effect beyond the effect of household size. For each additional household member, there is an associated increase of nearly 0.5 in the number of vehicles per household. Likewise, each worker is associated with an additional 0.14 vehicles. The effect of the number of children is negative after controlling for household size, perhaps indicating that the effect of the presence of children is already accounted for in the household size variable. Population density, as expected, is negatively associated with vehicle ownership, though the effect is relatively modest. At the sample mean level of density, which is around 3,900 people per square mile, a doubling of density is associated with a decrease of about 0.18 vehicles, or roughly a 10 percent decrease from the mean level of vehicle ownership in 2011. Fuel price does not appear to have much of an impact on vehicle ownership, at least not in the short term. The estimated coefficient for this variable is small and statistically insignificant. The same is true of the indicator variable for the 2011 survey, indicating that there does not appear to be a secular trend in vehicle ownership in either direction after accounting for income levels, household characteristics, and other relevant explanatory factors.

There does appear to be some variation in vehicle ownership levels associated with age. The omitted category among the age variables in the model is the 45 to 54 age group, and so each of the coefficients on the age category variables must be evaluated relative to this group. Accordingly, the younger age groups, specifically 25 to 34 and 35 to 44 have lower levels of vehicle ownership than the 45 to 54 group, after all other factors are controlled for. These appear to be the only age group variables in Model 1 with statistically significant effects. The older age category variables have successively larger negative effects as expected, though none of them appear to be significant.

The birth cohort variables, however, appear to nearly all have statistically significant effects. For these variables, the omitted category is the birth cohort corresponding to individuals born before 1923. As one might expect, subsequent birth cohorts have successively higher levels of car ownership, even after controlling for rising incomes and any demographic factors. This trend seems to plateau with the 1954 to 1963 birth cohort, corresponding to the latter half of the Baby Boom generation. After a decline in the next (1964 to 1973) cohort, there is a return to near the Baby Boom levels in the 1974 to 1983 cohort. The most recent cohort, 1984 to 1993, seems to decline sharply though, with the cohort effect in this group roughly similar to the earlier cohorts in the study (1924 to 1933 and 1934 to 1943). While the trend in the birth cohort variables follows a plausible path, it is important to note that the absolute magnitude of these cohort effects is relatively modest. Even the cohort with the highest level of car ownership (the 1954 to 1963 group) relative to the reference category (born before 1923) only had car ownership levels about 17 percent higher, after controlling for the other income and household factors. Likewise, the youngest cohort seems to have slightly lower car ownership than the preceding cohort (1974 to 1983), but only by about 5 percent, and the difference between their two coefficients is not statistically significant.

Models 2 and 3 are more restrictive specifications of the car ownership model, with the former including all variables except the birth cohort dummies, and the latter excluding both the age group and cohort dummies. Most of the coefficients in Model 2 appear to be relatively unaffected by the absence of the cohort variables. The age variables do appear to absorb some of their influence, as most of their coefficients become statistically significant and take on smaller magnitudes, especially among older age groups. This seems to be evidence of some degree of overlap between the age and cohort variables. The coefficients of the variables in Model 3 also appear to be relatively unaffected by the absence of the age and cohort variables, as they remain quite stable. The model fit declines only slightly, indicating that the household size and structure, income and location factors account for much of the model's explanatory power.

Table 4.6 provides the coefficient estimates for the second set of car ownership models, those with the alternate specification of car availability (defined as vehicles per licensed driver) as a dependent variable. The coefficients of determination for these models indicate that they generally provide a poorer fit to the data. The specification of the dependent variable as a ratio seems to negate the effect of the variable representing household workers, as this variable likely scales with the number of licensed drivers. Likewise, the effect of household size is greatly diminished and even becomes negative after accounting for other explanatory factors. In contrast, the variable for number of children changes its sign and magnitude in a manner similar to the household size variable. Income and population density remain important factors, though the dummy variable for observations in the 2011 survey also becomes more significant.

As with the car ownership models measuring the number of vehicles per household, the cohort variables appear to have larger and more statistically significant effects than the variables representing age groups. Also, similar to those models, the age variables become broadly significant and experience a downward shift when the birth cohort variables are excluded (as indicated by the coefficients for Model 5).

Table 4.6: Estimated coefficients for vehicle ownership model (dependent variable: number of vehicles per licensed driver)

	Model 4			Model 5			Model 6		
Variable	Coeff.	S.E.	Sig.	Coeff.	S.E.	Sig.	Coeff.	S.E.	Sig.
Household size	-0.095	0.006	***	-0.091	0.006	***	-0.093	0.006	***
Workers	-0.010	0.007		-0.013	0.007	*	0.013	0.006	**
Kids under 18	0.064	0.009	***	0.061	0.009	***	0.074	0.008	***
Population density	-2.51e-05	1.43e-06	***	-2.54e-05	1.43e-06	***	-2.42e-05	1.41e-06	***
Fuel price	0.006	0.019		0.001	0.019		0.001	0.019	
Year 2011	-0.067	0.041	*	-0.027	0.040		-0.069	0.040	*
Income									
Income (25K-50K)	0.144	0.020	***	0.146	0.020	***	0.143	0.020	***
Income (50K-75K)	0.203	0.021	***	0.208	0.021	***	0.213	0.021	***
Income (75K-100K)	0.203	0.021	***	0.209	0.021	***	0.222	0.021	***
Income (100K-150K)	0.243	0.021	***	0.249	0.021	***	0.264	0.020	***
Income (>150K)	0.266	0.022	***	0.271	0.022	***	0.290	0.022	***
Age									
Age_{18-24}	0.040	0.043		-0.007	0.029				
Age_{25-34}	-0.052	0.026	**	-0.067	0.015	***			
Age_{35-44}	-0.033	0.017	**	-0.028	0.013	**			
Age_{55-64}	0.019	0.017		-0.034	0.013	***			
Age_{65-74}	0.013	0.026		-0.114	0.016	***			
Age_{75-84}	0.008	0.038		-0.187	0.020	***			
Age_{85+}	0.026	0.060		-0.217	0.042	***			
Cohorts									
$Cohort_{1924-33}$	0.094	0.047	**						
$Cohort_{1934-43}$	0.155	0.052	***						
$Cohort_{1944-53}$	0.236	0.057	***						
$Cohort_{1954-63}$	0.318	0.060	***						
$Cohort_{1964-73}$	0.301	0.065	***						
$Cohort_{1974-83}$	0.272	0.070	***						
$Cohort_{1984-93}$	0.189	0.081	**						
Constant	0.960	0.068	***	1.239	0.040	***	1.185	0.039	***
Adjusted R^2	0.065			0.061			0.053		
N	13,068			13,068			13,068		

Trip Distance

In addition to inquiring about trends in trip rates among individuals in the sample, it also may be useful to examine trends in trip lengths over time, especially in light of recent observations regarding declining levels of per capita travel. One noted response to the run-up in gasoline prices during the early to mid-2000s was an increase in the likelihood of choosing closer destinations for discretionary trips and chaining trips to reduce overall travel distances. These kinds of behavioral changes, especially to the extent that they have become habitual, would likely show up in the more recent survey years.

Figure 4.6 plots summaries of average trip lengths by cohort. There appears a trend across cohorts of secular declines in trip distance, culminating in average trip lengths falling to between five and six miles among the most recent cohorts, as indicated by the downward shift among the trend lines across age groups. Also, downward slope of many of the cohort trend lines indicates shifts toward shorter trip lengths within each of the cohorts (with the exception of the oldest two) over time.

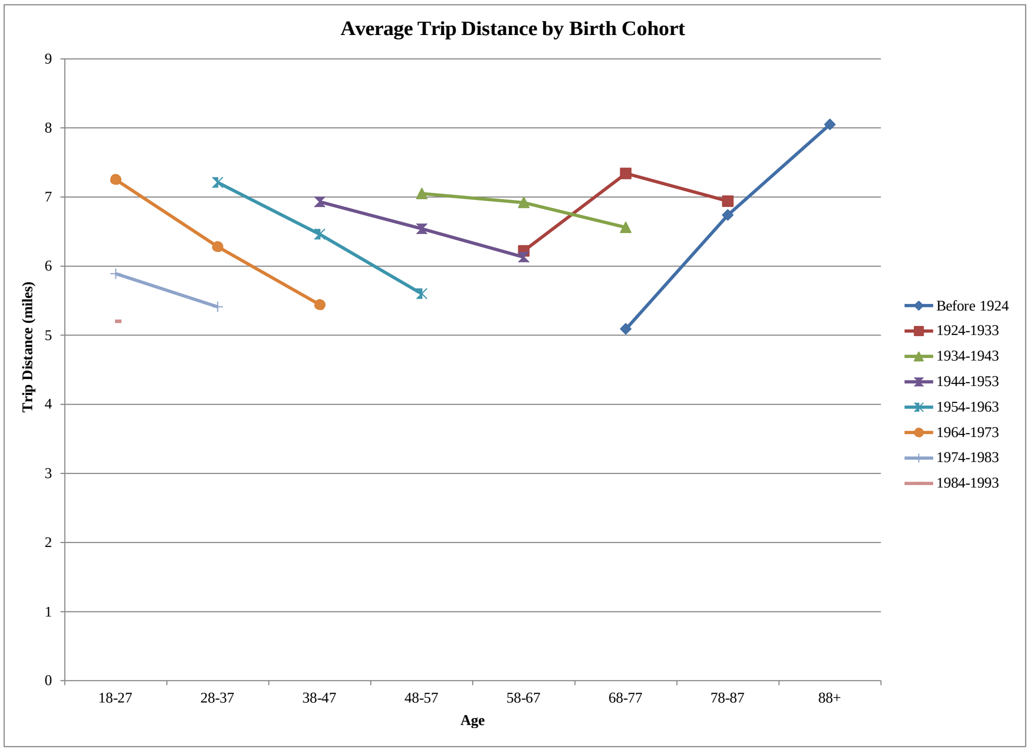


Figure 4.6: Summary of average trip distance by birth cohort for 1990, 2001, and 2011 surveys

Disaggregating the samples by gender seems to reveal that much of the observed decline in trip lengths seems to be concentrated among males, as is indicated in Figure 4.7. While many of the cohorts in the female sample appear to reveal trip length trends that are either relatively stable or declining slightly, virtually all of the cohorts in the male sample, with the exception of the oldest ones, show a distinct pattern of markedly declining trip distances. One possible explanation for this, especially among the more recent observations, may be the higher rates of unemployment and declining labor force participation rates among men. While it has been well documented that men were disproportionately impacted by the most recent recession in terms of unemployment, a longer-term trend of men dropping out of the labor force may also be impacting the amount of commuting undertaken on a regular basis. Since commute trips tend no average to be longer on average than non-work trips, any decline in the proportion of work trips may lead to declines in average trip length.

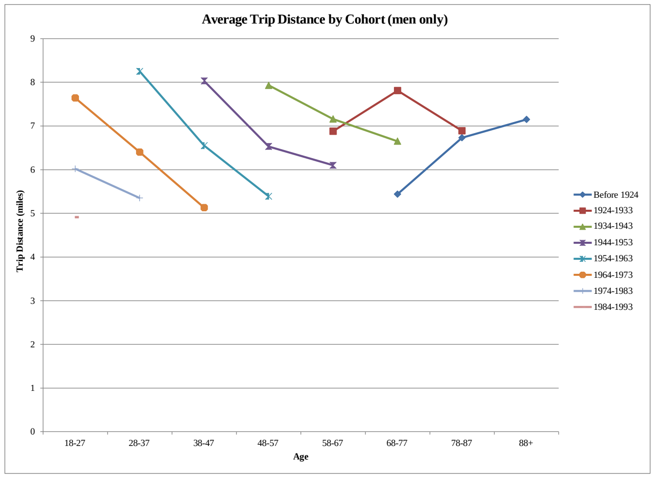
4.5 Discussion of Findings

4.5.1 Methodological Considerations

The results of the analysis suggest that there is some evidence of younger adults, those in the more recent birth cohorts, making fewer and shorter trips. An obvious, but important caveat here is that we still have relatively few observations at different points in time on which to make this judgment. This is especially true of members of the Millennial generation, many of whom have only recently begun to reach adulthood. The infrequency of in-depth surveys like the TBI makes longitudinal, intra-cohort comparisons difficult.

Another complicating factor is that the TBI does not typically collect information on race, ethnicity, or immigration status. It is important to note this omission for two reasons. First, it has been noted that African-American and Hispanic residents tend to be more likely to rely on public transit for more of their trips than white residents. It seems likely that recent immigrants might follow similar patterns, especially due to language barriers, income constraints or other factors. This may be influencing some of the observed changes in trip rates and lengths. Second, and relatedly, Census figures indicate that non-white residents accounted for much of the recent growth in Minnesota's population. These recent changes, unobserved in the TBI, may account for some of the recent shifts.

Moreover, there are several other socioeconomic factors that may coincide with the declines in travel among younger adults. The most obvious include economic factors. The most recent TBI survey was conducted in 2011, which was a couple of years after the official end of the most recent recession, but still during a period of slow recovery. Younger workers were more likely to unemployed or underemployed, or to have dropped out of the labor force entirely. There are also trends toward greater college participation rates in recent years. For young adults, some of this may due to poorer employment prospects, but this is still a trend that has been developing for decades. Relatedly, many young adults have been observed to be delaying marriage and child-bearing, which affects household formation and transition to life cycle stages that tend to be associated with greater amounts of travel.



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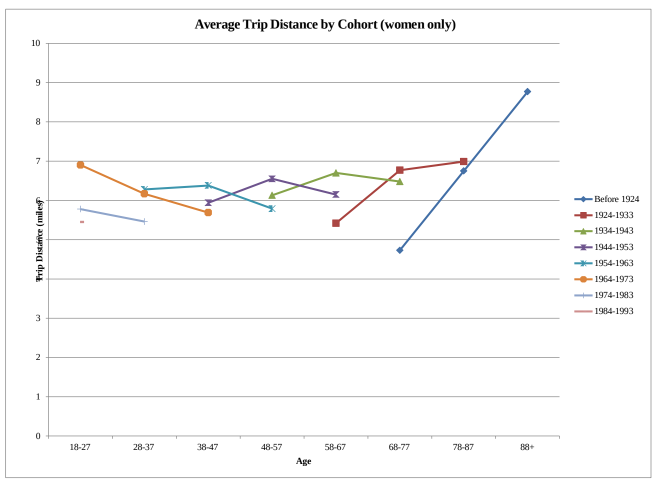

[women]

Figure 4.7: Average trip distance by birth cohort for men and women in the 1990, 2001 and 2011 surveys

Lastly, there is the matter of preferences. It is often assumed that young adults, particularly Millennials, have markedly different preferences toward residential location and choice of travel mode. Residential location patterns in particular may play an important role in explaining some recent travel behavior changes, but they must also be effectively disentangled from the other factors cited here.

4.5.2 Consistency With Other Findings

The evidence from the TBI surveys presents an emerging picture of levels of mobility that are reaching a level of saturation and even, to some extent declining. Trends in the various dimensions of travel behavior described here are also not unique, but indeed have been corroborated to some extent by studies using other data sets from the U.S. and abroad.

There has, in recent years, been emerging interest in the hypothesis of “peak travel” [11, 14, 15, 16, 21], beginning with observations of the flattening of the growth in vehicle-miles traveled (VMT) around the middle of the last decade (circa 2005). The definition of what constitutes peak travel has not always been consistent: some refer to trends in aggregate VMT, while others simply refer to trends in VMT per capita. These trends have been observed both in the U.S., as analysis of the most recent National Household Travel Survey (NHTS) data suggests [11, 22], as well as in many other high-income countries in Europe and North America [6]. One notable observation though, has been that the reasons for declining car travel have varied from place to place, with declines in the U.S. mostly representing lower overall levels of travel (as appears to the be case in the Twin Cities), while other countries such as Germany [11] have seen more modal substitution.

While many of the countries in which peak travel has been documented seem to have similar patterns of aging populations, there are also emerging trends relating to younger adults. Data from the TBI on licensure rates indicates a trend toward delaying the decision to obtain a license among teenagers. While 87 percent of teens in the 16 to 18 age group had a valid license in 1990, the same figure had fallen to 69 percent in the 2011 survey. Interestingly, the decision to delay obtaining a license does not appear to have precluded many younger people from eventually obtaining one. Similar figures for 18 to 24 year olds were 96.0 percent in 1990 and 93.4 percent in 2011, a much more modest rate of decline. Evidence on the fundamental causes of this decline is still scant, though results of a recent survey by Schoettle and Sivak [19] targeting non-licensed young adults in the 18 to 39 age range indicate that the reasons are primarily socioeconomic in nature, with the top reasons cited for not holding a license including being too busy, the expense of owning and maintaining a vehicle, and the ability to get transportation from others. The authors note further that non-license holders tended to have less education and higher levels of unemployment than the general population of the same age.

4.6 Conclusion

The most recent set of survey data from the TBI has revealed some noticeable changes in travel behavior in the Twin Cities region, some of which seem to break from longstanding trends when compared alongside earlier data sets. The saturation in licensure and car ownership rates, along with the aging of the population away from peak travel age groups and economic constraints, seems to have provided a strong force for slowing the growth in travel. Sorting out these relative causes is a difficult task, as the analysis presented here indicates. However, as the empirical applications demonstrate, cohort analysis techniques can represent a useful tool for decomposing some of the effects related to demographic transition. Different elements of the cohort analysis approach can also be more important in explaining different dimensions of travel behavior. For example, trip rates seem to be more sensitive to variations in the age group component of cohorts, while birth cohort effects showed up more strongly in the analysis of car ownership. The latter may be an indication that the lasting effects of an individual's experiences during his or her younger years may be more likely to manifest themselves in longer-term decisions such as vehicle ownership. The analysis of car ownership also seemed to indicate that there is likely some overlap between the effects of age groups and birth cohorts, especially when the number of cross-sections in pooled data are relatively smaller, as was the case with our analysis. This effect would likely be attenuated with additional years of data.

While other data sets, such as the American Community Survey (ACS), are conducted on a more frequent basis and hence could be a useful source for testing hypotheses about cohort effects related to travel behavior dimensions such as car ownership, their limited scope and general non-transportation focus limit the amount of information that could be extracted. On the other hand, the TBI household survey provides a rich set of household and person-level characteristics for analysis, but its infrequency and limited comparability across survey years makes longitudinal analyses difficult. One possibility for addressing both deficiencies would be to increase the frequency of TBI implementation. Smaller samples, collected every couple of years, rather than every decade, would allow more frequent analysis of key dimensions of travel behavior and the identification of trends. More broadly, it would also facilitate the kind of cohort analysis demonstrated here.

Other possibilities exist for the application of cohort analysis as well. While the present analysis has focused largely in dimensions related to aggregate amounts of travel, cohort techniques can also be applied to decisions such as mode choice to capture aspects such as preference evolution over time through the use of repeated cross-sectional surveys [5] to improve the robustness of fore- casting models. Furthermore, cohort techniques can be applied as part of microsimulation model systems used for longer-term forecasting to capture unobserved variations in preferences among age cohorts as they move through the population in successive forecast years.

"Intra-cohort" types of analysis, that is, following members of the same birth cohort over time, may be a valuable way to understand the longer-term variations between generations. As was previously mentioned, the Millennial generation is still fairly young, and so we have little evidence on which to draw firm conclusions about their preferences relating to location and travel choices. Considering that many members of this group will soon be reaching their peak travel years, it will be important to stay abreast of their behavioral tendencies. Likewise, with larger segments of the population reaching retirement age, it will be worthwhile to understand how they adjust their behavior to having fewer schedule constraints and managing the process of aging.

In addition to more practical considerations, some methodological questions remain regarding cohort analysis. For purposes of this study, we chose to disaggregate the population into cohorts based on 10-year intervals of birth years. While this seemed to produce satisfactory results, it is possible that better results could have been obtained by relying on cohorts of shorter or longer length. Further empirical study into the performance of different cohort definitions would be a worthwhile direction for future research.

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Chapter 5

Biking and Walking Over Time

5.1 Introduction

Transportation policies and plans encourage non-motorized transportation - walking and bicycling. Recent legislation, Moving Ahead for Progress in the 21st Century (MAP-21), requires state Department of Transportations (DOTs) and other agencies to integrate indicators of performance into system management and to establish performance measures for assessing progress towards system goals[10]. These agencies, which historically have used indicators such as commuting mode share to measure walking and bicycling, are seeking new measures that provide better understanding these modes. Challenges in fostering walking and bicycling include the lack of data for constructing comprehensive measures of walking and bicycling and important differences between pedestrians and bicyclists and the trips they make.

This chapter analyzes conducted by the the Metropolitan Council, the metropolitan planning organization in the Minneapolis-St. Paul Metropolitan Region (MSP) in 2001 and 2010 to document changes in walking and bicycling. Results from these diary-based household travel surveys offer new insights about nonmotorized travel that have implications for planning. We focus on the who, what, where, when, and why of non-motorized transportation: who pedestrians and bicyclists are, where they go and why, when they travel, and what factors are associated with the trips they make. We give careful attention to areas where pedestrians and bicyclists differ and how these differences affect planning and evaluation, the presence of a persistent gap in bicycling rates between men and women, and associations between bicycling and new dedicated infrastructure in the City of Minneapolis.

The timing of this report is auspicious because walking and bicycling are increasing in popularity and importance among transportation planners, policymakers, and researchers. Early editions of the included walking and bicycling in a broad category of modes called "other". The started to include walking and bicycling *specifically* in the 2001 survey, so this report provides insight on what has changed in walking and bicycling over the past decade.

While previous studies and evaluations have offered some insights into biking and walking, the is a unique opportunity to learn how people incorporate bicycling and walking into their regular travel behavior. The captures a full 24-hours worth of behavior for a sample of the 19/20-county[1] metropolitan region, affording researchers new opportunities to measure bicycling and walking at a finer level of geographic, demographic, and trip purpose detail. This addresses several notable limitations in existing data about bicycling and walking:

- Travel behavior surveys often have small sample sizes that do not necessarily represent an entire region. Additionally, many surveys rely on recalling a summary of biking or walking over a previous time interval, rather than prompting respondents to log every trip on an assigned day. The reaches a 1% sample of the entire metro region.
- Journey to work data from the US Census Bureau and American Community Survey (ACS) captures only the single mode used most frequently over the week prior to completing the survey for the purposes of commuting. Commuting is typically people's longest and least flexible trip; many other trip purposes may be more conducive to walking and cycling. Additionally, collecting only a single mode to represent one full week masks multimodal trips or part-time pedestrians and cyclists.
- Infrastructure traffic counts (e.g., trail counts) do not exclusively measure changing rates of bicycling and walking in the region; the results also reflect route *shifting* that may have occurred among existing pedestrians and cyclists. Travel behavior surveys are needed for measuring changes in rates of travel and mode shift.

5.1.1 Key Research Questions

Using data from the 2001 and 2010 , this study explores several questions about trends in bicycling and walking, including:

1. How have bicycling and walking changed in the evolving region over the past decade?
2. How do these trends vary by geography, distance, traveler demographics, and trip purpose?
3. What factors are associated with the propensity to walk or bicycle, and how do they differ between modes?
4. How has the gender gap in bicycling changed in the past decade?
5. How has bicycling infrastructure changed, and is it associated with changes in bicycling rates?

The chapter is organized as follows. In this introduction, we review literature and policy related to walking and bicycling to frame the research, and then identify key research questions and hypotheses. Next, we document the methods used to clean and harmonize the data for analysis across years and the types of analysis performed.

[1]The 2001 edition of the was administered to 20 counties, including Mille Lacs County. The 2010 version did not survey Mille Lacs County, for a total of 19 counties.

The results are divided into two main sections. In section 5.3, we provide descriptive results about walking and bicycling with several attributes: geography, distance, gender, age, and trip purpose. These correspond to key research questions (1) and(2) in section 5.1.1. The descriptive results are supplemented with hypothesis tests to identify statistically significant differences between 2001 and 2010, by attribute, and between modes. Section 5.4 contains results from tests and statistical modeling on the remaining three key research questions: (3) mode choice and the decision to walk or bicycle, (4) the gender gap in bicycling, and (5) dedicated bicycling infrastructure in Minneapolis and its association with bicycling.

Finally, we conclude with a discussion of implications for practice, limitations of the research, and methodological recommendations to enhance future bicycling- and walking-focused research.

5.1.2 Background and Literature

As public support for walking and bicycling has grown, the literature on measuring outcomes (e.g., rates of walking and bicycling) and performance management also has grown. Perhaps the most frequently reported measures of walking and bicycling are commuting mode shares based on the United States (US) Census Bureau journey to work question in the decennial censuses and ACS. The Census Bureau recently published its first report exclusively on walking and bicycling [21]. This report found, nationally, commuter mode share for walking declined slightly from 2.9% to 2.8% between 2000 and 2008-12, while commuter mode share for bicycling increased from 0.4% to 0.6% [21, p. 3]. In Minneapolis, which ranked 13th and 3rd, respectively, in walking and bicycling among cities over 200,000, walking to work declined from 6.6% to 6.4%, while bicycling to work increased from 1.9% to 4.1%, a "statistically significant" increase [21, p. 8]. Similar patterns occurred in St. Paul, which did not reach the top 15 cities in either mode.

The Alliance for Biking and Walking [1] summarizes a broad array of performance indicators for walking and bicycling based on different sources, including the ACS, travel behavior surveys, and facility counts. The Alliance shows that decisions to walk or bike are associated with trip purpose, weather, age, income, and gender, but notes the limitations of national data sources for assessing walking and biking.

Scholars have analyzed the effects of different factors in decisions to walk or bike. For example, Cervero and Kockelman [7] modeled the probability of non-personal vehicle trips using binary logit models and, after controlling for socio-demographic characteristics, found that density, (land use) diversity, and design were associated with mode choice. Barnes and Krizek [4] compared measures of bicycling frequency based on different data sources and use simple sketch planning methods to model bicycling demand. Notably, several studies about walking and bicycling travel choices have used similar regional travel behavior surveys. The Greater Toronto and Hamilton metropolitan area administers the every five years on a 5% sample of the region. Roorda et al [29] used this data to develop a modeling routine that better captures use of minor modes such as bicycling, though the authors state that the models predictive power for bicycling specifically is weak. Habib et al [15] use data from 1996, 2001, and 2006 to estimate a series of walking-trip generation models over time. They observed minimal change in baseline walking propensity and distance over the decade covered by the surveys, and modest decrease in the probability of an individual taking zero walking trips. Age, household structure, gender, and auto ownership, among others, were important predictors of walking. Pinjari et al [26] use the 2000 paired with aggregate geography indicators to model bicycle ownership and residential self-selection. Sociodemographic variables had a stronger effect on bicycle ownership than the authors indicators of living in a bicycle-friendly neighborhood, suggesting a self-selection effect.

One objective of these studies has been to identify factors that affect system performance and progress towards goals. MAP-21 legislation requires state DOTs and Metropolitan Planning Organizations (MPOs) to develop performance measures for transportation systems, but the impetus for performance indicators predates this federal requirement [10, 24]. The Federal Highway Administration (FHWA) [11] defines "Transportation Performance Management as a strategic approach that uses system information to make investment and policy decisions to achieve national performance goals" and is providing guidance for meeting requirements. For example, FHWA lists "sustainable transportation performance measures" that include "bicycle and pedestrian mode share" and "bicycle pedestrian activity and safety" [9]. In Minnesota, the Metropolitan Council has summarized network statistics (i.e., measures of system facilities), reports mode share based on ACS data and its own , and notes the need for additional measures [24, pp. 107-112]. Nonprofit organizations also have proposed various performance measures [1, 30].

Scholars also have described both the potential and limitations of performance management systems and provided guidance on strategies for implementation. Pratt and Lomax [27] foretold the need for better measures of multimodal system performance. Li et al. [19] describe data needs and other challenges to describing system performance but do not address non-motorized modes or infrastructure. Ramani et al. [28] provide a framework for integrating measures of sustainability into system management. Case studies illustrate dashboard and other approaches to communication of transportation performance measures (e.g., [12, 32]). Yetano [33] argues that public agencies will benefit from incremental approaches to institutionalization of performance management because dramatic changes may induce opposition. Ammons [2, p. 507] found in a cross-sectional analysis of municipalities that the "caliber of service…required to be ranked as a performance leader has improved…" but that a "longitudinal review…of individual cities provides only minimal support…that an advanced level of performance measurement acts as a catalyst for improved performance." Additional evidence on strategies for measuring system performance over time is needed.

5.2 Study Area, Data, and Methods

The Minneapolis-St. Paul Metropolitan Region (MSP) study area in 2010 comprised a 19-county metropolitan region with seven urban/suburban counties in Minnesota, and 12 "ring" counties (three of which are in Wisconsin). The 2001 study area also included Mille Lacs County, for 20 counties total and 13 ring counties. Tables 5.1 and 5.2 document the geographies included in the 19/20- and 7-county regions, as well as geographic groups used throughout the chapter for stratifying the sample and results. The population of the seven county Minneapolis-St. Paul Metropolitan Area (Twin Cities) in 2013 was 2.95 million; the population of the 19 county MSP region exceeded 3 million [25]. The Metropolitan Council has responsibility for transportation planning, and conducts surveys approximately every decade to inform transportation planning and modeling and other policy initiatives. Methodologies, basic descriptive statistics, and other results from the 2001 and 2010 are reported by the Metropolitan Council [22, 23].

Table 5.1: Single Geography Definitions in 2001 and 2010 TBI

Name	Included Geographies
Minneapolis-St. Paul Metropolitan Area (Twin Cities)	7 counties: Anoka, Carver, Dakota, Hennepin, Ramsey, Scott, Washington
Minneapolis-St. Paul Metropolitan Region (MSP)	19/20[1] counties, including: 7-county Twin Cities, Chisago, Goodhue, Isanti, LeSueur, McLeod, Rice, Pierce[2], Polk[2], Sherburne, Sibley, St. Croix[2], Wright
Suburban Counties	Anoka, Carver, Dakota, Scott Washington, plus the portions of Hennepin and Ramsey excluding the principle cities
Ring Counties	Chisago, Goodhue, Isanti, LeSueur, McLeod, Rice, Pierce[2], Polk[2], Sherburne, Sibley, St. Croix[2], Wright Mille Lacs[3]
Minneapolis	City of Minneapolis
St. Paul	City of St. Paul

These aggregation levels apply to trips or people identified by a single geography (e.g., trip origin or home).
[1] The 2001 survey also included Mille Lacs County
[2] County is located in Wisconsin
[3] 2001 survey only

As part of this study, the Metropolitan Council gave the University of Minnesota (UMN) research team data from travel behavior inventory surveys corresponding to the 1970, 1980, 1990, 2000, and 2010 census years. The surveys in 1970, 1980, and 1990 did not specifically include walking or bicycling as options in the travel diary; instead, these trips are included in a broad "other" category. This chapter focuses exclusively on the 2001 and 2010 surveys, which were the first two inventories in the region to include questions about walking and bicycling. The 2001 and 2010 differed in design, scope, and administration (Table 5.3). The 2010 survey revised wording of questions used in 2001, sampled more people but in one less county, and was administered over a longer time period (15 vs. 5 months, respectively). Among other substantive differences, the surveys defined "trips" differently and used different approaches to determining primary mode (Table 5.3).

These differences necessitated harmonization of data sets and the use of subsamples to con-

Table 5.2: Origin-Destination Geography Definitions in 2001 and 2010 TBI

Name	Included Geographies
Within Minneapolis	Trips that both start and end within the City of Minneapolis
St. Paul	City of St. Paul
Within St. Paul	Trips that both start and end within the City of St. Paul
Between Minneapolis and St. Paul	Trips that either start or end in Minneapolis (but not both) *and* either end or start in St. Paul (Similar for other O-D pairs)
"All other trips" (In the context of origin-destination pair geographies)	Trips that are neither entirely within Minneapolis nor entirely within St. Paul

These aggregation levels apply to trips identified by an origin-destination pair of geographies.

trol for the effects of seasonality. Harmonization involved recoding of 2001 trip records to match 2010 trip definitions, including specification of primary mode. The harmonization process is documented in full in the appendix of this study. To control for seasonality and its effects on mode choice, we use subsamples from the 2010 data set that match months for the 2001 . Although we include some findings from the entire 15-month sample from 2010, we focus on results for the five month period from April to August that enable direct comparison of the . Trip distances were estimated using Geographic Information System (GIS) Network Analyst shortest path routing tool. All descriptive statistics, significance tests, and modeling were computed using Stata 10.1. PostgreSQL/PostGIS and QGIS were used for data management and mapping.

The structure of questions in the and our analytic choices have complex effects on measures of walking and walking reported here. For example, the formats may have the effect of decreasing the walking mode share due to self-reporting and memory recall issues, and this effect may be different for the two survey versions. Respondent might not report short walking trips, particularly going for a recreational stroll or jog, as "trips." Conversely, focusing only on summer trips for consistency with the 2001 survey may increase estimates of walking and biking somewhat, but the effects are unclear because the summer sample ends in August while biking tends to peak in September. Group quarters housing (e.g., college dormitories) were surveyed in September 2010, meaning that college students are under-sampled in the summer subset. The model sections focus exclusively on adults, who may not be as inclined to walk or bike as children or teens who are unable to drive.

5.2.1 Survey Administration and Seasonality

Nonmotorized travel, especially bicycling, has a large amount of seasonal variation. Bicyclists and pedestrians are more sensitive to precipitation, temperature, and hours of daylight than other mode users [17]. Summer weather in MSP is usually conducive to nonmotorized travel, although heat and precipitation diminishes utility on some days. The extreme cold, wind chills, and snowfall of winter in MSP are less accommodating of walking and bicycling. These large seasonal swings highlight the importance of matching survey administration seasons between years.

The 2001 TBI was administered in April through August, capturing months when weather is typically conducive to biking and walking. The 2011 TBI, however, was administered year-round, from December 2010 through February 2012. Figure 5.1 shows the distribution of survey respondents by the month of their travel day. Results in section 5.3 will show monthly variation of walk and bike mode share, underscoring the importance of matching the survey administration periods (see Figure 5.4).

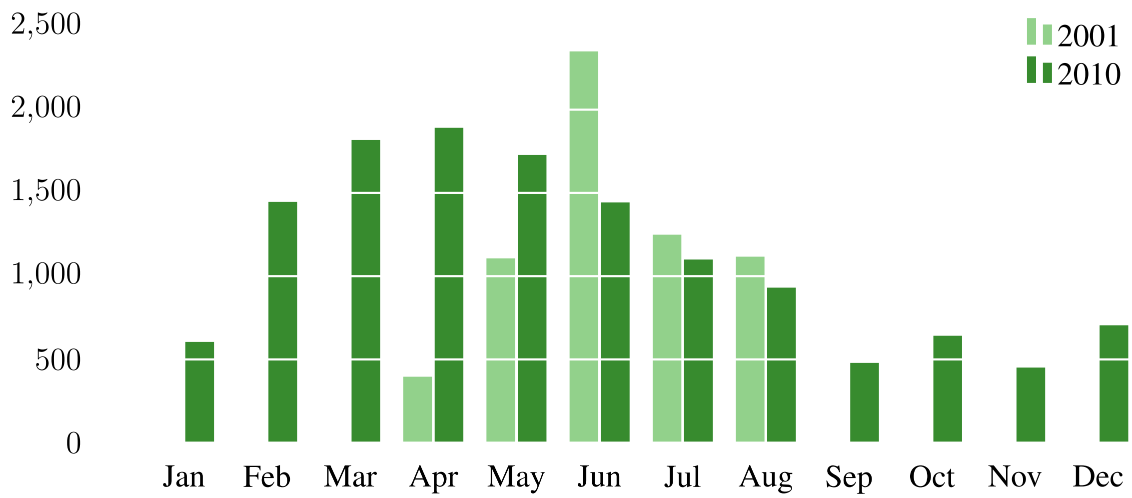

Figure 5.1: Number of Survey Respondents by Month of “Travel Day” (unweighted all months)

5.2.2 Trip Structure and Mode Definitions

Between 2001 and 2010, the structure of multimodal trips in the travel diary changed. In 2001, each trip record represented a segment of a trip completed by a single mode. Multimodal trips were reported using two or more separate records. Respondents were able to specify that the activity at intermediate destinations was to change modes (“Go on to other transportation”). The 2010 travel diary provided an option for respondents to list up to three modes for any given trip. Intermediate destinations were not listed.

Table 5.4 demonstrates this difference in data structure through a simplified multimodal trip example in which the respondent walked from home to a bus stop, rode a bus, and then walked from the bus stop to work. This trip would have three records in the 2001 dataset, but only one in the 2010 format. The data from 2001 were restructured to match 2011 before analyzing the data. However, the difference in how each survey prompted respondents to record their trips may affect how accurately people reported multimodal trips.

The Metropolitan Council defined a "primary mode" for multimodal trips in 2010. The definition was based on a hierarchy of modes; this hierarchy is independent from individual travel characteristics (e.g., segment duration or distance). After restructuring the 2001 data, the same hierarchy was applied to the 2001 data to identify primary mode. The hierarchy is defined in Table 5.5. It is applied starting with Rank 1, working down through the list. For example, any trip that includes travel by school bus, either alone or with any other mode(s), is assigned the primary mode of school bus. While nearly every trip starts or ends with walking (e.g., walking to the bus stop or parking ramp), this report defines walking trips as trips for which walking is the *primary* mode. Walking as an access or egress mode is not analyzed in this report.

5.2.3 Analytic methods

Section 5.3 presents a broad overview of walking and bicycling using descriptive statistics (primarily averages and frequencies) segmented by many attributes in our dataset (geography, age, gender, trip purpose, etc.). Descriptive statistics are supplemented with hypothesis tests (Chi-square (χ^2), t-test, and oneway ANOVA with Bonferroni post-hoc testing). Section 5.4 contains statistical modeling results from three focus areas: factors associated with mode choice, the gender gap in bicycling, and relationships between bicycling and dedicated infrastructure. The models in section 5.4 are supplemented with additional descriptive results and hypothesis tests where needed for context.

We use multinomial logistic modeling to identify factors associated with the decision to walk or bike instead of drive (section 5.4.1). We use binary logistic modeling to predict both probability of *participating* in bicycling (i.e., making at least one bicycle trip on an individual's assigned travel day) and probability of choosing to bicycle or drive for any given trip, using a series of gender interaction variables (section 5.5). Where necessary to support the models and statistical tests, additional descriptive statistics are shown in section 5.4.

Due to limited infrastructure data availability, our research about dedicated bicycle infrastructure and mode choice is performed only on a subset of the data from the City of Minneapolis. We use binary logistic modeling on this Minneapolis dataset to look for possible associations between dedicated bicycle infrastructure and the decision to bike or drive (section 5.9. Descriptive statistics about infrastructure are presented in section 5.9 alongside the model since they focus exclusively on the City of Minneapolis subsample.

Individual travel decisions may depend on household needs (e.g., driving a child to daycare) or household vehicle availability (e.g., one car available in a household of two or more drivers). Thus individual people or individual trips within a household are not independent and violate assumptions in standard statistical methods. To account for this problem, we sampled one individual or one trip per household and performed modeling only on these subsets. Where this sampling strategy was used, we describe additional methodological detail with the corresponding models and tests in section 5.4.

5.3 Descriptive Results and Hypothesis Tests

5.3.1 Overall Trends

The private auto consistently dominates travel in the region, while walking and biking comprise relatively small shares of trips. Figure 5.2 shows the large but declining mode share for auto trips in 2000 and 2010, while Figure 5.3 breaks out the remaining portion by mode. Bicycling grew from 1.4% of all trips in 2000 to 2.2% in 2010, an increase of 58%. Walking started with a larger share in 2000 (4.5%), but it grew by a smaller margin (44%) to 6.6% of trips in 2010.

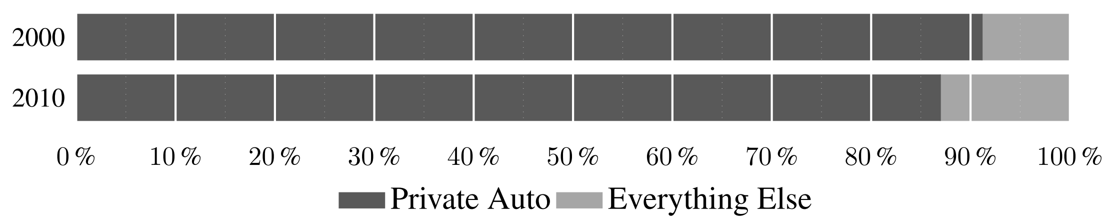

Figure 5.2: Mode Split Between Auto and Non-Auto Travel (unweighted summer only)

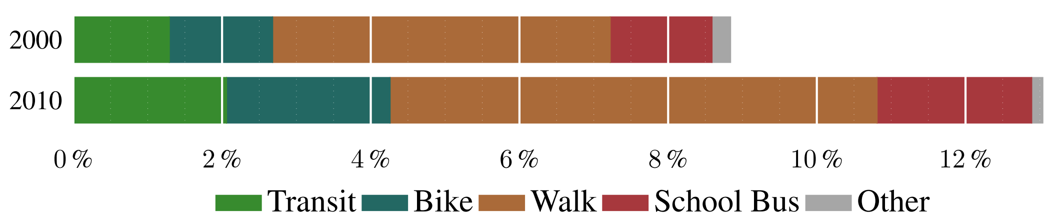

Figure 5.3: Mode Split Between Non-Auto Modes (unweighted summer only)

These relatively small mode shares (1.4 to 6.6%) translate to a substantial number of walk and bike trips on an average day in the region. Respondents made on average 3.8 trips per day in the 2010 survey. Using population weights provided by the Metropolitan Council to extrapolate the data to represent the whole region, this suggests about 12 million daily trips across the metro. The year-round average bicycle trip rate translates to over 190,000 bike trips per day across the metropolitan region. For walking, the estimate is over 735,000 trips per day. Table 5.9 summarizes trip frequencies by mode from the at the person level and estimates the regional trip volume.

The US Census and ACS journey to work data is frequently used in research about bicycling and walking. Tables 5.7 and 5.8 summarize the mode share evident in our sample alongside estimates from the 2000 Census and 2008-2012 ACS 5-year estimates. The year-round "commuters" column is the closest proxy to the Census/ACS data because it represents how many *people* walked or bicycled for their commute. However, the Census Bureau asks respondents what mode they used primarily over the course of a week, rather than a single-day sample, so part-time cyclists (i.e., people who bike only a few days per week or month) are underrepresented. This is evident especially in Table 5.8, where the Census Bureau reported a 4.1% bicycle commute share in the City of Minneapolis, which is less than half the bicycle commute share found in the 2011 dataset (9.2%).

5.3.2 Temporal patterns

Walking and bicycling vary significantly across seasons: both peak in late summer or early fall months, decline through the winter before increasing again through spring. The mode share for walking falls about 50% and never drops below the peak summer mode share for bicycling. In contrast, the mode share for bicycling drops nearly to zero in winter (Figure 5.4). The likelihood of walking and bicycling also differs by day of week. In 2010, walking and biking were relatively more common on Mondays, while driving was more popular on Fridays ($p<0.001$). Neither the 2001 nor 2010 survey covered weekend travel. This omission likely is another reason the under-represent actual rates of walking and bicycling.

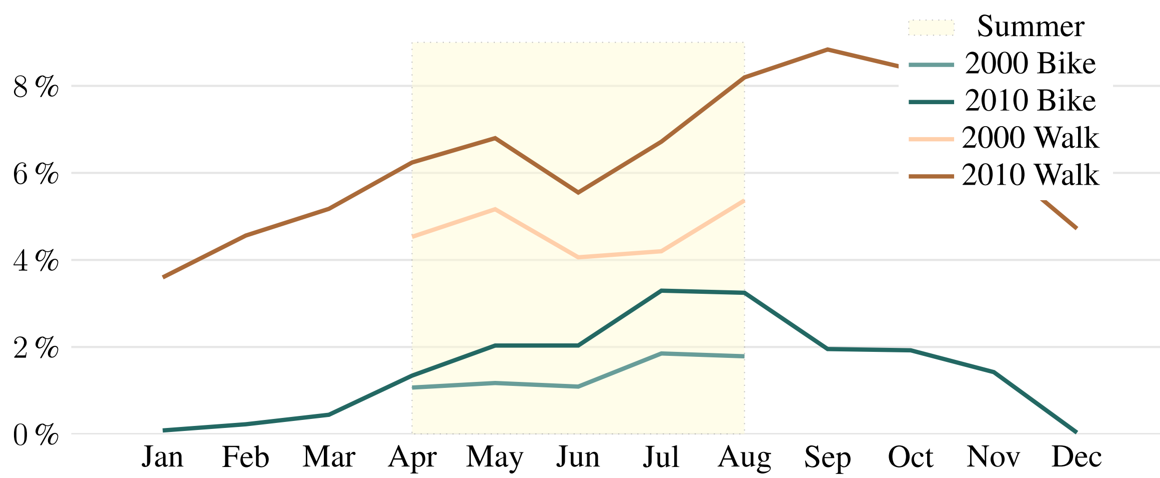

Figure 5.4: Walking and Biking Mode Share By Month for 2000 and 2010 TBI Respondents (unweighted all months)

Table 5.3: Key features of 2001 and 2010 Travel Behavior Inventories

Design Element	**2001 TBI**	**2010 TBI**	
Geographic scope	20 county metro region	19 county metro region	
Period of administration	5 months	15 months	
	4/2001 – 8/2001	12/2010 – 2/2012 (entire sample)	4/2011 – 8/2011 (matched sample)
Households in survey	6,219	14,055	7,491
Individuals surveyed	14,671	30,286	15,756
Females surveyed (%)	51.75%	52.43%	53.07%
Trip record definition	One segment of a trip completed by a single mode; no intermediate destinations (respondents could specify activity at intermediate destination was to change mode)	One trip to final destination including intermediate segments by different modes (respondents could specify up to three modes for any single trip)	
Trip mode definition	Mode used for trip segment as reported	Hierarchical determination of primary mode: 1. School bus 2. Transit 3. Auto 4. Bicycle 5. Walk 6. Other	

Table 5.4: Structure of Multimodal Trips in the 2001 and 2010 Surveys

Origin		**Mode**			**Destination**		
Location	Depart	1	2	3	Location	Arrive	Activity
One Multimodal Trip in 2001 Structure							
Home	8:00 AM	Walk			Bus Stop	8:10 AM	Change modes
Bus Stop	8:10 AM	Bus			Bus Stop	8:25 AM	Change modes
Bus Stop	8:25 AM	Walk			Work	8:30 AM	Go to work
One Multimodal Trip in 2010 Structure							
Home	8:00 AM	Walk	Bus	Walk	Work	8:30 AM	Go to work

Table 5.5: Primary Mode Definitional Hierarchy

Rank	Primary Mode	Possible Access Modes
1	School Bus	Transit, Auto, Bike, Walk, Other*, None**
2	Transit	Auto, Bike, Walk, Other, None
3	Auto	Bike, Walk, Other, None
4	Bike	Walk, Other, None
5	Walk	Other, None
6	Other	Other, None

*Other includes a wide range of modes, such as skateboarding, taxi, pedicab, etc. Only very small share of trips include a mode classified as “other”.
**Trips with only a single mode

Table 5.6: Mode Split for Summer Months - Unweighted

	2000	2010
Auto	91.16%	86.96%
Transit	1.29%	2.06%
Bike	1.39%	2.20%
Walk	4.54%	6.55%
School Bus	1.37%	2.08%
Other	0.25%	0.15%

Table 5.7: Census and TBI Walk Mode Share

	Year-round				Summer		
	Census JTW	Commuters	Work Trips	All Trips	Commuters	Work Trips	All Trips
Minneapolis 2001	6.6%				3.9%	4.4%	11.1%
Minneapolis 2010	6.4%	5.9%	6.5%	15.9%	5.0%	5.6%	16.0%
St. Paul 2001	5.4%				2.3%	3.5%	7.8%
St. Paul 2010	4.4%	5.3%	6.2%	12.3%	5.0%	6.1%	12.8%
Suburbs 2001	1.5%				0.8%	1.0%	3.2%
Suburbs 2010	1.3%	0.8%	1.2%	3.9%	0.8%	5.8%	4.2%
Ring 2001	3.4%				2.0%	2.9%	4.0%
Ring 2010	2.6%	1.9%	3.8%	3.7%	1.8%	2.6%	3.6%

Table 5.8: Census and TBI Bike Mode Share

	Year-round				Summer		
	Census JTW	Commuters	Work Trips	All Trips	Commuters	Work Trips	All Trips
Minneapolis 2001	1.9%				5.0%	5.4%	4.1%
Minneapolis 2010	4.1%	9.2%	10.0%	5.1%	10.8%	11.8%	6.4%
St. Paul 2001	0.7%				1.5%	1.6%	1.9%
St. Paul 2010	1.1%	3.1%	3.3%	1.9%	4.4%	4.5%	2.8%
Suburbs 2001	0.2%				0.6%	0.7%	1.0%
Suburbs 2010	0.4%	0.7%	0.9%	0.9%	1.2%	1.5%	1.4%
Ring 2001	0.2%				0.7%	1.0%	0.9%
Ring 2010	0.3%	1.0%	1.1%	0.8%	2.0%	2.3%	1.4%

Table 5.9: Mode Share and Estimated Number of Trips

			All Trips				Walk Trips		Bike Trips	
Geography	Number Surveyed	Population Estimate (Weighted)	Averag Trip Rate (Unweighted)	Median Trip Rate (Unweighted)	Averag Trip Rate (Weighted)	Trip Count Estimate (Weighted)	Averag Trip Rate (Weighted)	Trip Count Estimate (Weighted)	Averag Trip Rate (Weighted)	Trip Count Estimate (Weighted)
Overall	30,286	3,199,465	3.80	4	3.74	11,965,999	0.23	735,877	0.06	191,968
Minneapolis	3,538	299,687	4.29	4	3.93	1,177,770	0.68	203,787	0.24	71,925
St. Paul	2,288	211,710	4.17	4	4.13	874,362	0.52	110,089	0.08	16,937
Hennepin	7,055	686,488	4.00	4	4.00	2,745,952	0.18	123,568	0.04	27,460
Ramsey	2,174	210,543	3.96	4	3.80	800,063	0.21	44,214	0.10	21,054
Suburban 5	10,564	1,098,193	3.88	4	3.84	4,217,061	0.14	153,747	0.03	32,946
Ring 12	3,381	558,062	3.61	3	3.71	2,070,410	0.14	78,129	0.03	16,742
Missing geo	29,000	3,064,683	3.96	4	3.88	11,890,970	0.24	735,524	0.06	183,881

5.3.3 Trips by Geography

Biking and walking are a distinctly urban phenomenon. Figure 5.5 shows the summer mode shares for walk and bike in 2001 and 2010, grouped by the geography of the trip's origin (see Table 5.10 for detailed data). In 2010, the City of Minneapolis had the largest bicycle mode share, at 6.0%. The next highest mode share is less than half of what is observed in Minneapolis, and this occurs in Ramsey County excluding the City of St. Paul. The University of Minnesota's "St. Paul" campus is actually in the City of Falcon Heights, not St. Paul proper, which explains the relative share of bike trips in Ramsey County. Walking is similarly well-represented in urban areas relative to suburban and rural areas. The City of Minneapolis had nearly a 20% walk mode share in 2010, and the City of St. Paul had about 13%. None of the remaining suburban and rural geographies had double-digit walk mode shares.

Measured by summer mode share, walking and bicycling increased during the decade, though they together still accounted for less than 10 percent of all trips in the region, and they remained principally urban mode choices 5.10. While the overall increase in mode share among all trips was greater for walking (2%) than bicycling (0.8%), the percentage increase relative to each modes 2001 share was greater for bicycling (58%) than walking (44%). These large relative increases partly are a function of the small base mode shares in 2001. Statistical tests show the distribution of summer mode share in 2001 is significantly different than the 2010 distribution ($\chi^2 = 27.96$ for biking and $\chi^2 = 192.41$ for walking). Similarly, rates of walking and bicycling in 2001 and 2010 were also statistically significant ($\chi^2 = 579.26$).

These statistics mask significant differences in walking and bicycling mode share between Minneapolis and St. Paul and across the cities, the seven suburban counties, and the 12 ring counties (Tables 5.10 and 5.11). For example, measured by year-round origin mode share in 2010, walking accounts for a significantly higher proportion of trips in Minneapolis (18.3%) than in St. Paul (12.6%; $\chi^2 = 552.72$), and both cities' mode shares are significantly higher than in the suburban and ring counties, which range between three and four percent. There are significant differences in walking mode share between the suburban (3.1%) and ring (3.7%) counties ($\chi^2 = 11.07$). Walking mode shares are higher for Hennepin and Ramsey Counties, which contain Minneapolis and St. Paul, respectively, than for the other five suburban counties.

Patterns are similar for bicycling, though the relative mode shares are much lower. Bicycling mode share in Minneapolis is nearly triple that in St. Paul, and four to five times higher than rates in suburban and ring counties ($\chi^2 = 8,008.74$). One exception to this pattern is that bicycling mode share is higher in the suburban portions of Ramsey County outside the City of St. Paul than in the city itself, possibly due to the location of the UMN's St. Paul campus in suburban Ramsey County.

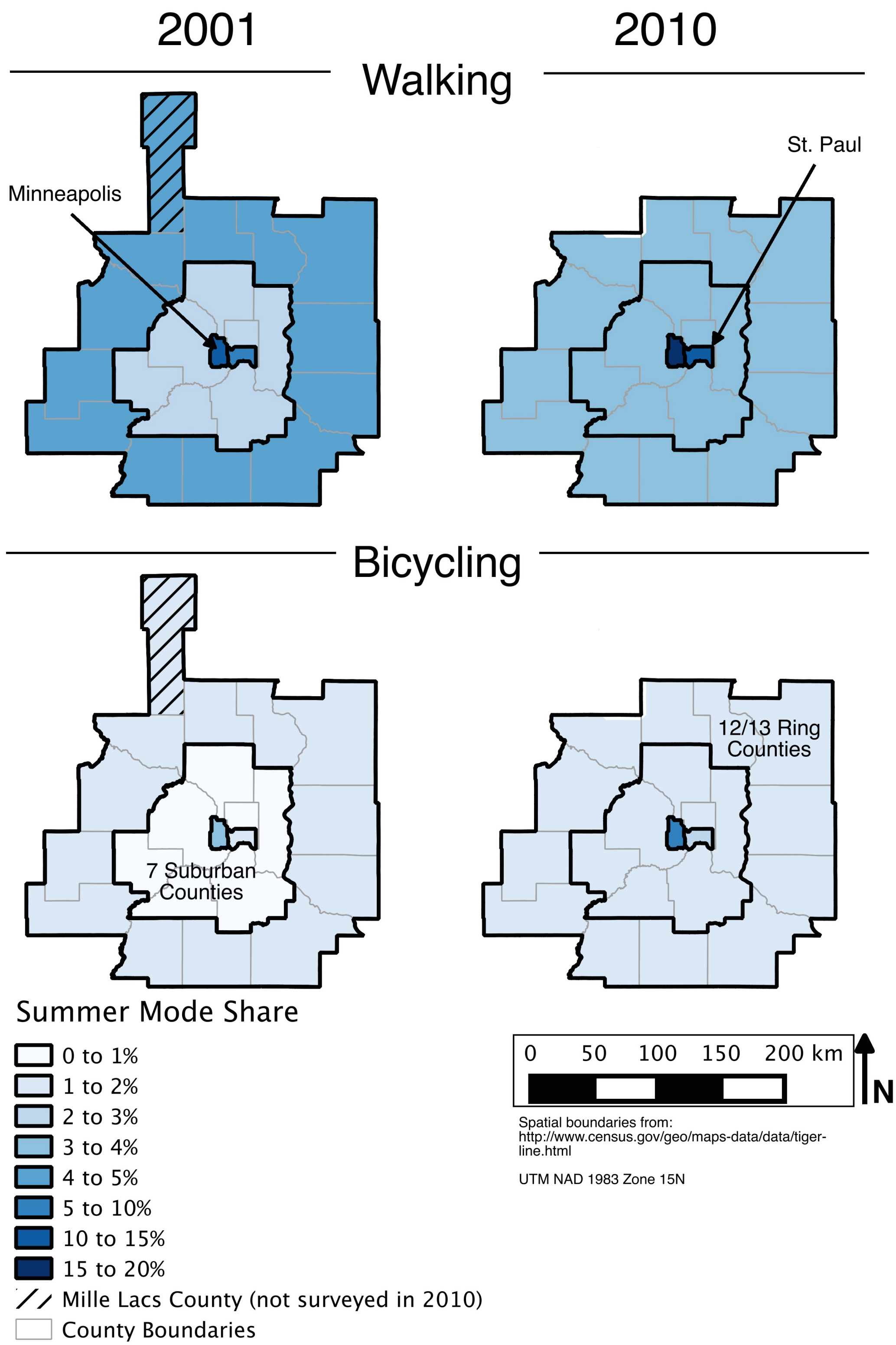

Figure 5.5: Summer mode shares by geography of trip origin

Table 5.10: Trip mode share by geography of trip origin

	MSP Region			Minneapolis			St. Paul			Suburban 7			Ring 12		
Primary	2001	2010		2001	2010		2001	2010		2001	2010		2001	2010	
Mode	Summer	Summer	Year	Summer	Summer	Year	Summer	Summer	Year	Summer	Summer	Year	Summer	Summer	Year
Auto	91.2%	87.0%	87.2%	76.4%	66.4%	67.3%	86.2%	79.4%	79.6%	94.4%	91.6%	91.6%	92.9%	92.0%	90.9%
Transit	1.3%	2.1%	2.1%	5.1%	7.5%	7.8%	2.8%	3.2%	3.8%	0.6%	0.9%	0.9%	0.2%	0.1%	0.1%
Bike	1.4%	2.2%	1.5%	3.9%	6.0%	4.9%	1.6%	2.9%	1.8%	0.9%	1.4%	0.9%	1.1%	1.7%	0.9%
Walk	4.5%	6.6%	6.1%	12.9%	18.6%	18.3%	7.9%	13.0%	12.6%	2.6%	3.5%	3.1%	4.2%	3.9%	3.7%
School Bus	1.4%	2.1%	3.0%	1.3%	1.3%	1.4%	1.0%	1.4%	1.8%	1.3%	2.4%	3.4%	1.5%	2.4%	4.4%
Other	0.3%	0.2%	0.2%	0.5%	0.2%	0.2%	0.6%	0.2%	0.4%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%

Percentages may not sum to 100% due to rounding.

Table 5.11: Participation in walking and bicycling by home geography and gender

	MSP Region			Minneapolis			St. Paul			Suburban 7			Ring 12		
Primary	2001	2010		2001	2010		2001	2010		2001	2010		2001	2010	
Mode	Summer	Summer	Year	Summer	Summer	Year	Summer	Summer	Year	Summer	Summer	Year	Summer	Summer	Year
All															
Walk	9.8%	13.5%	12.4%	21.8%	30.7%	29.4%	16.6%	24.4%	23.6%	7.5%	9.8%	8.8%	8.3%	7.6%	7.7%
Bike	2.6%	4.0%	2.6%	6.6%	11.4%	8.7%	4.3%	5.8%	3.8%	2.0%	2.6%	1.6%	1.8%	2.5%	1.3%
Male															
Walk	9.2%	12.3%	11.4%	22.5%	29.8%	28.5%	12.8%	21.6%	20.2%	7.0%	8.6%	8.0%	7.9%	7.3%	7.1%
Bike	3.3%	5.2%	3.5%	8.4%	13.9%	11.0%	6.4%	7.9%	5.2%	2.5%	3.5%	2.1%	1.7%	3.4%	2.0%
Female															
Walk	10.4%	14.7%	13.4%	21.1%	31.6%	30.3%	20.1%	26.9%	26.5%	8.0%	10.9%	9.5%	8.8%	7.9%	8.3%
Bike	2.0%	2.9%	1.9%	4.9%	8.8%	6.4%	2.5%	4.0%	2.5%	1.4%	1.8%	1.1%	1.8%	1.6%	0.7%

Participation defined as making at least one trip by this mode on travel day.

5.3.4 Mode Share by Origin-Destination Pairs

The proportions of trips within and across the two principal cities and their immediate counties changed throughout the decade. The share of walking trips within each of the two cities increased more than the share of inter-jurisdictional walking trips, but, with the exception of trips from Minneapolis to Ramsey County, inter-jurisdictional walking trips also increased. For example, walking trips between Minneapolis and St. Paul increased by a factor of about four, while inter-city bicycling trips increased by a factor of three.

Figures 5.6 and 5.7 present mode shares grouped by the origin-destination *pair* of each trip in 2000 and 2010. These charts reinforce the conclusions drawn from Figure 5.5 that biking and walking are primarily urban modes.

Bicycling achieved the highest mode share (almost 8%) in 2010 for trips that both started and ended within the City of Minneapolis, an increase of 36% over the 2000 mode share (5.8%). The next largest share was observed for trips between Minneapolis and St. Paul. In 2010, 5.7% of trips that started in one city and ended in the other were made by bicycle, representing a nearly 200% increase from 2000. The largest growth in bicycling, measured as percent increase from the 2000 baseline, was among trips between Minneapolis and the rest of Hennepin County. Although the actual mode shares were small (0.4% in 2000 and 2.1% in 2010), this represents a 486% increase over the decade. The average growth in bicycle mode share for all geographies combined was 58%.

While bicycling for inter-jurisdictional trips grew substantially in the past decade, walk trips almost universally start and end within the same city because of their shorter distance range. Within Minneapolis, the share of trips made by walking increased from 20% to 27%. By 2010, more than one out of every four trips made within the city was by walking. The walk share in St. Paul is smaller than the share for Minneapolis, but it is growing faster (54% versus 36%).

Table 5.12: Bike and Walk Share By Geography for Summer Months - Unweighted

	Bike		Walk	
	2000	2010	2000	2010
Within Minneapolis	5.83%	7.91%	20.08%	27.33%
Within St. Paul	1.93%	3.35%	13.08%	20.20%
Between Minneapolis				
& St. Paul	1.92%	5.73%	0.32%	1.41%
& Hennepin	0.36%	2.11%	0.87%	2.65%
& Ramsey	0.93%	3.12%	1.39%	0.87%
Between St. Paul				
& Ramsey	1.81%	1.22%	1.36%	3.36%

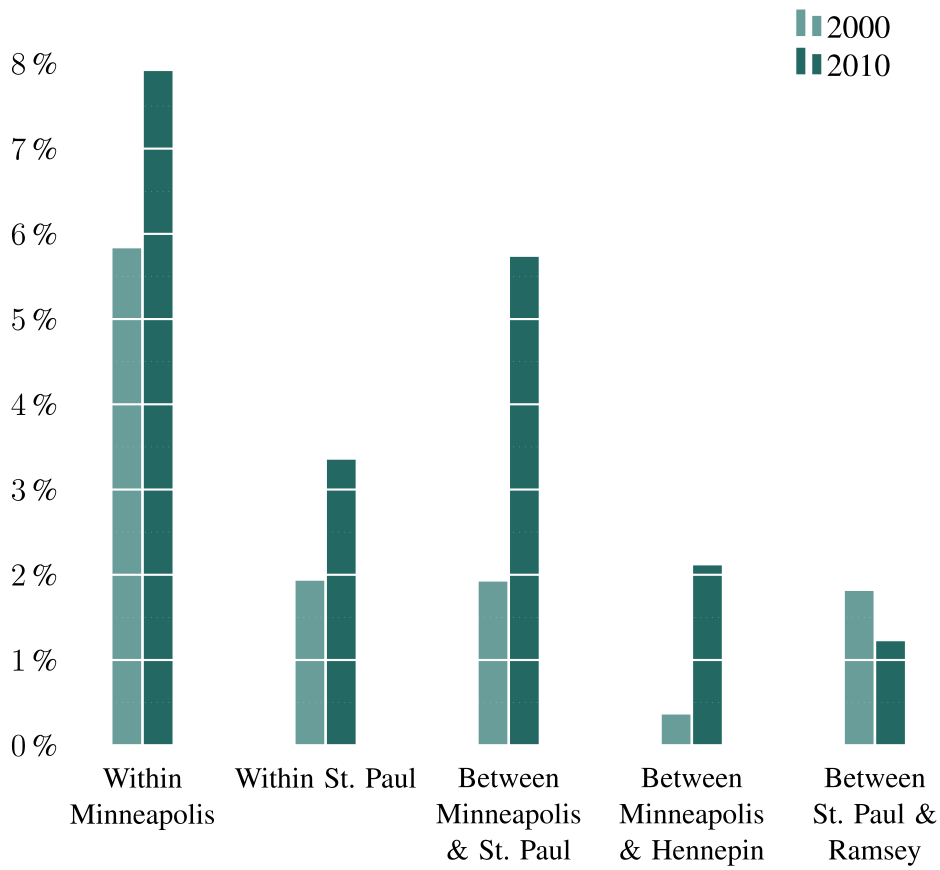

Figure 5.6: Bicycle Mode Share by Origin-Destination Geography (unweighted summer)

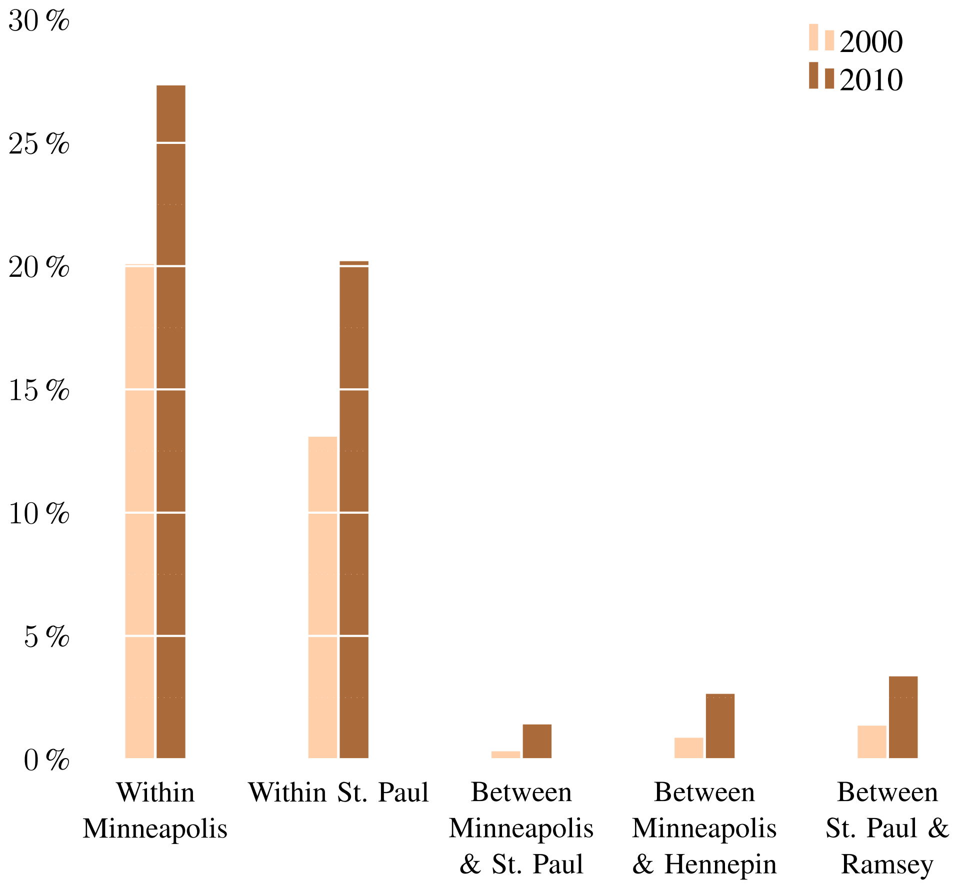

Figure 5.7: Walking Mode Share by Origin-Destination Geography (unweighted summer)

5.3.5 Trips by Distance

The trends in inter-jurisdictional biking and walking demonstrate the importance of distance in mode choice, and how biking and walking differ. Inter-jurisdictional trips are almost by definition longer than intra-jurisdictional trips, so they are less suitable for walking.

Figure 5.8 shows the share of trips made by biking and walking respectively by the estimated distance of that trip in 2000 and 2010. Walking is frequent for very short trips, while bicycling has a more even distribution for the first few miles. In 2010, over 50% of all trips shorter than 400 meters (1/4 mi) were made by walking, across the entire metro region.

The average length of trips taken by walking and bicycling are significantly different in 2010 ($p<0.001$) and are significantly shorter, on average than the average length of auto trips in both years ($p<0.001$). More than half of all walking trips are less than 800 meters (0.5 miles); comparable median lengths for bicycling and all trips are about 2.9 and 6.2 kilometers (1.8 and 3.9 miles), respectively, in 2010, and 2.1 and 6.1 kilometers (1.3 and 3.8 miles) in 2000 (Figure 5.8).

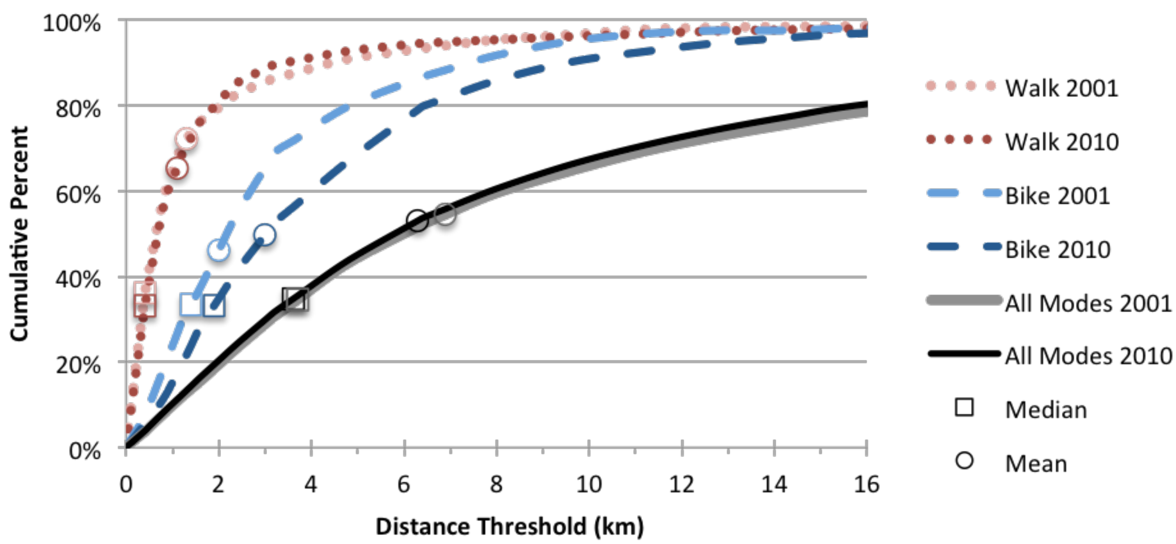

Figure 5.8: Cumulative share of trips by distance threshold

Figure 5.9 highlights the difference in typical trip distances for walking and biking. This chart shows the relative frequency of trips made by each mode within a range of distance categories. About 33% of all walk trips are shorter than 0.25 miles, and 75% are shorter than one mile. Conversely, less than 30% of all bike trips are shorter than one mile.

Figure 5.8, as noted, shows the cumulative percent of all bike or walk trips that are less than the distance threshold. Like Figure 5.9, this figure again emphasizes differences between bicycling and walking. The walking curve approaches 100% much faster than bicycling. Over 75% of walk trips are shorter than 1 mile, but the cumulative share of bicycle trips doesn't pass 75% until the 4-mile threshold. Both bicycling and walking are heavily skewed towards short trips relative to the whole sample of trips, where 20% are longer than 10 miles (Tables 5.13 and 5.14).

Table 5.13: Bike and Walk Share By Distance Threshold for Summer Months - Unweighted

	Bike		Walk	
	2000	2010	2000	2010
0 – 0.25	2.75%	3.19%	42.63%	52.01%
0.25 – 0.5	3.81%	3.08%	23.86%	33.45%
0.5 – 0.75	3.91%	4.44%	14.16%	18.51%
0.75 – 1.0	3.08%	4.83%	6.64%	11.63%
1.0 – 1.5	3.13%	3.73%	3.67%	7.06%
1.5 – 2.0	2.72%	3.42%	2.21%	3.55%
2.0 – 3.0	1.23%	2.70%	1.62%	1.63%
3.0 – 4.0	1.07%	2.91%	1.22%	1.17%
4.0 – 5.0	0.97%	1.99%	1.22%	0.69%
5.0 – 6.0	0.90%	1.71%	0.98%	0.81%
6.0 – 10.0	0.32%	1.07%	0.67%	0.83%
10.0 +	0.12%	0.35%	0.28%	0.65%

Table 5.14: Distribution of Travel Distances for Bike and Walk Trips, 2010 Summer Months - Unweighted

	Bike		Walk		All Modes	
	Percent	Cumulative	Percent	Cumulative	Percent	Cumulative
0 – 0.25	5.59%	5.59%	33.17%	33.17%	3.95%	3.95%
0.25 – 0.5	5.83%	11.43%	23.10%	56.27%	4.30%	8.25%
0.5 – 0.75	8.02%	19.45%	12.19%	68.46%	4.09%	12.35%
0.75 – 1.0	8.91%	28.36%	7.82%	76.28%	4.15%	16.50%
1.0 – 1.5	13.05%	41.41%	9.00%	85.28%	7.88%	24.38%
1.5 – 2.0	11.18%	52.59%	4.22%	89.50%	7.36%	31.74%
2.0 – 3.0	14.51%	67.10%	3.19%	92.68%	12.09%	43.83%
3.0 – 4.0	12.72%	79.82%	1.86%	94.54%	9.86%	53.68%
4.0 – 5.0	6.08%	85.90%	0.77%	95.31%	6.86%	60.54%
5.0 – 6.0	4.29%	90.19%	0.74%	96.05%	5.65%	66.19%
6.0 – 10.0	6.73%	96.92%	1.89%	97.93%	14.10%	80.29%
10.0 +	3.08%	100.0%	2.07%	100.0%	19.71%	100.0%

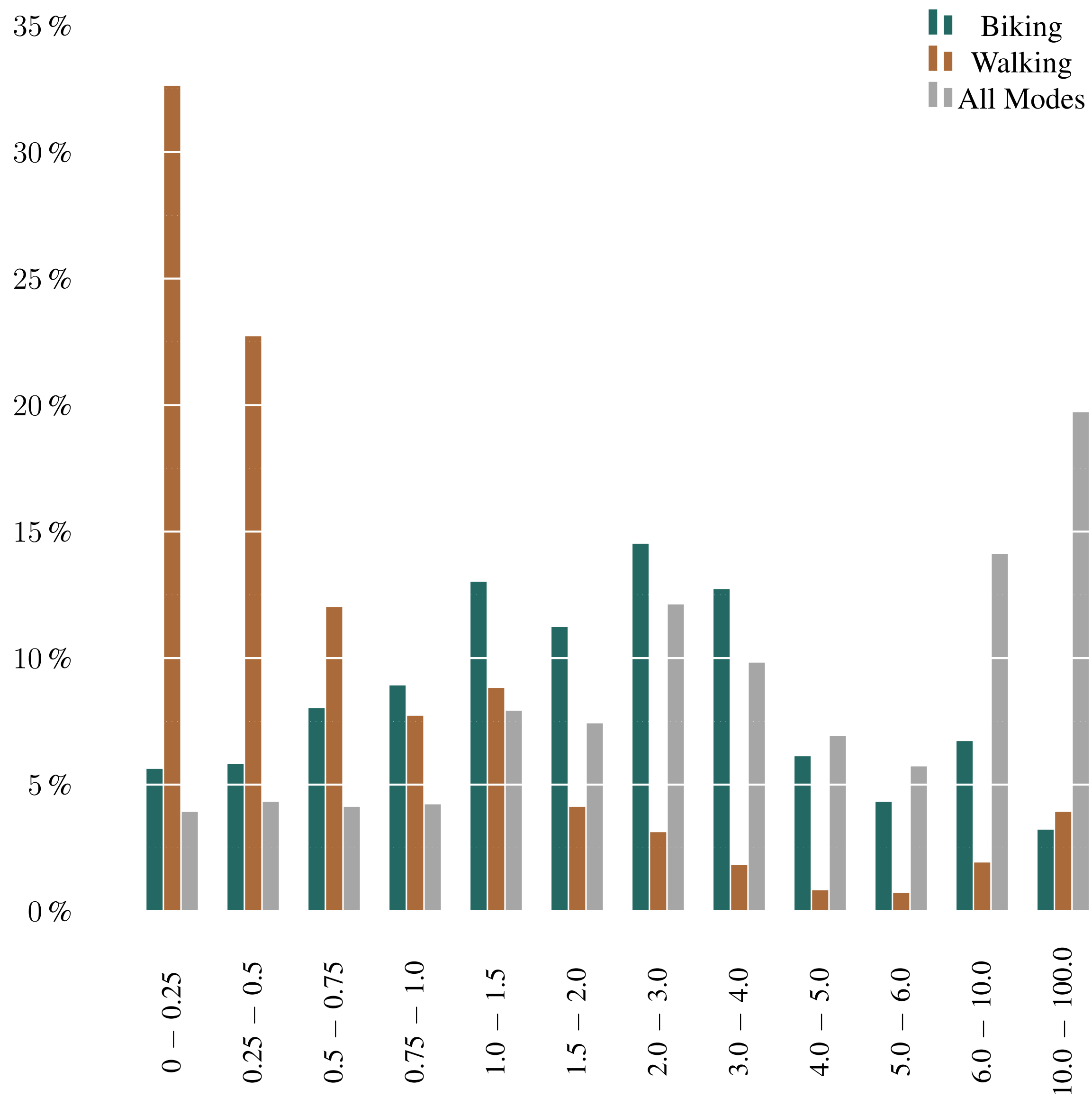

Figure 5.9: Relative Frequency of Walk and Bike Trips By Distance (unweighted summer 2010)

Short Trips by Geography

Interestingly, the rates of bicycling and walking for short trips also varies by geography (Table 5.15 and Figures 5.10 and fig:walk mode share geo 1mi). 82.9% of trips shorter than 400 meters ($1/4$ mi) that start and end within Minneapolis are made by walking or biking (combined). 78.8% of these trips within St. Paul are also made by nonmotorized modes. Conversely, only 40% of trips shorter than 400 meters ($1/4$ mi) are made by walking or bicycling in all other geographies excluding the principle cities, even though the trips are all the same distance.

Table 5.15: Mode share for very short trips, by geography

	0 – 400 Meters 0 – 0.25 Miles		0 – 1,600 Meters 0 – 1.0 Miles	
	2000	2010	2000	2010
Within Minneapolis	76.20%	82.86%	51.99%	63.27%
Within St. Paul	66.87%	78.83%	37.72%	49.50%
All other trips	28.28%	37.42%	15.57%	19.72%

5.3.6 Gender and Age

Table 5.11 summarizes person-level participation in walking and bicycling (i.e., the proportions of individuals by gender who completed at least one primary trip by walking or bicycling). Measured by differences in summer mode share, the proportions of men and women who took at least one primary trip by walking or bicycling increased in all subareas with one exception: the proportion of women in the ring counties who bicycled declined slightly. Across the region, and in most subareas, walking mode share for women was similar to, but slightly higher than for men in both 2000 and 2010. Bicycling, however, was highly gendered, and the disparity was not reduced over the decade, despite significant increases in bicycling overall. (Table 5.11)

With respect to age, younger individuals are much more likely than older individuals to walk and bicycle, and the effect is more pronounced with bicycling (Figure 5.12). Walking mode share declines from the teens and 20s, stabilizes in the 40s, and declines again in the 60s or 70s, remaining at nearly 5% for trips taken by people in the oldest age categories. Bicycling mode share, however, declines consistently through the decades, and accounts for virtually less than about 1% of all trips for people who are 60 or older. Some of the observed decline may be cohort-specific. 30-39 year olds bike less than 20-29 year olds for both years, but 30-39 year olds in 2010 would have been in the 20-29 bracket in 2001, and those groups bike at about the same rate.

Gender

In Section **??**, Figure 5.2 showed that bicycling increased marginally across the whole region, from 1.4 to 2.2% of all trips. However, these gains are not evenly distributed among men and women.

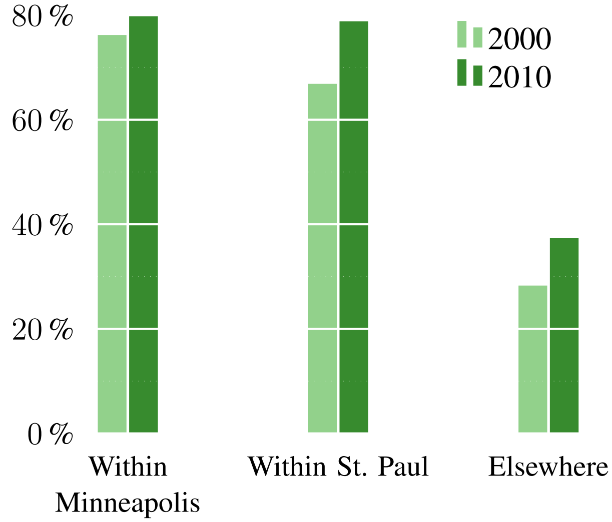

Figure 5.10: Walk+Bike Combined Mode Share for Trips Shorter than 400 meters ($1/4$ mi) by Geography (unweighted summer)

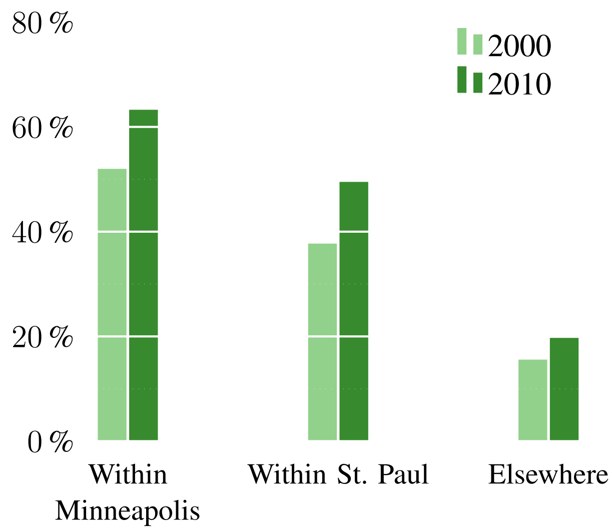

Figure 5.11: Walk+Bike Combined Mode Share for Trips Shorter than 1,600 meters (1 mi) by Geography (unweighted summer)

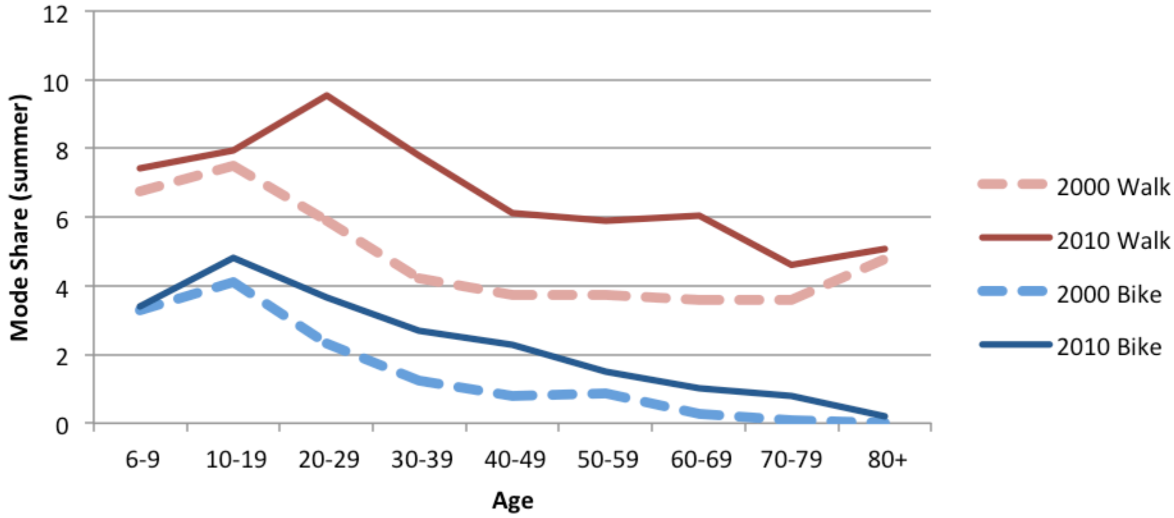

Figure 5.12: Summer mode share by age cohort

Proportionally, bicycling grew at nearly the same rate for men and women across the region: 58% and 57% respectively. For trips within Minneapolis, the bicycle mode share grew 44% between 2000 and 2010, while it only grew by 29% for men. The overall bicycle mode share for men in 2000 was approximately double the mode share for women, and this gap persisted in 2010. This same gap is evident for trips within the City of Minneapolis.

Age

As expected, bicycling is more common among younger people than older people. However, Figure 5.15 shows rates of bicycling increasing for all age groups, and most notably for adults between 20 and 50. Some of this may be a cohort effect: people in the 10-19 age bracket in 2000, which had the highest rate of bicycling, were in the 20-29 age group in 2010. However, for all cohorts that were 20 or older in the 2000 survey, the bicycle mode share increased over the decade. For example, the cohort that was 20-29 in the 2000 survey had a bicycle mode share of 2.32. The same cohort, which was 30-39 in the 2010 survey, had a bicycle mode share of 2.68.

Walking is much more evenly distributed across ages (Figure 5.16). All ages have a walk mode share over 3.5%, and all age groups saw higher mode shares in 2000 than 2010. Similar to biking, all cohorts increased their rates of walking over the decade. 20-29 year olds in 2000 had a walk mode share of 5.88%, and the mode share for the same cohort (30-39 year olds in 2010) was 7.79%.

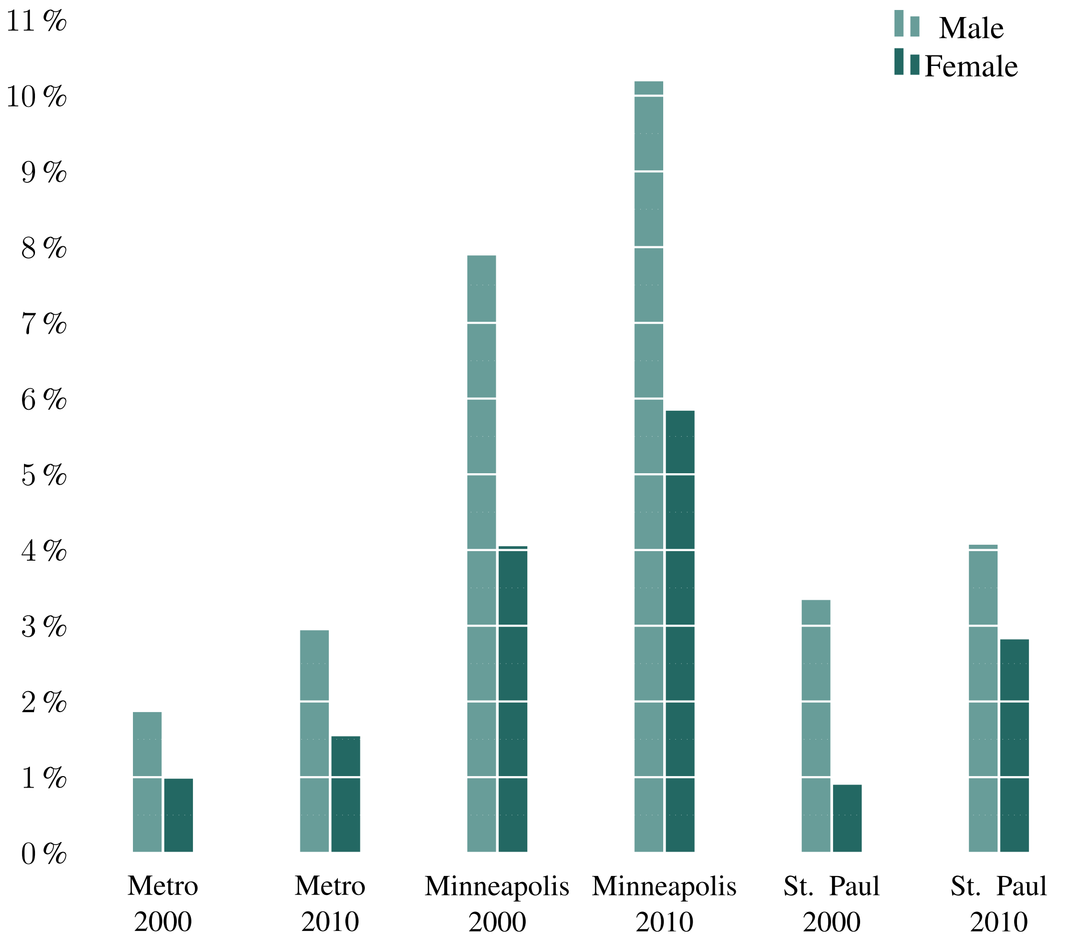

Figure 5.13: Bicycle Mode Share by Gender and Geography (unweighted summer)

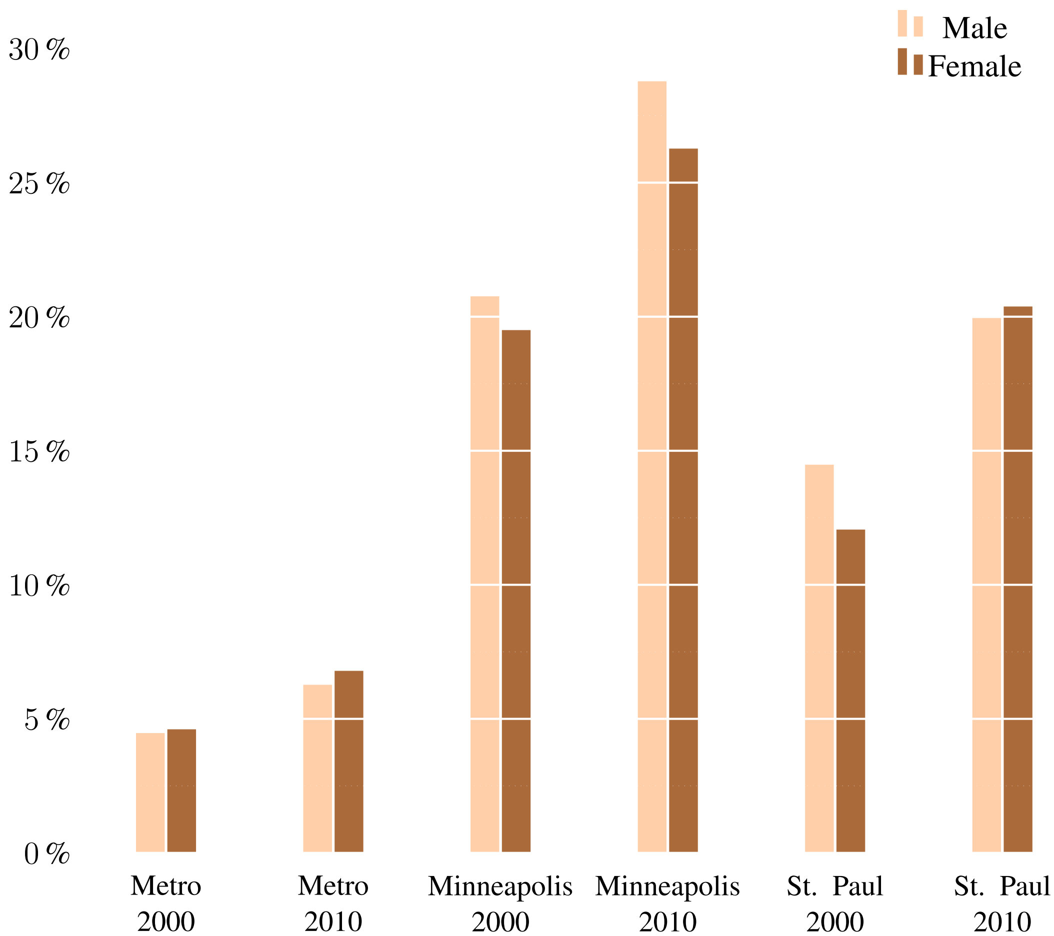

Figure 5.14: Walk Mode Share by Gender and Geography (unweighted summer)

Table 5.16: Bike and Walk Share By Geography and Gender for Summer Months - Unweighted

	Bike				Walk			
	Female		Male		Female		Male	
	2000	2010	2000	2010	2000	2010	2000	2010
Within Minneapolis	4.05%	5.84%	7.89%	10.19%	19.50%	26.27%	20.76%	28.78%
Within St. Paul	0.90%	2.82%	3.34%	4.07%	12.06%	20.38%	14.48%	19.95%
Between Minneapolis								
& St. Paul	1.90%	4.08%	1.93%	7.55%	0.32%	1.75%	0.32%	1.05%
& Hennepin	0.30%	1.31%	0.42%	3.05%	0.53%	2.74%	1.25%	2.55%
& Ramsey	0.94%	0.64%	0.91%	5.36%	0.00%	1.59%	2.74%	0.00%
Between St. Paul								
& Ramsey	0.29%	0.00%	3.51%	2.85%	1.71%	4.11%	0.96%	2.38%
Metro	0.98%	1.54%	1.86%	2.94%	4.61%	6.79%	4.47%	6.27%

Table 5.17: Bike and Walk Share By Geography and Age for Summer Months - Unweighted

	Bike		Walk	
	2000	2010	2000	2010
6 – 9	3.29%	3.39%	6.77%	7.43%
10 – 19	4.10%	4.83%	7.49%	7.93%
20 – 29	2.32%	3.67%	5.88%	9.54%
30 – 39	1.23%	2.68%	4.21%	7.79%
40 – 49	0.81%	2.30%	3.73%	6.10%
50 – 59	0.86%	1.50%	3.72%	5.89%
60 – 69	0.26%	1.03%	3.60%	6.05%
70 – 79	0.08%	0.78%	3.59%	4.61%
80 +	0.00%	0.20%	4.78%	5.09%

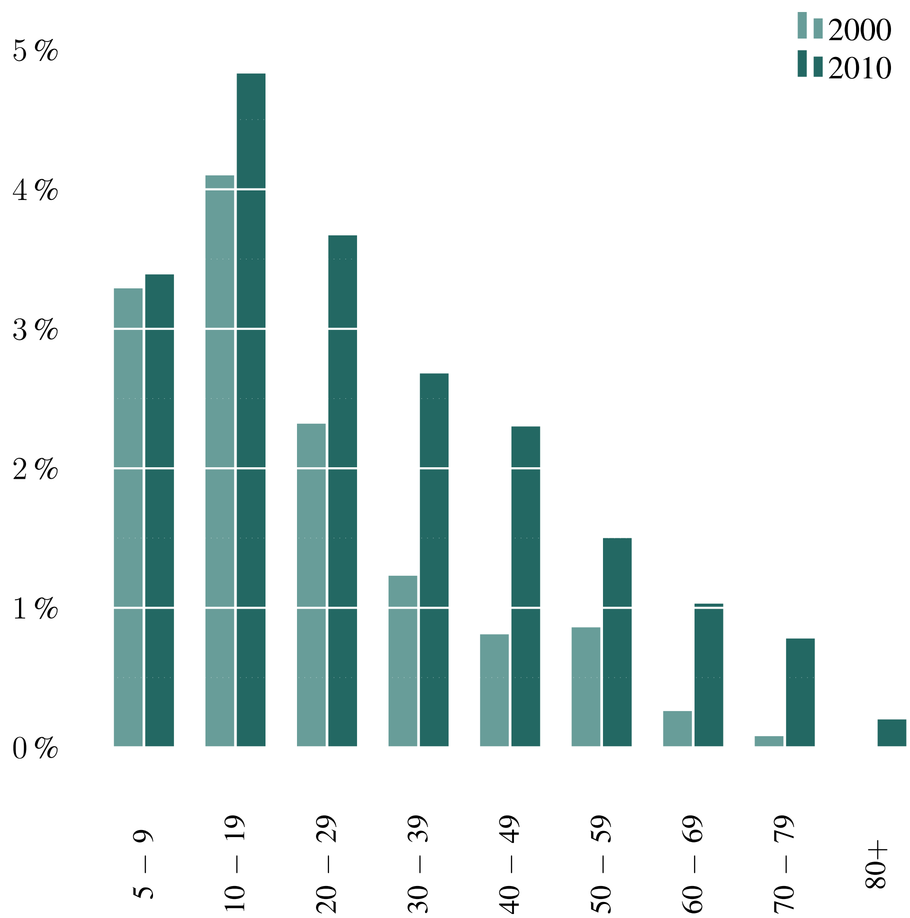

Figure 5.15: Bike Mode Share by Age (unweighted summer)

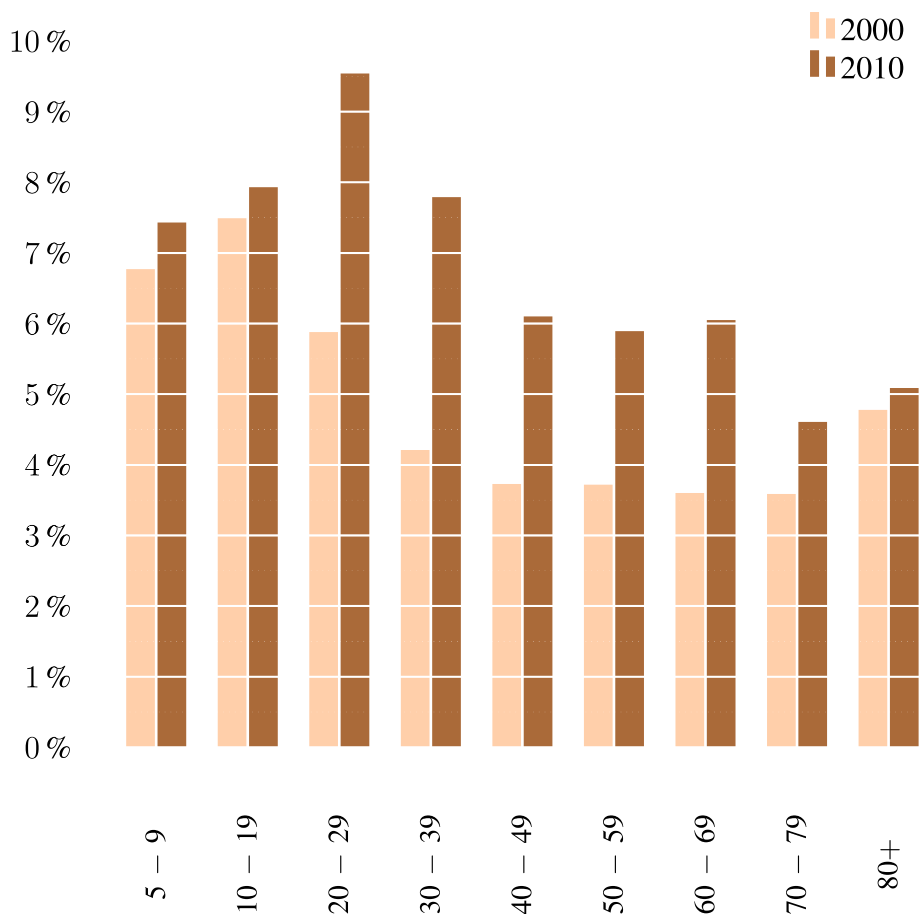

Figure 5.16: Walk Mode Share by Age (unweighted summer)

5.3.7 Trip Purpose

The classify numerous different trip purposes. Through the harmonization process between years, we reduced these to six categories: shopping, dining out, social/entertainment, school, work, and other. The reasons why people walk and bicycle share similarities but are changing over time. The largest differences among modes for trip purpose is for the category "other" (Figure **??**), which includes trip purposes such as picking up and dropping off passengers, or accompanying other people. While more 30% of all walking trips were taken for this purpose in 2000 and 2010, less than 20% of all bike trips were taken for this purpose. This difference may be an artifact of the challenges respondents face in classifying walking trips. Perhaps the most distinctive difference involves the percentage of trips taken for work: the proportion of bicycling trips taken for work is about double to triple the proportion of walking trips taken for work ($p<0.001$, both years), and significantly higher than the proportion of all trips taken for work ($p<0.001$, 2010). The largest change in trip purpose over the decade was the increase in bicycle trips for work, coupled with the reduction of bicycle trips taken for social/entertainment purposes. Relative to other modes, the proportion of both walking and bicycling trips taken for social/entertainment purposes is higher than for all modes, but this proportion declined during the decade, perhaps because of the recession.

Figures 5.17 and 5.21 show the relative frequency of six "trip purpose" categories within each mode for bicycling and walking. Trip purposes refer to home-based trips to- or from- a location in this category.

Bicycle Trip Purposes

In Figure 5.17, it is clear that bicycling has shifted over the past decade from primarily shopping and social trips to commuting. In 2000, nearly 25% of all bike trips in the region were for shopping, and over 35% of all bike trips were for social or entertainment purposes. By 2010, the share of bike trips that were for shopping declined to less than 15%, and 25% for social and entertainment. The change in shopping trips by bike follows the overall decline in shopping, from 30% to 20% of trips by all modes. However, the shift away from bicycle trips for social and entertainment is disproportionate relative to the broader trend, which held constant for trips of all modes. Commute trips represented about 20% of all trips in 2000 and 2010, but they grew from 17% in 2000 to 32% of all bicycle trips in 2010.

In addition to differences between men and women in overall rates of bicycling, there is evidence of gender differences by trip purpose. The disproportionate shift for social and entertainment trips was similar for men and women. Nearly all the gains in bicycle commuting can be attributed to male bike commuters, while women experienced modest shifts in school, work, and other trips.

Figure 5.20 shows the gender gap in bicycle commuting over time and by geography. The most striking difference is for commute trips that start and end within the City of Minneapolis. A modest gender gap for commute trips within Minneapolis in 2000 widened substantially when the bike commute mode share for men doubled and only increased by a few percentage points for women.

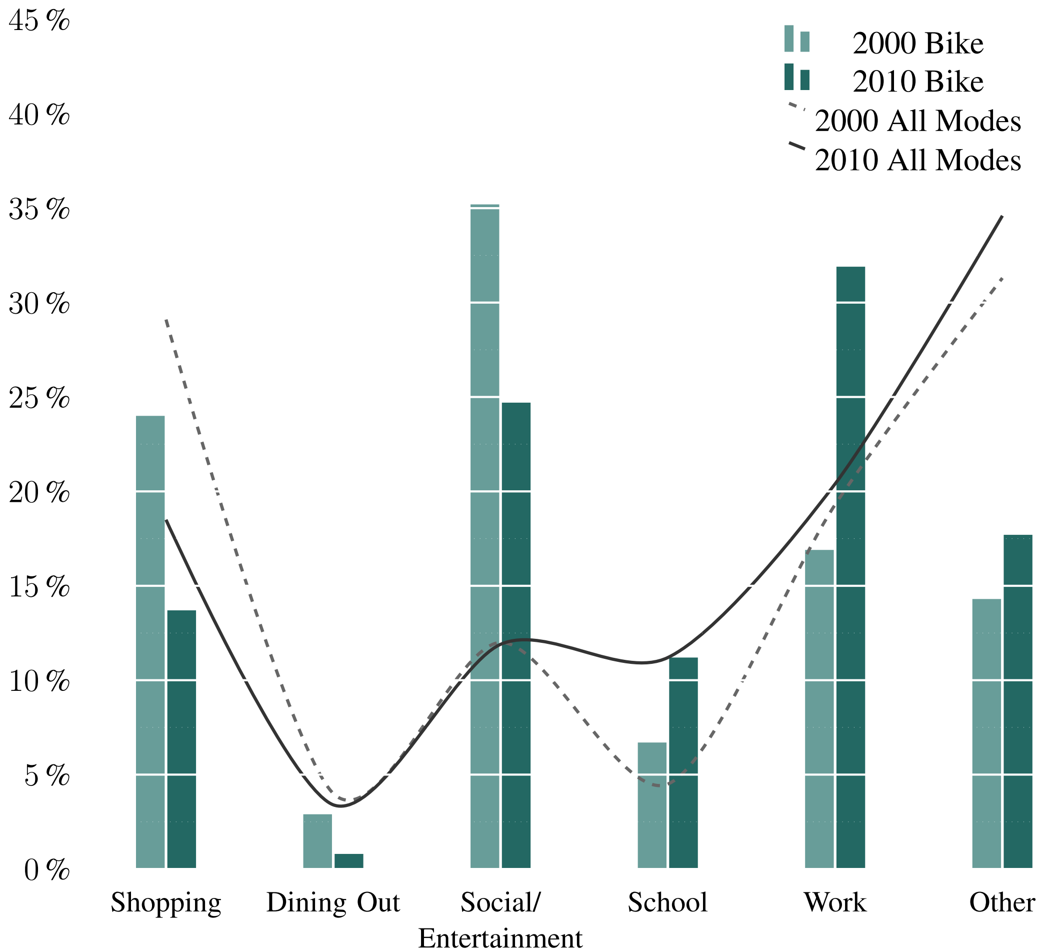

Figure 5.17: What percent of trips by this mode are for this purpose (unweighted summer)

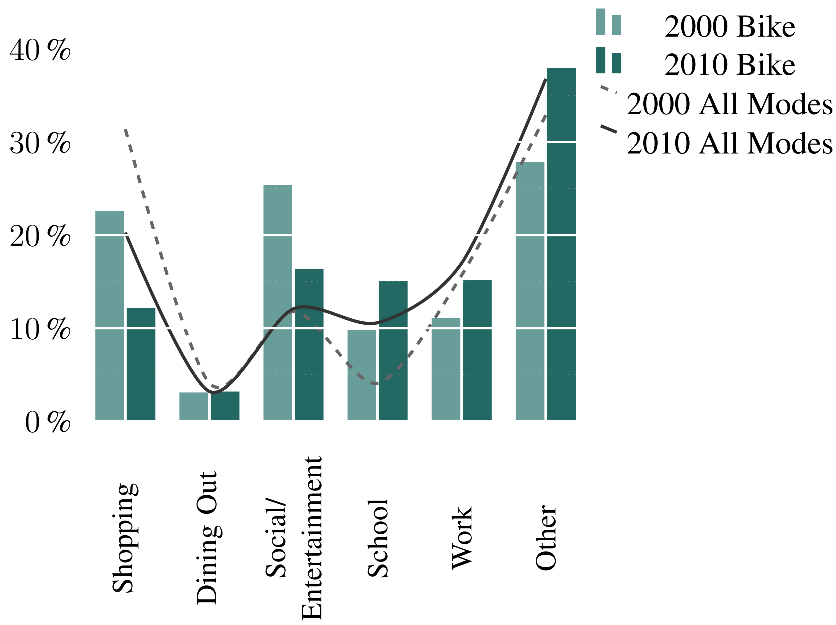

Figure 5.18: Female: What percent of trips by this mode are for this purpose (unweighted summer)

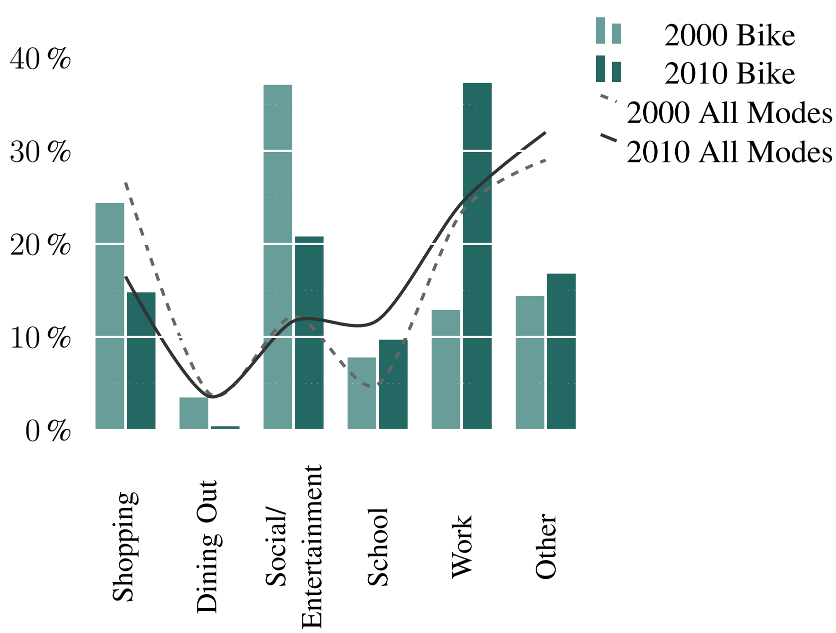

Figure 5.19: Male: What percent of trips by this mode are for this purpose (unweighted summer)

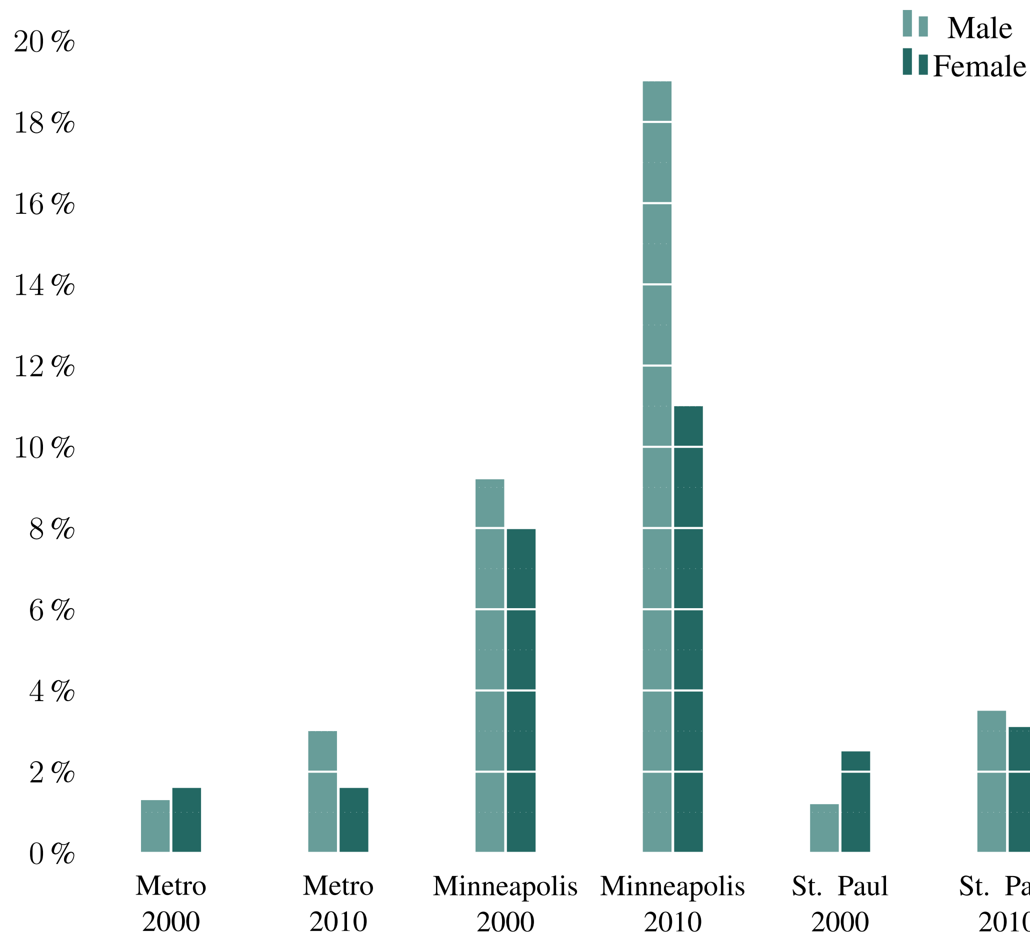

Figure 5.20: Bicycle Commute Mode Share by Gender and Geography (unweighted summer)

Pedestrian Trip Purposes

Walk trip purposes shifted marginally between 2000 and 2010, but with few exceptions, these changes are proportional to shifts in trips among all modes. School trips as a percent of all walk trips increased, but so did school trips as a percent of trips by all modes. Social and entertainment trips declined as a share of all walk trips disproportionately to trips for this purpose by all modes, similar to the trend observed in bicycling.

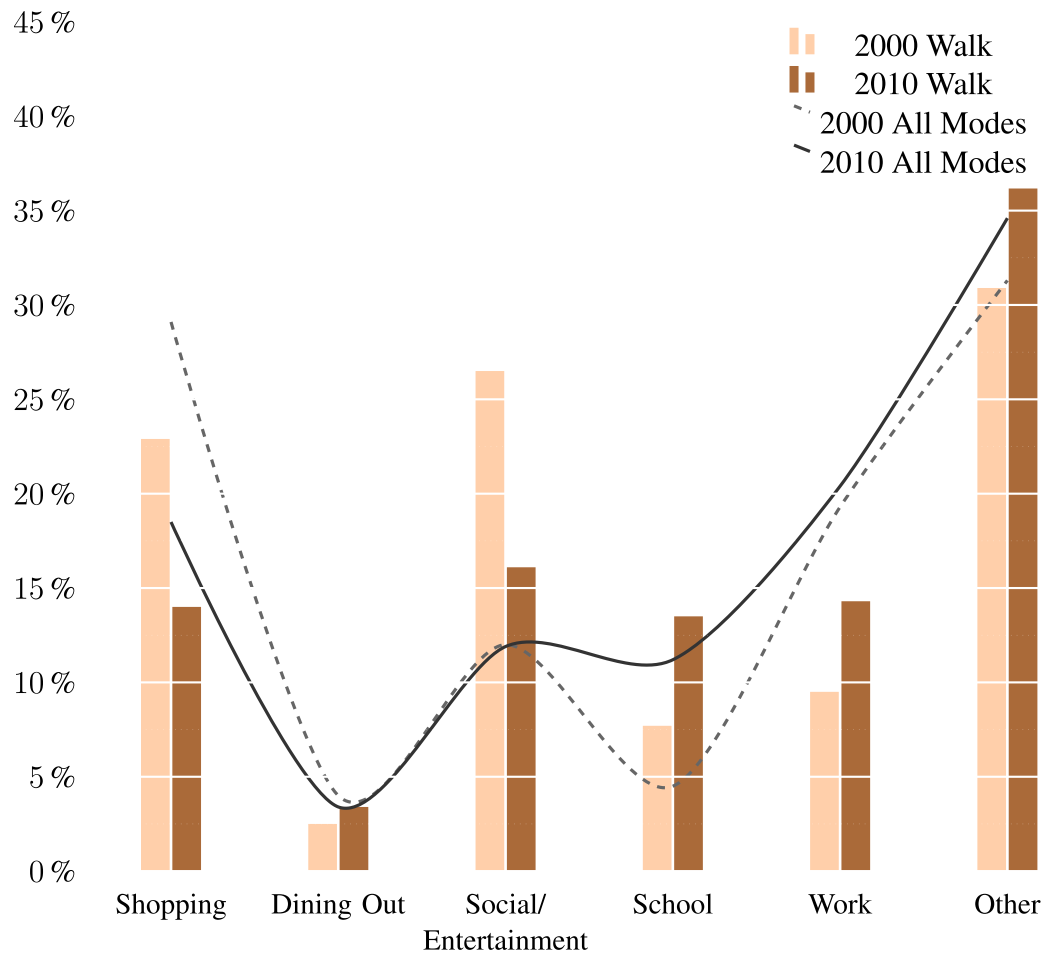

Figure 5.21: What percent of trips by this mode are for this purpose (unweighted summer)

There are no notable differences in trip purposes or shifts in walking between men and women.

Walk commuting grew quite a bit within Minneapolis and St. Paul, but the metro-wide change was marginal.

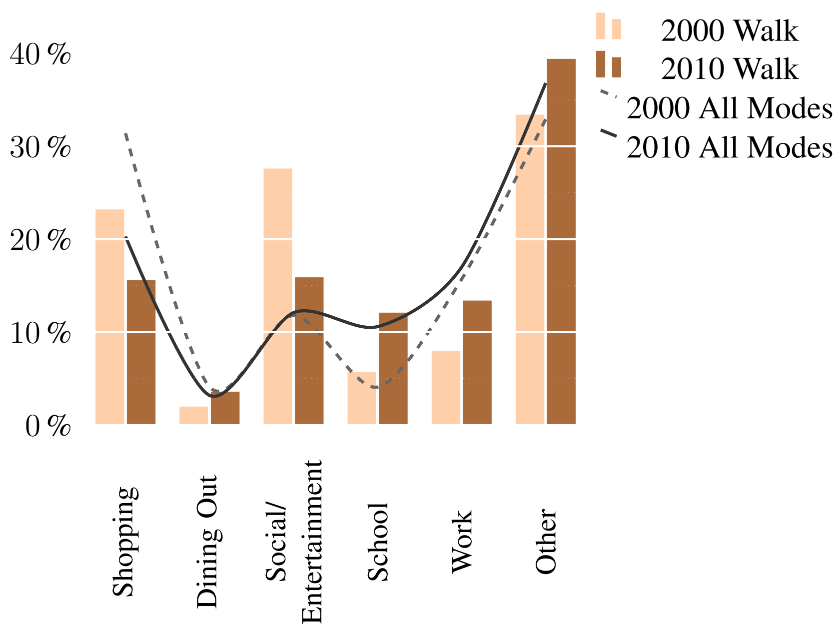

Figure 5.22: Female: What percent of trips by this mode are for this purpose (unweighted summer)

5.4 Statistical Modeling Results

5.4.1 Walk and Bike Mode Choice

We use multinomial logistic models to analyze the likelihoods that trips will be made by walking or bicycling, relative to a baseline of driving, and identify factors associated with walking and biking. We estimated models for the 2001 and 2010 data separately. We started with the same set of 38 independent variables about weather and travel day characteristics, individual and household demographics and socio-economic measures, trip purpose, and geography. We used backwards-stepwise removal to retain only variables that were significant at $p<0.1$ for at least one mode's equation. The 2001 and 2010 models were tested on the other years data, and the overall fit was similar if slightly diminished. Because the trip dataset contains multiple trips from the same people and households, including "duplicate" trip entries where multiple members of a household traveled together, we randomly selected walking, bicycling, and driving trips made by adults ages 18 and older, such that each trip in the sample comes from a unique household.

Model Results

To understand how various factors affect the likelihood of decisions to walk or bicycle rather than drive, and to see if those factors have changed over time, we estimated multinomial logistic models using data from 2000 and 2010. The results show that different factors affect the likelihood of taking a trip by walking and bicycling and that these factors have varied somewhat over time

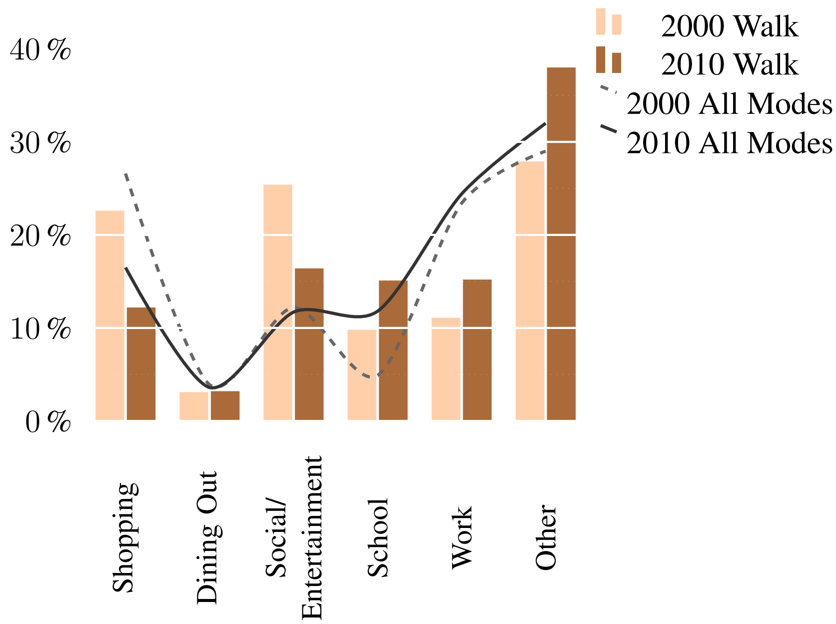

Figure 5.23: Male: What percent of trips by this mode are for this purpose (unweighted summer)

(Tables 5.18 and 5.19). Chi square tests show that the equations for walking and bicycling in each model are significantly different ($\chi^2 = 88.67$ in 2001 and $\chi^2 = 147.17$ in 2010).

In the 2001 model, five of the 17 variables are significant for both walking and biking. However, for two of those (having a driver's license and trips within Minneapolis), there is no significant difference between walking and biking. Shorter travel distances and having a college degree both increase the relative probability for walking and biking, but to different extents. Having a college degree increases the relative chance of walking by a factor of 1.302, but the for biking is nearly double the change in odds for walking (2.495). Conversely, while each additional kilometer of travel decreases the probability of walking instead of driving by a factor of 0.785, the probability of biking is reduced slightly less, by a factor of 0.873.

The probabilities of walking and bicycling are strongly and significantly associated with whether a trip is for work or non-work activities, and whether the trip is home-based. Home-based work trips have a reduced relative probability of walking by 40% (p=0.012) in 2001, while the relationship with bicycling is positive but insignificant. Work-based trips to destinations other than home is associated with more than doubling the chance that a trip is made by walking instead of driving (p<0.000), while they cut the relative probability of bicycling by over half (p=0.030).

Weather phenomena (rain events and hot, humid days) are associated with a decreased probability of biking by factors of 0.643 and 0.587 respectively. Being male, a student, younger than 56, and having a low household income (less than $30,000 per year in 2001) are associated with a higher relative chance of biking instead of driving. Being female cuts the relative probability of biking in half (0.489), while gender has no significant association with walking.

While starting and ending a trip within Minneapolis increases the relative chance of walking

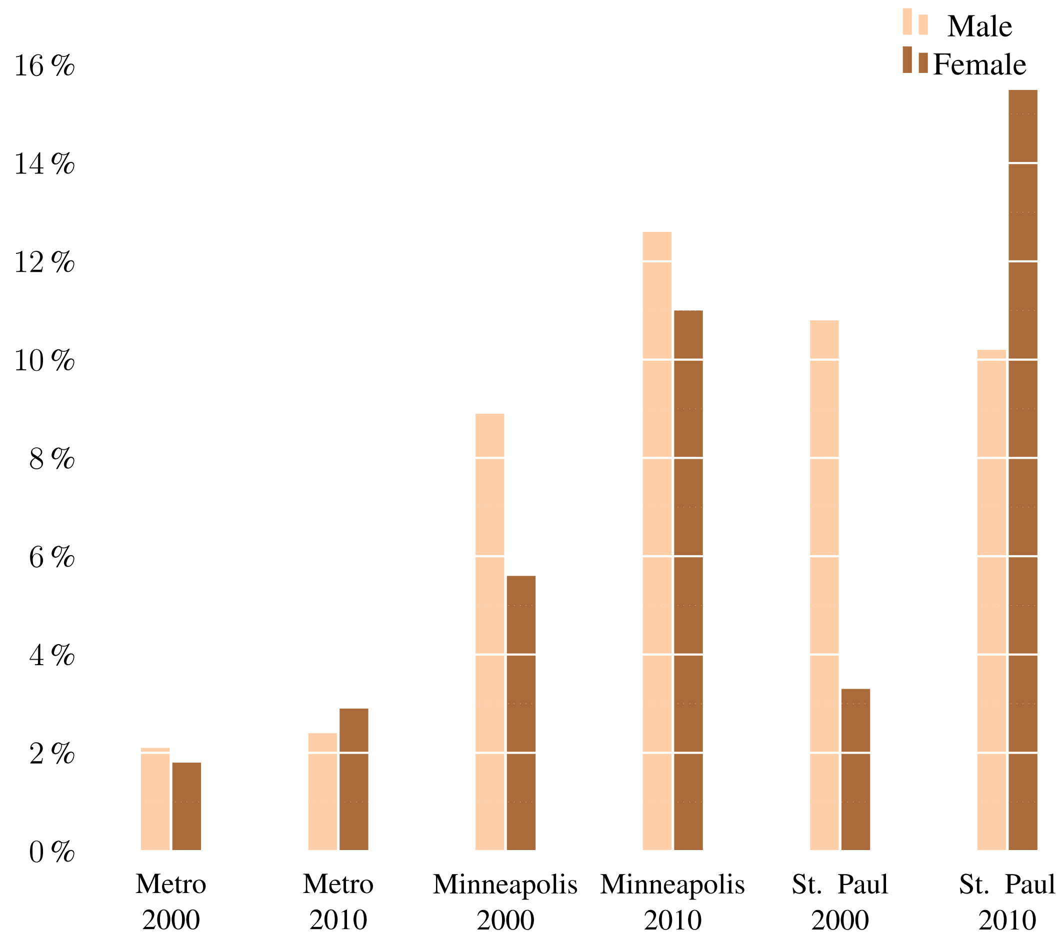

Figure 5.24: Walk Commute Mode Share by Gender and Geography (unweighted summer)

or biking equally by a factor of about 6, St. Paul trips and intercity trips have different modal effects. Starting and ending within St. Paul increases the relative probability of walking by a factor of 3.417, while traveling between Minneapolis and St. Paul increases the relative probability of biking by a factor of 3.915. In any case, starting and ending ones trip within the urban core decreases the relative probability of driving.

Most of the variables from 2001 are also significant for at least one mode in 2010, though there are differences between the models. None of the day-of-week variables or measures of heat and humidity remained in the 2010 model, and the income categories are replaced by a measure of how many cars are available in the household. The 2010 model also has a larger share of variables for which the coefficients for walking and biking are both significant but not significantly different from each other. In addition to having a driver's license and starting and ending within Minneapolis (like the 2001 model), being younger than 56 or a student, having a college degree, and starting and ending within St. Paul also increase the probability of both walking and biking relative to driving by roughly the same ratios.

In the 2010 sample, a similarity to the 2001 model is each additional kilometer of travel distance reduces the for both walking and bicycling, but the effect on walking is stronger (a factor of 0.745 versus 0.945). Circuity is newly significant in the 2010 model for walking only, perhaps reinforcing the sensitivity of walk trips to distance. Trips between Minneapolis and St. Paul increase the relative chance of biking in the 2010 model, with no effect on walking, though the in 2010 is larger than in 2000 (5.922 versus 3.915), suggesting an increase in willingness to bicycle for inter-jurisdictional trips.

Work-based trips and walking are significantly associated in both 2001 and 2010 (=2.122 and 1.799 respectively). Unlike the 201 model, home-based work trips are significantly associated with bicycling in 2010; commuting more than doubles the relative probability of bicycling over home-based nonwork trips. In 2010, bicycling is also negatively associated with non-home based, non-work trips, while these have no apparent association with walking. Walking shows no significant relationship with either of these trip purposes. Rain and gender are also unassociated with walking but significantly decrease the relative probability of biking.

Table 5.18: Variables used in mode choice modeling, with descriptive statistics

Variable	Type	Description	Mean (SD) or Frequency	
			2001	2010
Dependent variable				
Walk trip	DV	Value: Primary mode (walking)	13.73%	12.90%
Bike trip	DV	Value: Primary mode (bicycling)	2.72%	4.11%
Auto trip	DV	Value: Primary mode (private auto)	83.55%	82.99%
Characteristics of travel day				
Monday	Binary	Trip occurs on a Monday	24.85%	25.40%
Hot and humid	Binary	Trip occurs on a day where heat index exceeds temperature	40.11%	23.28%
Rain	Binary	Rain event in the metro on travel day	46.19%	49.88%
Characteristics of individual or household				
Number of kids	Scale	Number of kids between ages 6 and 18 in household	0.30 (0.69)	0.31 (0.71)
Age $\geq$ 56	Binary	Traveler's age is 56 or older	24.22%	41.57%
Driver's license	Binary	Traveler has a driver's license	97.70%	97.16%
Female	Binary	Traveler is female	54.09%	55.71%
Income $<$\$30k	Binary	Household income is less than \$30,000	16.81%	14.42%
30k $\leq$ income $<$50k	Binary	Household income is between \$30,000 and \$50,000	21.08%	15.58%
Number of cars	Scale	Number of cars available in household	1.88 (0.94)	2.04 (1.09)
College degree	Binary	Traveler has at least a 4-year college degree	52.76%	44.37%
Student	Binary	Traveler is a student	7.88%	8.23%
Trip purpose or type				
Home-based work trip	Binary	Trip starts at home and ends at work, or vice versa	26.74%	26.24%
Work-based trip	Binary	Trip starts or ends at work, and the other point is not home	12.70%	11.50%
Other-based trip	Binary	Trip does not start or end at home or work	16.84%	19.77%
Trip geography				
Within Minneapolis	Binary	Trip starts and ends within Minneapolis	12.90%	10.46%
Within St. Paul	Binary	Trip starts and ends within St. Paul	4.44%	4.15%
Between Minneapolis & St. Paul	Binary	Trip starts in Minneapolis and ends in St. Paul, or vice versa	1.44%	1.52%
Travel distance	Scale	Estimated shortest path travel distance (km)	11.85 (15.53)	11.86 (15.10)
Circuity	Scale	Ratio of travel distance to airline distance	1.28 (0.39)	1.26 (0.26)

Table 5.19: Multinomial logit mode choice model results – 2001 TBI

Variable	Walking Coeff	Walking P-Val	Walking RRR	Biking Coeff	Biking P-Val	Biking RRR	Difference
Characteristics of travel day							
Monday	-0.29	0.048	0.747 **	0.20	0.437	1.221	t
Hot and Humid	-0.06	0.619	0.939	-0.53	0.029	0.587 **	t
Rain	-0.09	0.457	0.915	-0.44	0.051	0.643 *	
Characteristics of individual and household							
Number of kids	0.19	0.024	1.209 **	-0.02	0.895	0.976	
Age $\geq$ 56	-0.14	0.334	0.867	-1.09	0.002	0.337 ***	t
Driver's license	-2.36	0.000	0.094 ***	-2.70	0.000	0.067 ***	
Female	-0.08	0.501	0.922	-0.72	0.001	0.489 ***	t
Student	-0.01	0.950	0.987	0.73	0.015	2.070 **	t
Income <$30k	-0.08	0.624	0.922	0.52	0.072	1.680 *	t
Income $30 – 50k	-0.32	0.044	0.726 **	0.13	0.652	1.136	
College degree	0.26	0.038	1.302 **	0.91	0.000	2.495 ***	t
Trip purpose or type							
Home-based work trip	-0.50	0.012	0.608 **	0.36	0.159	1.437	t
Work-based trip	0.75	0.000	2.122 ***	-1.05	0.030	0.349 **	t
Trip geography							
Within Minneapolis	1.79	0.000	6.007 ***	1.85	0.000	6.347 ***	
Within St. Paul	1.23	0.000	3.417 ***	0.73	0.101	2.077	
Btw. Mpls & St. Paul	-0.02	0.986	0.983	1.37	0.039	3.915 **	
Trip travel distance	-0.24	0.000	0.785 ***	-0.14	0.000	0.873 ***	t
Constant	1.20	0.001	***	-0.35	0.508		
Number of observations						3,605	
Log-likelihood Constant only model						-1,877.442	
Log-likelihood Full model						-1,266.413	
LR χ^2 test of model significance						1,222.058	
McFaddens Pseudo-R^2						0.3255	
χ^2 test that walking/biking equations are the same						88.670 ***	

Significance thresholds: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

^{t} indicates difference between walking and bicycling coefficients is significant at $p < 0.1$.

Table 5.20: Multinomial logit mode choice model results − 2010 TBI

	Walking			Biking			Difference
Variable	Coeff	P-Val	RRR	Coeff	P-Val	RRR	
Characteristics of travel day							
Rain	-0.03	0.852	0.973	-0.50	0.024	0.606 **	t
Characteristics of individual and household							
Number of kids	0.13	0.229	1.140	0.40	0.003	1.494 ***	t
Age $\geq$ 56	-0.39	0.024	0.678 **	-0.75	0.010	0.471 ***	
Driver's license	-1.96	0.000	0.141 ***	-1.76	0.000	0.173 ***	
Female	0.07	0.625	1.077	-1.27	0.000	0.282 ***	t
Student	1.01	0.000	2.736 ***	0.88	0.010	2.410 ***	
Number of cars	-0.21	0.007	0.810 ***	-0.14	0.208	0.872	
College degree	0.40	0.010	1.490 ***	0.54	0.021	1.719 **	
Trip purpose or type							
Home-based work trip	0.23	0.352	1.252	0.87	0.001	2.394 ***	t
Work-based trip	0.59	0.009	1.799 ***	-0.51	0.215	0.602	t
Other-based trip	0.30	0.101	1.343	-1.04	0.022	0.353 **	t
Trip geography							
Within Minneapolis	1.67	0.000	5.312 ***	2.07	0.000	7.908 ***	
Within St. Paul	0.85	0.001	2.334 ***	0.83	0.089	2.283 *	
Btw. Mpls & St. Paul	0.17	0.830	1.183	1.78	0.000	5.922 ***	t
Trip travel distance	-0.29	0.000	0.745 ***	-0.06	0.000	0.945 ***	t
Circuity	-0.46	0.074	0.633 *	-0.35	0.480	0.705	
Constant	1.60	0.002	***	-0.17	0.843		
Number of observations					2,502		
Log-likelihood Constant only model					-1,377.679		
Log-likelihood Full model					-939.434		
LR χ^2 test of model significance					876.490		
McFaddens Pseudo-R^2					0.3181		
χ^2 test that walking/biking equations are the same					.000	***	

Significance thresholds: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

^{t} indicates difference between walking and bicycling coefficients is significant at $p < 0.1$.

5.5 Gender Gap in Bicycling

The evidence in Section 5.3.6 suggests that despite increases in cycling from 2001 to 2010, the gender gap in bicycling has persisted (see Figures 5.13 and 5.20 and Table 5.17).

We propose six hypotheses about factors that may affect men's and women's decisions to bicycle differently, including trip distance, trip purpose, age, children in the household, weather, and geography. We use hypothesis tests to understand the nature of the gender gap, and binomial logistic modeling to test whether the hypothesized factors are significantly associated with bicycling, and whether that association differs for men and women.

5.5.1 Gender Gap Background

The gender gap in bicycling is well-known, and yet not very well understood. Many bicycle studies control for gender while modeling [6, 16, 34], but only a limited number specifically target the gender gap in their hypothesis. Popular media coverage of the gender gap in bicycling focuses on a few main hypothesized causes: for example, risk aversion among women [3] and gendered economic and cultural forces that constrain women's travel [5].

Emond et al. tested a series of individual factors and social and physical environment conditions, and found that many of these affect men and women differently [8]. Several of their variables had significant interactions with gender in a binary logistic model of participation in bicycling, including comfort level while bicycling, needing a car for travel during the day, biking in youth, self selection, and transit access [8]. Krizek et al. focused on the impacts of bicycle facilities on men's and women's cycling [18]. Women in their study were willing to travel farther out of their way to use dedicated facilities. They noted that trip purposes varied between men and women, in addition to safety perceptions and facility preferences and value. Twaddle et al. found different patterns of participation and frequency for men and women [31]. They discovered that men are more likely to be regular cyclists while women are more likely to be potential or occasional cyclists.

More generally, many studies have shown significant differences in men's and women's travel. Women on average make more trips but have shorter commutes [13, 14, 20] even after stratifying by occupational category [20], though Gossen and Purvis found that the commute distance gap closed between 1990 and 2000 [14]. They bear a disproportionate burden of care taking responsibilities (both children and elder care). McGuckin and Nakamoto showed that women are more likely to chain trips and have less flexibility in their daily travel [20]. Trip chaining in particular complicates how trip purposes are measured. Guiliano and Schweitzer argue that policies designed to discourage auto use by increasing costs or uncertainty are "likely to disproportionately affect women" and that women place a higher value on travel time than men [13].

5.6 Methodology

Based on literature about the potential causal mechanisms for the gender gap, we identified six factors that may have different effects on men's and women's bicycling rates. This is not an exhaustive list of factors that may vary by gender, but an initial framework for exploring the gender gap.

1. Trip distance is differently associated with the likelihood that men and women will ride, with longer distances having a greater negative effect on women
2. Trip purpose is differently associated with the likelihood that men and women will cycle, with women being less likely to cycle for work due to complex travel patterns and different professional appearance standards for men and women
3. Weather may have a stronger impact on women specifically for commuting
4. Presence of children is likely to have greater effect on women to the extent that women on average still bear a disproportionate share of childrearing responsibilities
5. Older age may be more likely to reduce cycling among women
6. Geography, both as it correlates with distance and with jurisdictional policies that promote or hinder bicycling, will affect men and women differently

5.6.1 Data and Sampling

We used binary logistic regression to analyze bicycling measured in two different ways. We estimated models for 2001 and 2010 data separately, but used the same variables in each to facilitate comparison. For each variable we test, we also test an interaction with that variable and gender. We also used exclusively binary variables in the models for ease of interpreting the interaction effects. Because the trip dataset contains multiple trips from the same people and households, including duplicate trips where multiple members of a household traveled together and each reported their own trip, we randomly sampled trips and people such that no household is represented more than once in either dataset. For the trip dataset, one bicycle or auto trip was sampled from each household. For the person table, one person who made bicycling and/or driving trips on their travel day was sampled from each household.

All subjects under 18 were removed from the dataset for this section of analysis. All subjects for whom the gender variable was missing were removed as well. We randomly sampled the dataset to include one adult per household.

5.6.2 Variables

Bicycling can be measured in a number of ways. For this study, we consider two binary measures: a trip-level variable (mode choice) and a person-level variable (participation). Participation is defined as an individual making one or more trips by bicycle at any time on their travel day, among people who made at least one trip by any mode.

Table 5.21 summarizes the independent variables used to measure these six hypotheses by showing the frequency of each binary variable for men and women in each survey year. Measures of trip characteristics (distance, purpose) are aggregated for the person model. A gender-interaction variable was created for all independent variables to see if the associations between these variables and bicycling differ for men and women.

5.7 Hypothesis Test Results

Table 5.22 summarizes the two measures of bicycling for both survey years (participation and trip mode choice). Using χ^2 tests, we show that there is a gap in both percent of women participating in bicycling and in the percent of bicycle trips made by women. Rates of bicycling have increased by a significant amount between 2000 and 2010 (Table 5.22), but bicycling among men grew faster.

Table 5.23 summarizes the results from a series of χ^2 tests on the pooled 2000/2010 data, 2001 summer data alone, 2010 summer sub-sample alone, and 2010 full year sample, about multi-bicyclist households. Men are about twice as likely to participate in bicycling as women if no other adult in their household bikes. However, among people who live with another adult bicyclist, the rates of bicycling increase almost ten-fold, and the gender gap disappears. This finding was significant for all data samples tested.

Additionally, these results show changing effects over time. The percent difference in number of women being the only bicyclist in the household and number of men being only bicyclist grew from 2000 to 2010. We can see the percent difference between participation rates for men and women decreasing over time. The ratio of female bicyclists to male bicyclists in single-biker households dropped from 0.464 in 2000 to 0.360 in 2010, but it grew in multi-biker households from 0.891 to 0.994.

Gender, Bicyclists, and Age

Table 5.24 shows that while there are statistically significant differences between the four groups tested (male and female bicyclists and non-bicyclists), a bonferonni post-hoc test found that the difference is largely due to bicyclists being younger than non-bicyclists, with no clearly gendered pattern. This challenges our hypothesis that age will affect women more strongly than men.

Table 5.25 shows the results from a t-test on whether the number of bicycle trips per person differs by gender, specifically among people who were identified as having made at least one bike trip on their travel day. Among people who biked on their travel day, rates of bicycling between men and women do not differ much. In 2000, the difference was barely significant at the $p<0.1$ level. In 2010, there was no significant difference between men and women.

This suggests that much of the remaining gender gap can be attributed to a participation gap, not an intensity gap. Between 2000 and 2010, the significant difference in number of bike trips per day disappeared. If the participation gap remained constant, then the gains we see over the past decade in closing the gender gap can be attributed to women who bike being able to bike more often.

Table 5.21: Independent Variables

	Trips					People			
	2000		2010			2000		2010	
Variable	Men	Women	Men	Women		Men	Women	Men	Women
Characteristics of this trip:					**At least one trip is:**				
Less than 5km	35.2%	42.2%	37.1%	40.5%	Less than 5km	23.1%	30.9%	24.5%	31.0%
Between 5 and 10km	20.8%	21.1%	21.5%	25.1%	Between 5 and 10km	26.0%	30.1%	27.8%	31.9%
Within Minneapolis	8.6%	8.3%	8.0%	7.5%	Within Minneapolis	14.2%	15.1%	14.8%	15.8%
Within St. Paul	3.5%	4.1%	4.9%	4.5%	Within St. Paul	6.0%	7.5%	8.4%	9.3%
Either starts or ends in Minneapolis	14.1%	11.5%	13.9%	12.5%		0.0%	0.0%	0.0%	0.0%
Either starts or ends in St. Paul	7.8%	7.4%	8.5%	8.5%		0.0%	0.0%	0.0%	0.0%
Home-based work	30.0%	24.0%	29.0%	19.2%	Home-based work	63.7%	52.3%	55.7%	41.6%
Traveling with another household member			74.8%	68.7%	Traveling with another household member			85.2%	84.0%
Characteristics of travel day:					**Characteristics of travel day:**				
Rain event	47.5%	44.1%	49.1%	50.0%	Rain event	46.6%	43.4%	48.6%	49.7%
Heat index exceeds high temperature	39.6%	42.3%	22.4%	23.7%	Heat index exceeds high temperature	38.7%	42.4%	24.0%	23.7%
Characteristics of household and individual:					**Characteristics of household and individual:**				
Children under 18	27.7%	28.3%	27.8%	23.7%	Children under 18	25.7%	28.3%	26.6%	22.7%
Age is 50 or older	35.2%	36.2%	56.2%	60.6%	Age is 50 or older	37.8%	39.6%	58.3%	63.0%
Lives in Minneapolis	15.5%	13.6%	14.9%	14.0%	Lives in Minneapolis	14.9%	14.7%	15.9%	15.0%
Lives in St. Paul	6.0%	7.1%	9.5%	8.8%	Lives in St. Paul	6.2%	7.1%	8.9%	9.6%
Female	0.0%	0.0%	100.0%	100.0%	Female	0.0%	0.0%	100.0%	100.0%
N	1,937	2,175	2,396	2,983	N	2,088	2,576	2,689	3,378

Table 5.22: Dependent Variable

	2000				2010			
	Male		Female		Male		Female	
Number and percent of trips made by:								
Bicycling	117	6.0%	63	2.9%	213	8.9%	120	4.0%
Auto	1,820	94.0%	2,112	97.1%	2,183	91.1%	2,863	96.0%
TOTAL	1,937	100%	2,175	100%	2,396	100%	2,983	100%
Gender difference?		$\chi^2 = 24.1904$	$p < 0.000$			$\chi^2 = 54.1972$	$p < 0.000$	
Difference between years for women?						$\chi^2 = 4.6625$	$p < 0.031$	
Difference between years for men?						$\chi^2 = 12.3611$	$p < 0.000$	
Number and percent of people who made:								
1+ Bike trip(s)	53	2.5%	37	1.4%	127	4.7%	74	2.2%
No bike trip(s)	2,035	97.5%	2,539	98.6%	2,562	95.3%	3,304	97.8%
TOTAL	2,088	100%	2,576	100%	2,689	100%	3,378	100%
Gender difference?		$\chi^2 = 7.4002$	$p < 0.007$			$\chi^2 = 29.9721$	$p < 0.000$	
Difference between years for women?						$\chi^2 = 4.5452$	$p < 0.033$	
Difference between years for men?						$\chi^2 = 15.4698$	$p < 0.000$	

Table 5.23: Summary of Chi2 Test Results for Multi-Bicyclist Households

	No other bicyclists			Other bicyclists		
	Men	Women	Sig?	Men	Women	Sig?
Pooled Data	2.88%	1.20%	0.000	19.63%	18.59%	0.833
2000 Summer	1.94%	0.89%	0.000	15.62%	18.60%	0.736
2010 Summer	3.70%	1.46%	0.000	21.33%	18.58%	0.642
2010 Full Year	2.62%	1.02%	0.000	23.33%	18.75%	0.398

Table 5.24: Oneway ANOVA Results for Gender and Age among Bicyclists and Non-bicyclists

	Pooled			2000			2010		
	Mean	SD	Sig	Mean	SD	Sig	Mean	SD	Sig
[a]Male Nonbicyclists	49.70	16.14	b,c,d	45.92	15.43	b,d	52.84	16.04	b,c,d
[b]Male Bicyclists	43.46	13.88	a,c	37.23	11.60	a,c	46.10	13.96	a,c
[c]Female Nonbicyclists	51.34	16.47	a,b,d	46.61	15.89	b	54.90	16.00	a,b,d
[d]Female Bicyclists	41.99	13.21	a,c	38.86	12.07	a,c	43.46	13.54	a,c
	F = 33.05			F = 9.80			F = 31.46		
	P = 0.000			P = 0.000			P = 0.000		

Table 5.25: T-test Results for Frequency of Bicycle Trips Among Identified Bicyclists, by Gender

	Male			Female			Difference	
	Mean	SD	N	Mean	SD	N	2-tailed	1-tailed
2000	2.90	2.09	59	2,45	1.20	38	0.1811	0.0906
2010	2.62	1.71	134	2.48	1.31	81	0.5071	0.2536

5.8 Models

Table 5.26 provides an abstract summary of all eight models tested. The first four model participation in bicycling on the person's travel day, and models 5 through 8 focus on tripwise mode choice. For each year within these sets, the model is shown two ways: one simple version with no gender interaction variables, and one full model with all explanatory variables interacted with gender. Detailed results for the full, interacted models are presented in Tables 5.27 and 5.28.

Model Fit

Binary logit regression does not have the R^2 measure in linear regression, where the value represents the percent of variation in the dependent variable that can be explained by the independent variables. Instead, the pseudo-R^2 measures the relative improvement of the model compared to a constant-only model, or a model with no variables. The interpretation is different, and while the theoretical range is from 0 to 1 like traditional R^2, the values tend to be a bit lower.

The pseudo-R^2 (McFadden's) values for the participation models range from 0.165 to 0.181 for 2000 and 2010. They are higher for the mode choice model, at 0.224 and 0.242 respectively. For both types of models, the pseudo-R^2 improves slightly between 2000 and 2010. The mode choice model performs better than the participation model, which is reasonable given the aggregated explanatory variables for the participation model.

Individual Participation Model

In 2000, network distance, children, age, and living in Minneapolis are significant both in the simple model and after gender interaction terms are added (5.26). Adding the interaction terms makes the binary gender variable insignificant, though most of the interaction terms themselves are also insignificant. Only female interacted with home-based work and female interacted with age over 50 are significant. The age coefficient is negative, meaning that being over 50 is associated with a reduced chance of making one or more bike trips on the travel day. The gender-age interaction term is positive, however, which mitigates some of this age effect for women. For men, being over 50 reduces the odds of biking instead of driving by a factor of 0.27.

The positive coefficient on home-based work trips contradicts our hypothesis that women are less likely to bike commute than men, relative to other trip purposes. Making shorter trips, living in Minneapolis, and not having children are associated with an increased chance of bicycling, but the effect for these does not vary between men and women.

In 2010, many of the same variables are still significant. Shorter trips, younger age, and living in Minneapolis are associated with increased odds of biking. Weather phenomena are significant before gender is controlled. The positive coefficient on hot and humid weather may be due to the relatively cold spring experienced in 2011 when the survey was being administered. Similarly to 2000, living in Minneapolis is positive and significant. Making trips within Minneapolis and St. Paul are also significant in 2010.

Adding gender interaction terms makes the binary gender variable insignificant, but the only significant interaction term is age. In 2010, the coefficient on the interaction term is negative, meaning that being over 50 is associated with a stronger reduction in odds of biking for women than for men. The relationship between bicycling, men, and age is waning; in 2010, they experiened a smaller dropoff in bicycling after the age of 50, while the bicycling gender gap appears to be expanding for older women. The 2000 results, and this reversal in 2010, are difficult to explain. The 2000 result in particular is contrary to our hypothesis about age affecting women more strongly in a negative direction, though one would expect an improvement between 2000 rather than a decline as the Baby Boomer generation reaches retirement age and has more leisure time. It is possible that increases in rates of bicycling over the past decade have been largely among younger people. Programming and new infrastructure have been concentrated in the urban core, which may correlate with age. Alternatively, it's possible that this is a reflection of shifting age cohorts such that the average age of women over 50 is increasing with longer life expectancies.

Trip Model

More variables are significant in all versions of the trip mode choice model, but like the participation model, most of the gender interaction terms are not significant. Home-based work trips interacted with gender is significant and positive in 2000, consistent with the participation model but contrary to our initial hypothesis. Evidence from the literature shows that women on average have shorter commutes and are more likely to chain several stops along their commute trip. The relationship between gender and bicycling for home-based work trips may reflect these attributes. In particular, the trip records are structured around single trips, not chains, so commute trips that include other stops, such as running errands or dropping children off at daycare or school, would not be classified as home-based work trips.

The gender-age interaction term in 2010 is significant and negative, also consistent with the participation model. The trip model reinforces the possibility that the gender gap is getting worse for women over 50.

Trips starting or ending in Minneapolis (but not both) has a negative interaction term. For men, a trip with one end in Minneapolis and the other outside the city increases the chances of bicycling being the chosen mode by a factor of 4.36 in 2010. The gender interaction term mitigates this effect for women, reducing her odds of bicycling for the same trip. Distance range for biking increased from 2000 to 2010 in both the participation model and the mode choice model, with no immediately apparent differences by gender. However, the significant interaction term on trips with one end in Minneapolis in 2010 is possibly related. Interjurisdictional trips will be longer on average than intracity trips, which may explain why the female interaction term is negative despite the effect for men being strong and positive.

Having children was positive and significant in both 2000 and 2010, with an increasing coefficient. Additionally, the interaction term with children was not significant for either year. This suggests that children may not be the source of a gender gap; indeed, having children appears to be associated with increased bicycling, possibly due to parents bicycling with their kids.

Table 5.26: Variable Summary of Simple and Full (with interactions) Trip Mode Choice and Individual Participation Models

	Person model						Trip Mode Choice Model					
	2000			2010			2000			2010		
	Simple	Full		Simple	Full		Simple	Full		Simple	Full	
Variable	Coeff	Coeff	X	Coeff	Coeff	X	Coeff	Coeff	X	Coeff	Coeff	X
Trip Characteristics												
Network distance < 5km	+	+	0	+	+	0	+	+	0	+	+	0
Network distance 5 - 10km	+	+	0	+	+	0	+	+	0	+	+	0
Within Minneapolis	+	+	0	+	+	0	0	0	0	+	0	0
Within St. Paul	+	+	0	+	+	0	0	0	0	+	+	0
Starts or ends in Minneapolis	0	0	0	+	+	-						
Starts or ends in St. Paul	+	0	0	+	+	0						
Home-based work	+	0	+	+	+	0	0	0	+	+	+	0
Travel Day Characteristics												
Rain event	-	0	0	-	-	0	0	0	0	-	0	0
Heat index > temperature	0	0	0	+	0	0	0	0	0	+	0	0
Household and Individual Characteristics												
Has kids	+	+	0	+	+	0	-	-	0	0	0	0
Age is 50 or older	-	-	0	-	-	-	-	-	+	-	-	-
Lives in Minneapolis							+	+	0	+	+	0
Lives in St. Paul							0	0	0	0	0	0
Female	-	-		-	0		-	0		-	0	
Constant	-	-		-	-		-	-		-	-	

+ indicates positive and significant at p<0.1
- indicates negative and significant at p<0.1
0 indicates $p \geq 0.1$

Table 5.27: Trip Mode Choice Model Results

	2000			2010		
Variable	Coeff	P-Val	OR	Coeff	P-Val	OR
Trip Characteristics						
Network distance < 5km	2.41	0.000	11.17	2.14	0.000	8.47
Network distance 5 - 10km	1.31	0.003	3.71	1.26	0.000	3.54
Within Minneapolis	1.56	0.000	4.77	1.97	0.000	7.19
Within St. Paul	0.81	0.044	2.25	0.57	0.072	1.76
Starts or ends in Minneapolis	-0.22	0.664	0.80	1.47	0.000	4.36
Starts or ends in St. Paul	0.84	0.105	2.32	0.52	0.079	1.68
Home-based work	0.02	0.955	1.02	0.99	0.000	2.70
Gender - Trip Interaction						
Network distance less than 5km	0.29	0.707	1.33	-0.11	0.824	0.90
Network distance 5 to 10km	0.16	0.848	1.17	0.39	0.410	1.48
Within Minneapolis	0.32	0.420	1.37	-0.15	0.646	0.86
Within St. Paul	-0.59	0.433	0.56	0.43	0.361	1.54
Starts or ends in Minneapolis	0.64	0.437	1.90	-0.91	0.033	0.40
Starts or ends in St. Paul	-0.38	0.685	0.68	-0.14	0.786	0.87
Home-based work	0.83	0.046	2.29	0.05	0.882	1.05
Travel Day Characteristics						
Rain event	-0.28	0.184	0.75	-0.28	0.075	0.75
Heat index > temperature	-0.11	0.610	0.90	0.29	0.108	1.34
Gender - Travel Day Interaction						
Rain event	-0.16	0.659	0.85	-0.06	0.820	0.94
Heat index > temperature	-0.24	0.503	0.79	0.03	0.909	1.03
Household and Individual characteristics						
Has kids	0.58	0.011	1.78	0.83	0.000	2.28
Age is 50 or older	-1.26	0.000	0.28	-1.04	0.000	0.35
Female	-1.58	0.052	0.21	-0.45	0.388	0.64
Gender - Household and Individual Interaction						
Has kids	0.31	0.417	1.36	-0.41	0.168	0.66
Age is 50 or older	0.69	0.152	2.00	-0.62	0.059	0.54
Constant	-4.50	0.000	0.01	-4.45	0.000	0.01
N		4112			5379	
LL		-573.46			-946.23	
Pr Chi^2		0.000			0.000	
Pseudo R^2		0.2242			0.2424	

Table 5.28: Individual Participation Model Results

Variable	2000 Coeff	2000 P-Val	2000 OR	2010 Coeff	2010 P-Val	2010 OR
Aggregate Trip Characteristics						
Avg. network distance < 5km	1.75	0.000	5.78	1.25	0.000	3.49
Avg. network distance 5 - 10km	1.27	0.004	3.55	0.73	0.006	2.07
Within Minneapolis	0.00	0.993	1.00	0.54	0.101	1.71
Within St. Paul	-0.44	0.621	0.64	0.78	0.067	2.18
Home-based work	-0.18	0.551	0.83	0.71	0.001	2.03
Gender - Trip Interaction						
Avg. network distance < 5km	-0.39	0.577	0.68	0.39	0.439	1.48
Avg. network distance 5 - 10km	-0.50	0.485	0.61	0.37	0.474	1.45
Within Minneapolis	1.20	0.141	3.32	-0.15	0.791	0.86
Within St. Paul	0.56	0.660	1.75	-0.19	0.788	0.82
Home-based work	1.18	0.018	3.24	-0.31	0.345	0.73
Travel Day Characteristics						
Rain event	-0.13	0.667	0.88	-0.22	0.247	0.80
Heat index > temperature	-0.15	0.627	0.86	0.23	0.290	1.25
Gender - Travel Day Interaction						
Rain event	-0.54	0.264	0.58	-0.29	0.369	0.75
Heat index > temperature	-0.59	0.214	0.55	0.44	0.191	1.55
Household and Indiviudal Characteristics						
Has kids	-0.70	0.083	0.50	0.09	0.697	1.09
Age is 50 or older	-1.31	0.001	0.27	-0.46	0.027	0.63
Lives in Minneapolis	1.48	0.004	4.40	1.36	0.000	3.91
Lives in St. Paul	0.45	0.620	1.56	0.50	0.275	1.66
Female	-1.19	0.131	0.30	-0.59	0.313	0.55
Gender - Household and Individual Interaction						
Has kids	0.63	0.292	1.87	0.01	0.969	1.01
Age is 50 or older	1.02	0.065	2.78	-0.67	0.062	0.51
Lives in Minneapolis	-0.86	0.288	0.42	-0.03	0.960	0.97
Lives in St. Paul	-1.31	0.394	0.27	-0.52	0.522	0.59
Constant	-4.43	0.000	0.01	-4.58	0.000	0.01
N			4664			6067
LL			-371.16			-723.03
Pr Chi^2			0.000			0.000
Pseudo R^2			0.1649			0.1807

5.9 Bicycle Infrastructure

Between 2001 and 2010, local governments in MSP invested heavily in new infrastructure for bicycling. Our analyses in Sections **??** and 5.5 showed that bicycling has increased from 2001 to 2010, particularly among men for the purpose of commuting, but that a gender gap in bicycling persists. Here we explore the potential relationship between infrastructure and the likelihood of bicycling.

Consistently maintained infrastructure data over time was only available for the City of Minneapolis, so we limit our analyses to Minneapolis residents who participated in the , and in particular, only their trips that both started and ended within the City of Minneapolis. Of the 172,632 trips in the database for 2000 and 2010, only 22,210 (12.9%) were made by Minneapolis residents, and only 12,042 (7.0%) of those both started and ended within the city. An additional 1,322 trips were removed due to missing data about age, gender, trip purpose, and distance, leaving 10,720 valid cases. The 2000 survey had 3,327 trips, and the 2010 survey had 7,393 trips. Restricting the 2010 sample to April through August only leaves 4,102 trips for 2010. Table 5.29 shows the number of valid Minneapolis trips and other trips for 2000 and 2010. The number of people and households making at least one valid trip are also shown. The rate of bicycling and walking among trips within Minneapolis made by Minneapolis residents with no other missing key variables are overall much higher than excluded cases, limiting the generalizability of these results.

Table 5.29: Minneapolis Infrastructure Subsample Case Identification

	Valid Mpls Cases			Other Cases		
	2000	2010		2000	2010	
		Summer	Winter		Summer	Winter
Trip cases[1]	3,327	4,102	3,291	53,484	57,758	50,670
Pct. Walk	17.9%	21.5%	20.4%	3.7%	5.5%	4.7%
Pct. Bike	6.7%	9.1%	5.7%	1.1%	1.7%	0.4%
Person cases[2]	942	1,327	1,060	11,087	12,870	11,854
Avg. valid trips per person	3.53	3.09	3.10	0.00	0.00	0.00
Avg. all trips per person	5.58	5.04	4.79	4.65	4.29	4.12
Household cases[3]	636	836	683	5,015	6,257	5,463
Avg. valid trips per household	5.23	4.91	4.82	0.00	0.00	0.00
Avg. all trips per household	9.32	9.04	8.30	10.15	8.68	8.84

[1] Valid trip is Mpls resident, within Mpls, no missing data on key variables
[2] Valid person made at least one valid trip on travel day
3 Valid household made at least one valid trip on travel day

Bicycle infrastructure availability changed significantly between 2000 and 2010 (see Tables 5.30, 5.31, and 5.32 and Figures 5.25−5.28). In 2001, people making trips by bicycle had an average of 182 meters of bike lanes within 400 meters of their home, while people making auto trips only had 53 meters. Bike paths had the opposite trend: auto trips averaged 70 meters of trail around the traveler's home, while bike trips averaged 34 meters. Both of these differences are significant with $p < 0.01$. In 2010, there was no significant difference between average bike lane supply near bicyclists and auto drivers (134 and 131, respectively). For bicyclists, this represents a modest decline from 2001 ($p < 0.1$). For drivers, the increase is much more notable ($p < 0.01$). The decline in bicycle lanes near the homes of people making bike trips may be due to bike lane facilities being upgraded to dedicated paths. Trail supply near the home tripled for cyclists, and increased about 50% for auto drivers (both differences $p < 0.01$). Similar to lanes, there was no significant difference between supply near cyclists and drivers in 2010. Table 5.32 shows the combined total of lane plus trail infrastructure. The difference in supply near cyclists and drivers in 2001 was significant, but the supply for auto tripmakers nearly doubled over the next decade while there was no significant net change for cyclists. By 2010, there was no significant difference in the quantity of dedicated lane and trail infrastructure around the homes of cyclists and auto drivers.

Table 5.30: Meters of bike lane within 400 meters of home, by mode

	Bike Mean (SE)	Auto Mean (SE)	Difference by mode
2000	181.61 (25.79)	53.24 (4.81)	***
2010	133.56 (19.70)	131.06 (6.75)	
Difference by year	*	***	
Significance thresholds: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$			

Table 5.31: Meters of bike trail within 400 meters of home, by mode

	Bike Mean (SE)	Auto Mean (SE)	Difference by mode
2000	34.12 (9.24)	70.00 (4.44)	***
2010	121.59 (13.88)	105.11 (4.45)	
Difference by year	***	***	
Significance thresholds: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$			

5.9.1 Models

Table 5.33 shows results from the stepwise development of the binary logistic mode choice model of bicycling (versus driving). Table 5.34 presents full, detailed results for the final models (Model 4) from Table 5.33.

Table 5.32: Meters of bike infrastructure (lanes+trails) within 400 meters of home, by mode

	Bike Mean (SE)	Auto Mean (SE)	Difference by mode
2000	215.72 (29.26)	123.23 (6.43)	***
2010	255.15 (24.59)	236.17 (7.84)	
Difference by year		***	
Significance thresholds: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$			

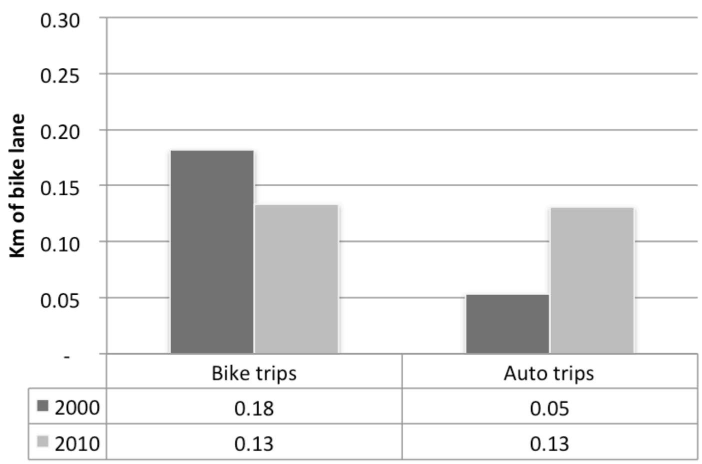

Figure 5.25: Average supply of bike lanes (km) within 400 meters of home, by trip mode and survey year

As described in Section **??**, the infrastructure mode choice model was performed on a random sample of one adult trip per household. As previously mentioned, however, the pool of cases with nonmissing data and in the correct geography was limited. In the 2001 Minneapolis modeling sample, there were 490 trips, 38 (8%) of which were made by bicycle. In 2010, 61 of 601 (10%) observations were bike trips (Table 5.34). This constrains the number of variables we may use while modeling to prevent overfitting.

For modeling, infrastructure is measured as kilometers of on-street bicycle lane within 400 meters of the trip-maker's home. Off-street trails were also tested, both alone and as part of a total lane+trail infrastructure sum, but were not significant in the models.

Age, gender, commute trips, and network distance are significant in both the 2000 and 2010 models. In 2010, commute trips were associated with a 417% increased chance of a trip being made by bicycle instead of driving, relative to non-work trips. Older age, being female, and longer distances were associated with decreased probability of bicycling. Kilometers of bike lane within 400 meters of home was significant in the 2000 model, but not the 2010 model. In 2000, each additional kilometer of bike lane was associated with a nearly 3-fold increase in the chance of

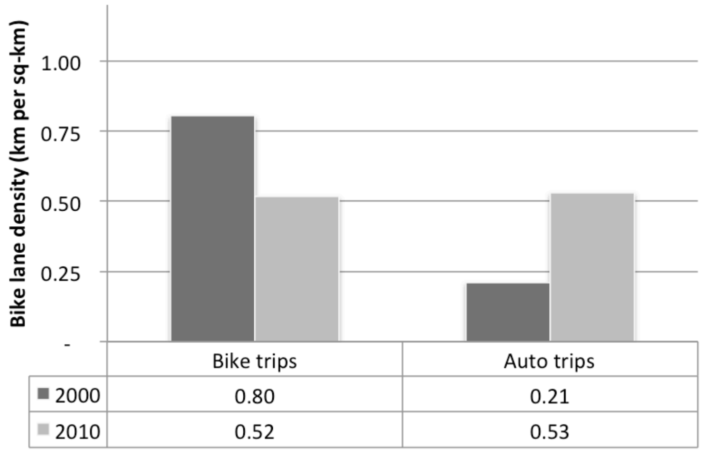

Figure 5.26: Average density of bike lanes ($^{km}/_{km^2}$) within 400 meters of home, by trip mode and survey year

bicycling.

As shown in Tables 5.30 and 5.31, the quantity and density of bicycle facilities in Minneapolis increased significantly between 2001 and 2010 for bicycling households and auto households alike. By 2010, access to bicycle facilities was no longer significantly associated with propensity to bicycle, presumably due to even facility coverage throughout the city.

Pseudo-R^2 in binary logistic regression is not directly analogous to an R2 value in linear regression. The McFadden Pseudo-R^2 represents how a model performs compared to a *constant only* model. The McFadden Pseudo-R^2 is 0.1808 for the 2000 model and 0.1508 for the 2010 model. Table 5.33 shows the stepwise process used for adding variables to the model, including the pseudo-R^2 for each step. In 2000, the pseudo-R^2 increased from 0.169 to 0.181 when the bike lane variable was added. In 2010, the pseudo-R^2 did not change between these two steps, meaning that the variable offered no improvement in fit over a model with no variables.

A chow test between the two models shows that while there is an overall difference between the 2000 and 2010 models, none of the individual coefficients are significantly different between years. The p-value for the difference between the 2000 and 2010 bike lane variable is *almost* significant at the $p < 0.1$ level, which is consistent with the variable being significant in one year and not the other, and the lack of change in pseudo-R^2 value when bike lanes were added to the 2010 model.

5.9.2 Conclusions

Walking and bicycling trips are taken by different people for different reasons at different times for different distances, and the factors that are associated with individuals decisions to walk or bicycle rather than drive also are different. These differences have important implications for performance management, including the choice of performance measures to assess progress towards multi-modal goals. At the regional level, travel behavior inventories provide useful data that planners

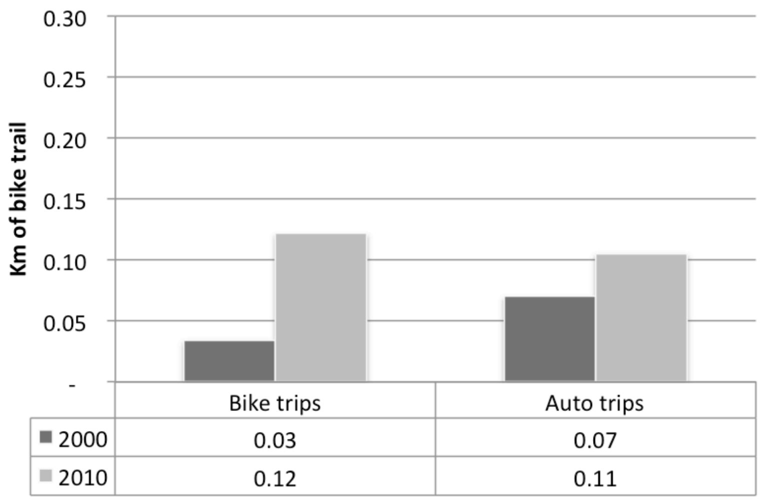

Figure 5.27: Average supply of bike trails (km) within 400 meters of home, by trip mode and survey year

can use to develop nuanced performance measures that complement measures derived from the ACS.

5.9.3 Major Findings

This research project allowed us to address the five key questions outlined in section A.1.

Question (1): Walking and cycling have both increased from 2001 to 2010, but they grew at different rates.

Question (2): Bicyclists and pedestrians, and their bike and walk trips, differ by demographics, geography, distance and trip purpose. The differences between pedestrians and cyclists warrant greater attention.

Question (3): Weather, personal demographic and household, and trip factors are all associated with propensity to walk or cycle for any given trip. Some factors differ between modes (e.g., gender), while some factors appear to affect walking and bicycling similarly (e.g., having a driver's license).

Question (4): Despite gains in rates of cycling overall, a gender gap persists. Most of the observed growth in cycling from 2001 to 2010 came from increases in men bicycle commuting. The gap appears to be in bicycling *participation* rates of men and women; there was no observed gap in *frequency* of making bicycle trips among cyclists.

Question (5): Access to bike lanes is no longer a significant factor associated with likelihood of bicycling in Minneapolis in 2010 due to widespread increased access to facilities.

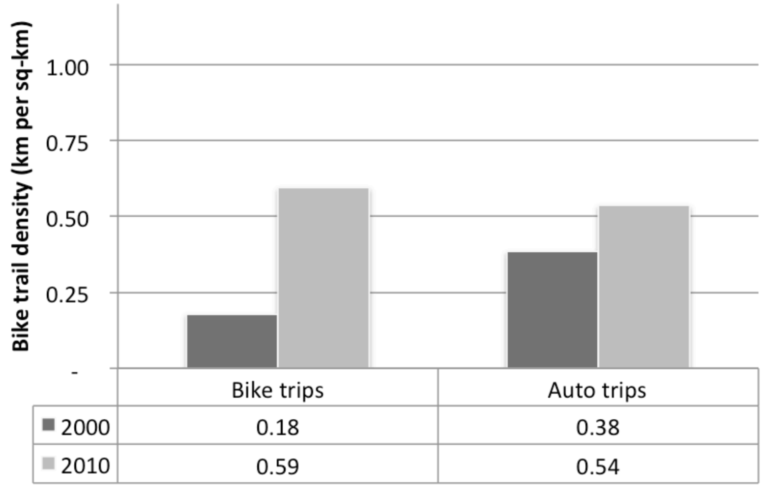

Figure 5.28: Average density of bike trails ($^{km}/_{km^2}$) within 400 meters of home, by trip mode and survey year

5.9.4 Implications for Performance Management

One of the most important findings from this research is that the US Census and ACS journey to work data substantially *underestimates* the rates of walking and bicycling. In the 12/13 ring counties, the measure of bicycle commuting was *triple* the size of the ACS estimate for the same trip purpose and geography. Part-time or occasional cyclists, non-commuting bicyclists, and multimodal travelers are undercounted due to the structure of the census question: reporting a single mode to represent work travel for an entire week. The ACS commuting data is used frequently when discussing nonmotorized transportation planning because covers the entire United States consistently, but reliance on these data above other sources may undermine planners' goals by minimizing the importance of walking and cycling relative to other modes. When cross-regional comparisons necessitate its use, local measures, such as , can enhance ACS journey to work data by providing scaling factors or a relative measure for perspective.

Mode choice models (such as the multinomial logistic models presented here) are a useful tool for assessing policy-relevant factors that affect individual travel decisions and can inform the selection of performance measures. For example, a gender gap between males and females exists for bicycling but not walking (for all trips for all purposes). Hence, educational programs and performance measures for women in bicycling may be warranted; similar measures for walking may not be needed.

The significant spatial variation in walking and bicycling indicates planners need to think very carefully how to establish performance goals and measures to assess progress towards them. Targets for walking mode share, for example, should not be the same for Minneapolis as any of the smaller communities in the ring counties, because the factors that support walking (e.g., density, diversity, design) vary both within and across jurisdictions. Another way of saying this is that performance measures need to be context-sensitive and reflect both historical urban form and the

Table 5.33: Stepwise binary logistic regression of biking (versus driving)

	Model 1	Model 2	Model 3	Model 4
2000 (N=490)				
Age	-0.079 ***	-0.078 ***	-0.078 ***	-0.078 ***
Female	-0.662 ^{t}	-0.672 ^{t}	-0.615 ^{t}	-0.599 ^{t}
Home-based work trip		0.381	0.724 ^{t}	0.720 ^{t}
Network distance (km)			-0.281 **	-0.270 **
Km of bike lane within 400m of home				1.016 ^{t}
Constant	0.883	0.697	1.570 *	1.432 ^{t}
McFadden Pseudo-R^2	0.115	0.119	0.169	0.181
2010 (N=601)				
Age	-0.056 ***	-0.056 ***	-0.056 ***	-0.056 ***
Female	-0.820 **	-0.758 **	-0.784 **	-0.785 **
Home-based work trip		1.186 ***	1.435 ***	1.429 ***
Network distance (km)			-0.120 *	-0.121 *
Km of bike lane within 400m of home				-0.127
Constant	0.797	0.377	0.829	0.861
McFadden Pseudo-R^2	0.099	0.139	0.151	0.151

*** $p < 0.001$
** $p < 0.01$
* $p < 0.05$
^{t} $p < 0.1$

constraints it imposes upon mode choice. As a practical matter, policy choices and investments to increase walking and bicycling will be made by local elected officials, so performance measures specific to jurisdictions may be appropriate. Establishment of different performance measures across jurisdictions, however, increase complexity and has the potential disadvantage of complicating communication of key messages about regional performance. At the spatial scale of a region, tradeoffs in establishing performance measures appropriate to the diverse communities within the region cannot be avoided.

The significant temporal variation in walking and bicycling raises the question of whether year-round or summertime data should be used to develop performance measures for these modes. While year-round data provide more complete measures and are directly comparable to measures for other modes, they fail to convey important information, such as peak demand. Given the different concerns and priorities of stakeholders in regional transportation systems, significant public engagement will be needed to assess inevitable tradeoffs in choices among indicators and to arrive at a set of robust measures that inform system management.

Closer examination of the gender gap in bicycling revealed some encouraging information. The gender gap appears to be attributable to a *participation* gap, rather than a frequency gap, so ongoing measurement should focus on what factors are associated with increasing participation. In this scenario, targeting programs at encouraging women to try bicycling may be more effective than encouraging female bicyclists to ride more. For people who live with a bicyclist, rates of bicycling overall are much higher and there is no apparent gender gap among members of these multi-bicyclist households. Whether this is a causal relationship, and in what direction, is unclear. But the finding suggests new ways to measure progress. Monitoring participation rates at the individual and household level over time may lead to effective strategies for increasing participation within households.

Findings from the hypothesis tests show that women bike less than men, and that growth in bicycling has been slower for women than for men over the past decade. However, certain indicators demonstrate progress. Women in households with another bicyclist participate in biking at a rate roughly equal to men, and the share of women and men who bicycle is ten times higher in households with another bicyclist than households without. Among people who biked at least once on their travel day, an observed bicycle trip frequency gap in 2000 closed over the next decade, so that in 2010, there was no significant difference in trip frequency between female and male bicyclists.

These findings and conclusions are important for practice and research because understanding the nuances of the gender gap is essential for targeting programs effectively. For example, the hypothesis tests show that the gender gap may be attributable to a gap in participation, but once that barrier is crossed, there was no observed gender gap in bicycling frequency.

In the mode choice models, commute trips were *not* associated with reduced likelihood of bicycling for women in particular. Additionally, the interaction term for women over 50, while negative and significant in the mode choice models for both years, decreased in magnitude over the decade. This directly contradicts the findings from the participation model, where the interaction between gender and age appeared to be worsening.

We found that infrastructure was a significant factor in predicting bicycling in 2001, but by 2010, the quantity of bicycle lanes around the home no longer differentiated bicyclists from non-bicyclists. This is encouraging; infrastructure has expanded considerably in the City of Minneapolis over the study duration. That bike lanes are no longer significant suggests pervasive and easy access to infrastructure *throughout* the city. Infrastructure measures like the ones used here (e.g., quantity near home or a destination) could be implemented to track progress on infrastructure expansion independently from travel outcomes.

5.9.5 Implications for Future Research and Data Collection

Our analyses of also identified areas where attention to methodology may improve measures. The 2010 , which collected data year round, provides richer data than the 2000 , but neither provides data on an ongoing basis. A significant limitation of the use of to establish performance measures is that they typically are completed decennially. Moving to rolling administration of the travel survey as is done with the ACS would provide more current data to assess performance, but, of course, would introduce new administrative, financial, and technical challenges. With respect to the instrument, a non-trivial number of trips for walking and bicycling had "home" as both the origin and destination, which means that when GIS is used to calculate trip distance, the distance for these trips is zero. Distance could be imputed from time, but this procedure introduces additional error into analyses. One practical implication is that trips taken for exercise or leisure may not be adequately represented in findings.

Some of the data limitations identified have specific implications for measuring travel equity across gender. Trip chains are difficult to identify when travel diaries treat each component as a distinct trip. Research has shown that women are more likely than men to chain multiple stops into the commute trip. As a result, women's commute "trips" may be less easily identifiable as a commute trip. A chain during which the traveler drops their child off at school on the way to work would be classified as one home-based non-work trip and one work-based trip. The positive relationship observed in this sample between women, bicycling, and home-based work trips may actually be a relationship between women *who do not have obligations on the way to and from work*, bicycling, and commute trips.

Another data limitation that may produce biased results about the gender gap in bicycling is how trips with multiple people are classified. We used the variable "has children" as a proxy for whether a person has care taking responsibilities that would constrain their travel choices. However, a better measure would be simply how many other people accompanied the traveler on their trip. Both the 2000 and 2010 TBIs asked this question, and asked *which* household members were on the trip. However, the wording of this question in the 2000 TBI precluded collecting meaningful answers from people making trips by any mode other than a private vehicle.

Finally, performance measures like these need to be integrated with other measures to enable decision-makers to fully understand whether policies, investments, infrastructure, and programs are having desired effects. For example, significant differences in walking and bicycling exist between Minneapolis and St. Paul. Minneapolis was the principal beneficiary of infrastructure improvements made as part of the Nonmotorized Transportation Pilot Program (NTPP); comparatively few investments were made in St. Paul. Yet these findings do not confirm cause and effect: they are much too coarse. Infrastructure data availability constrains doing a more spatially detailed analysis. Even with the large sample size of the TBI, restricting the sample to Minneapolis cases only that were not missing any essential pieces of information limited the methods and variables we could use to measure relationships between bicycling and infrastructure. Consistently maintained and consolidated pedestrian infrastructure data is even more challenging to procure, but would prove useful, for example, for understanding the relationships between sidewalks and crossing facilities and propensity to walk.

Table 5.34: Final mode choice model of bicycling (versus driving)

	2000				2010				Chow Test	
Variable	Coef	SE	OR	Sig	Coef	SE	OR	Sig	χ^2	P-val
Age	-0.078	0.018	0.925	***	-0.056	0.011	0.945	***	1.05	0.31
Female	-0.599	0.363	0.549	t	-0.785	0.293	0.456	**	0.16	0.69
Home-based work trip	0.720	0.388	2.054	t	1.429	0.323	4.176	***	1.97	0.16
Network distance (km)	-0.270	0.089	0.763	**	-0.121	0.058	0.886	*	2.00	0.16
Km of bike lane within 400m of home	1.016	0.539	2.763	t	-0.127	0.469	0.881		2.56	0.11
Constant	1.432	0.738		t	0.861	0.579			0.37	0.54
Full model comparison									18.19	0.01 **
N Observations			490				601			
N Bike trips			38				61			
McFadden Pseudo-R^2			0.1808				0.1508			

*** $p < 0.001$
** $p < 0.01$
* $p < 0.05$
^{t} $p < 0.1$

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Appendix A

Development of the Travel Behavior Over Time Database

A.1 Introduction

The Travel Behavior Over Time (TBOT) project is designed to provide new insights into travel behavior in the Minneapolis - Saint Paul region by analyzing travel survey data collected by the Metropolitan Council over the past several decades. This chapter describes the results of Task 2, "Data Collection and Preparation." The first goal of this task was to create a single database containing Travel Behavior Inventory (TBI) data from all available decades. In completing this task, researchers assembled datasets from the various TBIs and compiled them into a single database and a harmonized data format. This harmonized format allows analysis of travel behavior over time without the need for specialized tools or methods for interpreting each year's data.

The second goal of this task was to add contextual information to the harmonized TBI data. Each TBI recorded the home, work, and school locations of each survey respondent, as well as origin and destination locations and times for each trip. To facilitate the various research goals of subsequent tasks in the TBOT project, these location- and time-related data were linked to external data sources, including Census geography, fuel prices, weather data, and transportation system metrics such as accessibility and transit service.

The following sections describe the development of the TBOT database as well as its structure and content. Section A.2 discusses the data processing methods used during conversion and harmonization of TBI data, and described the assignment of contextual data values to the harmonized data. Section A.3 describes the database itself, including the structure of all data tables and the formats used for storing data values.

A.2 Methodology

The process of preparing four decades of TBI data for integrated analysis took place in three principal steps. First, the data for each decade's TBI was converted from its original format to an SQL format and imported into the TBOT database. Next, the imported TBI data was combined with geometry published from the US Census Bureau and the Metropolitan Council in order to associate each TBI data record with an appropriate point location or geographic context. Finally, TBOT researchers examined the structure of the TBI data across all four decades and translated each into a common format that allows integrated analysis with a minimal loss of information. The following sections describe these steps in detail.

A.2.1 Original TBI Data Conversion

Specific data conversion processes varied depending on the original year of the TBI data; each was archived in a different format. To prepare the original datasets for import into the TBOT database, each was first converted to a comma-separated values (CSV) format using UTF-8 (extended ASCII) encoding. These intermediate CSV files are included in the TBOT file archive. The CSV files were imported into the database using PostgreSQL's native `COPY FROM` command; the database structure is described in section A.3. These steps were designed to update the format of each TBI's data while preserving its structure and meaning. The following sections note necessary modifications that were made to the original TBI data for each year.

1980 TBI Data

The following modifications were made during conversion of the data from the 1980 TBI:

- Empty fields in the original data were represented by a single 1-character blank space; these were translated to an empty string.
- The original data did not provide a single unique identifier field for person records; a unique identifier was constructed by concatenating the household identifier and person identifier fields.
- The original data did not provide a single unique identifier field for trip records; a unique identifier was constructed by concatenating the household identifier, person identifier, and trip identifier fields.

1990 TBI Data

The following modifications were made during conversion of the data from the 1990 TBI:

- In the original data's person table, the `EMPSTATE` field contained a leading space (e.g., "` MN`" rather than "`MN`"). This space was removed.
- The original data represented integer-valued fields as decimal numbers (e.g., "`1234.00`" rather than "`1234`"). These were converted to integer representations.

2000 TBI Data

No modifications were necessary for data from the 2000 TBI.

2010 TBI Data

The following modifications were made during conversion of the data from the 2010 TBI:

- In the original data's person table, a few records contained very small (e.g. 1.4×10^{-57}) fractional values in the `WRKHRS` field. These were converted to zero.

- In the original data's person table, a few records contained decimal values (e.g. "`44.92757254`" in the `SCHSTATUS` field; these were replaced with -1 (indicating non-student status).

A.2.2 Data Harmonization

The research team completed a "harmonization" process to identify compatible variables across 2010, 2000, 1990, and 1980 surveys. Response values were recoded to ensure consistency of analysis.

Value Mapping Across Years

Each variable is documented using a table describing the final variable name and values, and the mapping of these values across survey years. For example, refer to Table B.63 about the "telework" variable in the person table. In 2000, survey respondents were asked to indicate whether they ever work from home: yes or no. In 2010, respondents also had the option of indicating that they work from home only. Since this option was not available in respondents in 2000, these responses have been recoded to "yes". This recode is evident from the Final column's entry "1: Yes" mapping to both values "1" and "3" in the 2010 column.

Data Resolution

Where consistency with all years would have required considerable loss of resolution or data quality due to question or category wording of one year, duplicate versions of the variable were kept. An asterisk ("*") in the variable name is used to indicate a calculated variable. For example, age is a numeric variable for three survey years and a binary indicator in one year. Rather than collapse all four years into a single binary indicator, two variables were constructed: the numeric variable for the three applicable years, and a binary indicator that is consistent across all four years. This is shown in Tables B.45 and B.46. The "*" for the values in 2010, 2000, and 1990 shows that the new variable was calculated from the range of ages from 5 to 15 and 16 or older.

Standard Response Categories

Where applicable, binary indicator variables were renamed so that a value of 1 indicates the presence of the variable title and 0 indicates absence. For example, the gender variable has been recoded into two binary variables called female and male, shown in Tables B.47 and B.48, where a value of 1 indicates that the respondent is the same gender as the variable title. A value of 1 in the driver license variable indicates that the respondent has a driver license.

Missing Values

Separate "missing" categories were used to distinguish "Don't Know", "Refused", and "Inapplicable" where identifiable from the original data. In STATA, missing values are indicated by a period followed by an optional letter code (e.g., "..a"). Database exports can remove these STATA-specific codes for compatibility with other statistical software packages.

Additional Recoding

Researchers may request additional variables to be created by recoding existing variables differently or calculating interactions. The following is a list of recoding and variable creation still in progress:

- Infer homemaker status in 2000 based on presence of other working adult, age range, and children in the home (Table B.58)
- Construct an alternate hours worked variable from time use patterns inferred by trip end and start times (Table B.59)
- Infer disaggregated college or graduate school type based on highest level of education completed. E.g., if a person indicates that they are a college or graduate student and has completed a 4-year/bachelor's degree, they are assumed to be a graduate student (Table B.54)
- Construct an indicator variable for "teleworks almost every day (4-5 days per week)" to replace lost resolution of the 2010 response "works from home only" (Table B.63 and Table B.64)
- Use origin and destination data to assign trip purposes to 1980 categories
- Identify and restructure multimodal trips for compatibility between the 2010 format and the 2000/1990 format

A.2.3 Adding Geographic Context

In all original TBI datasets, locations and trip endpoints are identified by the TAZ they fall within. However, TAZ definitions varied over time; each of the TBI datasets from 1980 to 2010 uses a different TAZ structure. Additionally, TAZs are defined specifically for transportation analysis and align only partially with Census geometry. This poses a challenge for integrated analysis.

The 2000 and 2010 TBI datasets provide improved geographic resolution by identifying locations and trip endpoints with latitude and longitude coordinates, along with TAZ identifiers.

To facilitate longitudinal analysis of the TBI data, locations and trip endpoints in the harmonized data are tagged with as many cross-decade geographic identifiers as possible. For example, the latitude and longitude data for 2000 and 2010 allows locations to be resolved to a specific point in space. This point is then compared with TAZ and Census geometry for all decades, and tagged with the appropriate identifiers. Thus, a trip endpoint from the 2000 or 2010 datasets is associated with Census geometry from 1990, 2000, and 2010, and is assigned TAZ identifiers from 1980, 1990, 2000, and 2010.

For 1980 and 1990 TBI data where latitude and longitude information are not available, location datapoints are tagged with as many identifiers as possible without generating ambiguity. Because TAZ definitions have generally decreased in area over time, this means that 1990 (and later) locations can be accurately assigned to (larger) 1980 TAZs, but the reverse is often not true.

A.2.4 Linking to Contextual Data

The TBOT database is designed to hold data describing the transportation, weather, and economic context in which travel took place. The geographic context identifiers described in subsection A.2.3, combined with trip timestamps, are the primary mechanism for linking TBI data to this contextual information.

Accessibility, which expresses the number of opportunities reachable by a particular mode within a particular travel time, is used as a key identifier of the transportation context in which trips took place. The Access to Destinations projects calculated auto, transit, biking, and walking accessibility to jobs and other types of destinations for the years 1995, 2000, 2005, and 2010. This information is available at the TAZ level for auto, and at the Census block level for other modes. Accessibility data has been transferred from the Access to Destinations database to the TBOT database so that it can be associated directly with household locations and trip endpoints.

Historical weather data is available from the National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center. Daily minimum, maximum, and mean temperature as well as precipitation totals are available to provide a summary of the weather context in which travel took place. This information has been identified and acquired, but is not yet stored in the TBOT database. TBOT researchers assigned to subsequent research tasks will associate this data with TBI trip records as appropriate to achieve specific research goals.

Historical fuel price data, a key economic consideration involved in travel and location decisions, is available from the U.S. Energy Information Administration. It provides average weekly fuel prices for the state of Minnesota since 2000, and for the midwest region for earlier years. This information has been identified and acquired, but is not yet stored in the TBOT database. TBOT researchers assigned to subsequent research tasks will associate this data with TBI trip records as appropriate to achieve specific research goals.

A.3 Database Configuration and Structure

A.3.1 Software and Hardware Configuration

The TBOT database is hosted on a dedicated computer located at the University of Minnesota's Civil Engineering building and backed up locally and remotely via CrashPlan. Data storage, indexing, and access is provided by PostgreSQL 9.2, a widely-adopted and SQL-compliant database engine. Geospatial database capabilities are provided by PostGIS 2.0.4, an extension for PostgreSQL. Data files are stored in a redundant hard disk array to reduce the risk of data loss in the case of hardware failure.

The database can be accessed over the UMN network by researchers for use during subsequent TBOT tasks. Access is password-protected to prevent disruptive use during the TBOT project. At the completion of the TBOT project, an archive of the full TBOT database can be made available on request.

A.3.2 Encoding of Geospatial Data

The PostGIS extension allows geometry objects to be stored directly in the database, eliminating the need for maintaining separate files and allowing spatial analysis queries to be executed directly by the database. The Census and TAZ geometry described above is stored using this extension. Within the database, geometry objects are represented using the "well-known binary" (WKB) format defined by ISO/IEC 13249-3 and adopted by all major geospatial database engines. All geospatial data in the TBOT database is stored using the NAD83/UTM (zone 15N) coordinate system and projection after being converted as necessary from its original format.

A.3.3 Table Organization

The TBOT database contains a total of 28 tables, which can be divided into three categories. *TBI data tables*, listed in Table A.1, contain data for each decennial survey, translated directly from the original format as described in subsection A.2.1. *Geographic data tables*, listed in Table A.2, contain identifiers and geometric descriptions of Census tabulation units and TAZs. These tables constitute a functional geodatabase, and can be accessed directly from within GIS environments such as ArcGIS. *Harmonized data tables*, listed in Table A.3, contain TBI data covering 1980–2010 in the unified format described in subsection A.2.2.

A.3.4 Table Structure

Original Survey Data

Data collected during the 1980, 1990, 2000, and 2010 TBI surveys were added to the TBOT database with as few modifications as possible. Except as described in subsection A.2.1, field names, field order, and data types in the original data tables are identical to those in the survey data files archived by the Metropolitan Council.

Table A.1: TBI Data Tables in TBOT Database

Table Name	**Description**
tbi1980_hh	1980 TBI household data
tbi1980_per	1980 TBI person data
tbi1980_trip	1980 TBI trip data
tbi1990_hh	1990 TBI household data
tbi1990_per	1990 TBI person data
tbi1990_trip	1990 TBI trip data
tbi2000_hh	2000 TBI household data
tbi2000_loc	2000 TBI location data
tbi2000_per	2000 TBI person data
tbi2000_trip	2000 TBI trip data
tbi2000_veh	2000 TBI vehicle data
tbi2010_hh	2010 TBI household data
tbi2010_per	2010 TBI person data
tbi2010_trip	2010 TBI trip data

Table A.2: Geographic Data Tables in TBOT Database

Table Name	**Description**
taz1980	1980 Transportation Analysis Zones
block1990	1990 Census blocks
blockgroup1990	1990 Census block groups
tract1990	1990 Census tracts
taz1990	1990 Transportation Analysis Zones
block2000	2000 Census blocks
blockgroup2000	2000 Census block groups
tract2000	2000 Census tracts
taz2000	2000 Transportation Analysis Zones
block2010	2010 Census blocks
blockgroup2010	2010 Census block groups
tract2010	2010 Census tracts
taz2010	2010 Transportation Analysis Zones

Table A.3: Harmonized Data Tables in TBOT Database

Table Name	**Description**
tbi_harmonized_hh	Harmonized household data
tbi_harmonized_per	Harmonized person data
tbi_harmonized_trip	Harmonized trip data

Harmonized Data

The harmonized data tables contain data from all TBIs in a single unified format. The structures of the harmonized data tables are described in the appendices. Section B.0.5 describes the harmonized household table, subsection B.0.6 describes the harmonized person table, and subsection B.0.9 describes the harmonized trip table. Many of the values in these tables were recoded or recalculated as described in subsection A.2.2.

Appendix B

Additional Tables and Figures

The results of the weighted employment accessibility measures by auto are shown in Figures B.1-B.2. The expected relationship of higher accessibility in the center of the region are apparent. The scale is the same for each of the maps, in order to show how accessibility is changing in the region.

Table B.1: 2010 Correlation Matrix for auto users 2010

WT	-0.07	1.00																
age10	-0.04	-0.03	1.00															
age20	-0.05	-0.02	-0.03	1.00														
age40	0.06	0.00	-0.06	-0.18	1.00													
age50	-0.03	0.03	-0.07	-0.21	-0.45	1.00												
age60	-0.02	-0.01	-0.04	-0.11	-0.24	-0.28	1.00											
Male	0.07	0.06	0.00	0.00	0.02	-0.03	0.00											
VPD	0.03	0.03	-0.03	-0.07	0.00	0.08	0.00	0.05	1.00									
HHsize	0.06	-0.01	0.08	0.07	0.27	-0.24	-0.28	0.11	-0.12	1.00								
SFhome	0.04	0.02	0.02	-0.08	0.08	0.04	-0.08	0.09	0.11	0.31	1.00							
Children	0.05	0.00	0.01	-0.12	0.44	-0.22	-0.22	0.07	-0.05	0.68	0.18	1.00						
D_{io}	0.20	0.01	0.04	-0.05	0.03	0.01	-0.02	0.04	0.15	0.13	0.10	0.08	1.00					
D_{jo}	-0.15	0.05	0.05	0.04	0.00	0.00	-0.02	0.01	0.09	0.05	0.04	0.02	0.48	1.00				
A_{iEa}	-0.22	0.00	-0.03	0.06	-0.02	-0.02	0.01	-0.04	-0.15	-0.14	-0.14	-0.10	-0.90	-0.40	1.00			
A_{jEa}	0.16	-0.05	-0.06	-0.04	0.01	0.00	0.00	0.00	-0.08	-0.05	-0.04	-0.01	-0.40	-0.91	0.40	1.00		
A_{iRa}	-0.23	-0.01	-0.03	0.05	-0.02	-0.02	0.01	-0.04	-0.15	-0.14	-0.13	-0.09	-0.90	-0.40	0.99	0.40	1.00	
A_{jRa}	0.15	-0.04	-0.06	-0.04	0.01	0.00	0.01	0.00	-0.09	-0.05	-0.04	-0.02	-0.41	-0.91	0.40	0.99	0.41	1.00
T_W	0.11	-0.51	-0.05	-0.03	0.00	0.02	0.00	0.02	0.02	-0.03	-0.01	-0.04	0.06	-0.03	-0.07	0.04	-0.07	0.04
	T_E	WT	10	20	40	50	60	Male	VPD	HHS	SFH	Child	D_{io}	D_{jo}	A_{iEa}	A_{jEa}	A_{iRa}	A_{jRa}

Table B.2: Regressions to predict commuting duration by auto without collinear variables 1

Variable	2010		2000		1990	
Age	Coefficient		Coefficient		Coefficient	
yr	(t-value)		(t-value)		(t-value)	
10	-5.72	***	-6.81	***	-6.24	***
	(-2.95)		(-3.15)		(-4.67)	
20	-1.42	*	-1.34	*	-1.25	*
	(-1.81)		(-1.48)		(-2.85)	
40	0.571		0.725		0.703	
	(0.98)		(2.54)		(1.064)	
50	-1.16	**	-0.361	**	-1.32	**
	(-2.06)		(-0.728)		(-2.21)	
60	-0.943		-0.524		-0.613	
	(-1.35)		(-0.353)		(-0.985)	
Male	1.55	***	1.795	**	1.924	**
	(4.30)		(6.25)		(7.04)	
SFhome	-0.272		-0.542		-0.941	
	(-0.481)		(-0.364)		(-0.321)	
VPD	0.236		0.345		0.327	
	(0.579)		(0.642)		(0.457)	
Children	-0.354		0.021		-0.645	
	(-0.983)		(1.35)		(-1.32)	
HHsize	0.198		0.572		0.243	
	(0.917)		(1.02)		(0.962)	
A_{iEa}	-2.45E-05	***	-9.865E-06	***	-1.023E-05	***
	(-23.58)		(-12.27)		(-21.367)	
A_{jEa}	2.123E-05	***	3.258E-05	***	3.21E-05	***
	(21.053)		(26.45)		(25.41)	
Constant	21.68	***	28.47	***	27.68	***
	(19.17)		(23.67)		(19.37)	
Sample Size	5228		2978		6574	
Adj. R^2	0.1347		0.1782		0.1245	
F	67.63	***	58.39	***	54.63	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

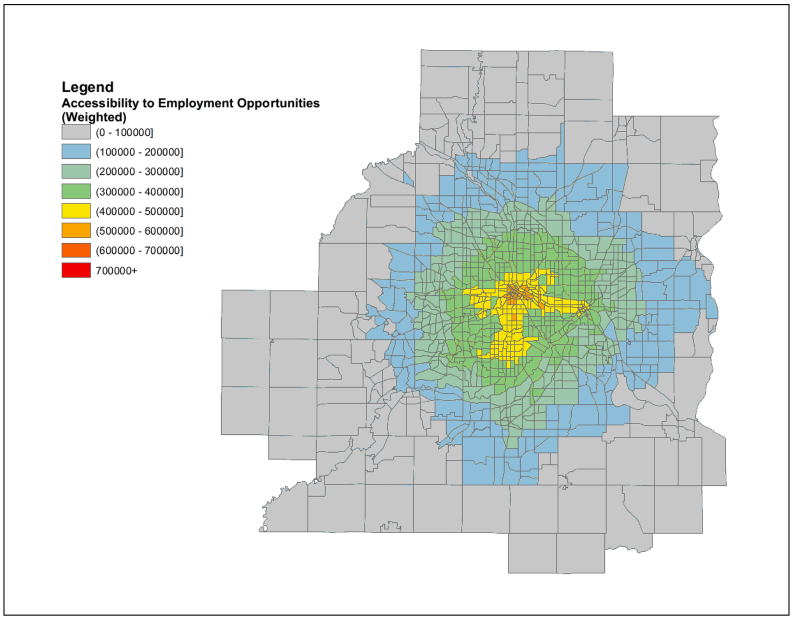

Figure B.1: 1995 Employment Accessibility by Auto

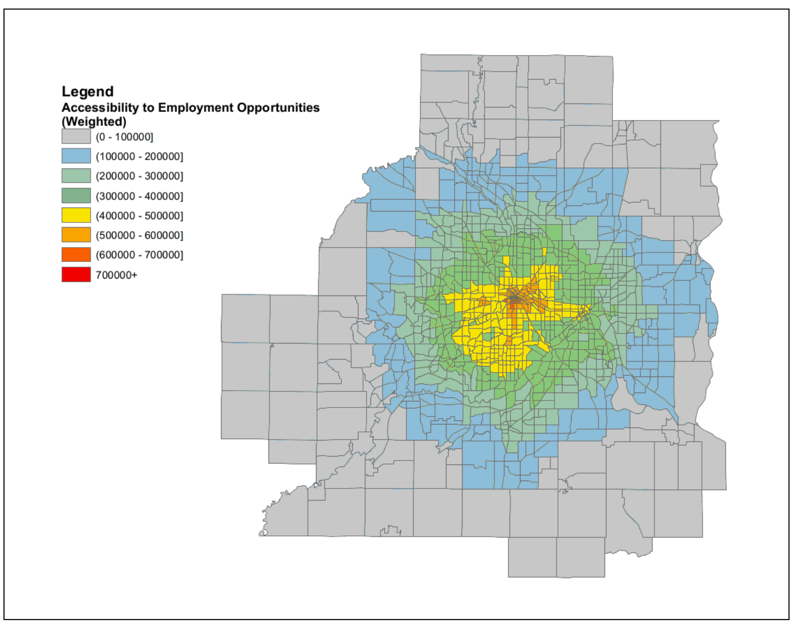

Figure B.2: 2000 Employment Accessibility by Auto

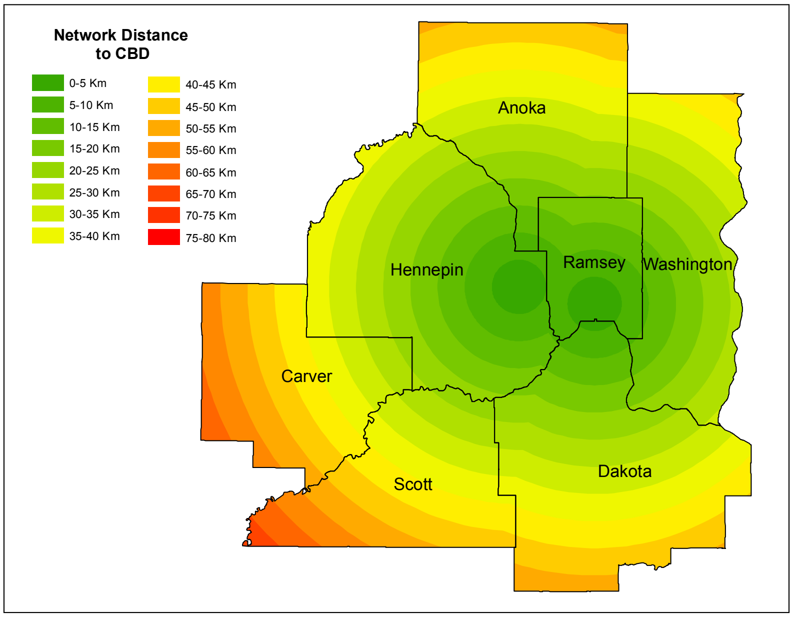

Figure B.3: Idealized Distance from CBD

Table B.3: Regressions to predict commuting duration by auto without collinear variables 2

Variable	2010		2000		1990	
Age	Coefficient		Coefficient		Coefficient	
yr	(t-value)		(t-value)		(t-value)	
10	-5.78	***	-6.79	***	-6.22	***
	(-2.97)		(-3.14)		(-4.42)	
20	-1.56	**	-1.32	*	-1.53	
	(-1.97)		(-1.45)		(-2.82)	
40	0.543		0.723		0.713	
	(0.933)		(2.42)		(1.061)	
50	-1.19	**	-0.357	*	-1.27	**
	(-2.12)		(-0.734)		(-2.19)	
60	-1.03		-0.531		-0.619	
	(-1.463)		(-0.354)		(-0.979)	
Male	1.50	***	1.80	**	1.928	**
	(4.153)		(6.31)		(7.00)	
SFhome	-0.250		-0.548		-0.940	
	(-0.442)		(-0.342)		(-0.328)	
VPD	0.193		0.361		0.336	
	(0.473)		(0.679)		(0.424)	
Children	-0.347		0.027		-0.648	
	(-0.963)		(1.27)		(-1.27)	
HHsize	0.213		0.534		0.187	
	(0.985)		(1.07)		(1.342)	
A_{iRa}	1.857E-05	***	1.042E-05	***	2.624E-05	***
	(23.39)		(18.84)		(22.47)	
A_{jRa}	-1.645E-05	***	-2.031E-05	***	-2.89E-05	***
	(-20.283)		(-24.12)		(-28.02)	
Constant	21.71	***	27.64	***	24.92	***
	(18.02)		(24.52)		(20.37)	
Sample Size	5228		2978		6574	
Adj. R^2	0.1299		0.1706		0.1452	
F	64.85	***	54.23	***	53.47	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.4: Regressions to predict time spent at work for auto users without collinear variables 1

Variable	2010		2000		1990	
Age	Coefficient		Coefficient		Coefficient	
yr	(t-value)		(t-value)		(t-value)	
10	-118.1	***	-103.0	***	-115.3	***
	(-5.148)		(-3.81)		(-6.39)	
20	-22.2	**	-20.52	**	-21.2	**
	(-2.39)		(-3.14)		(-2.56)	
40	1.32		1.63		1.34	
	(0.193)		(0.23)		(0.34)	
50	4.01		4.52		4.37	
	(0.604)		(0.902)		(0.621)	
60	-1.03		-8.34		-10.26	
	(-1.25)		(-1.86)		(-1.69)	
Male	18.8	***	20.5	***	22.97	***
	(4.41)		(5.02)		(4.82)	
SFhome	-6.65		-5.87		-5.57	
	(-0.994)		(-0.27)		(-0.921)	
VPD	7.24		8.56		7.984	
	(1.51)		(1.71)		(1.62)	
Children	-10.1	**	-13.1	*	-11.2	*
	(-2.38)		(-4.02)		(-3.01)	
HHsize	-2.11		-2.18		-2.14	
	(-0.827)		(-0.80)		(-1.23)	
A_{iEa}	-8.613E-05	***	-1.241E-04	***	-2.078E-05	***
	(-5.49)		(-2.86)		(-3.45)	
A_{jEa}	3.994E-05	***	4.008E-05	***	4.357E-05	***
	(2.65)		(3.65)		(4.35)	
Commute Duration	0.628***	0.545	***	0.423	***	
	(3.83)		(4.23)		(3.37)	
Number of Work Trips	-148.5	***	-132.8	***	-134.2	***
	(-43.55)		(-32.56)		(-37.52)	
Constant	606.2	***	578.7	***	562.8	***
	(41.63)		(21.5)		(20.3)	
Sample Size	5228		2978		6574	
Adj. R^2	0.2815		0.1342		0.224	
F	147.2	***	110.5	***	141.1	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.5: Regressions to predict time spent at work for auto users without collinear variables 2

Variable	2010		2000		1990	
Age	Coefficient		Coefficient		Coefficient	
yr	(t-value)		(t-value)		(t-value)	
10	-118.1	***	-102.6	***	-116.2	***
	(-5.145)		(-3.83)		(-7.32)	
20	-22.6	**	-20.41	**	-20.31	
	(-2.42)		(-3.22)		(-2.45)	
40	1.34		1.62		1.26	
	(0.195)		(0.232)		(0.333)	
50	4.12		4.49		4.671	
	(0.621)		(0.82)		(0.574)	
60	-1.03		-8.39		-9.36	
	(-1.24)		(-1.82)		(-1.66)	
Male	18.7	***	20.26	***	22.37	***
	(4.37)		(5.28)		(6.17)	
SFhome	-6.47		-5.80		-5.62	
	(-0.967)		(-0.215)		(-0.824)	
VPD	7.13		8.52		7.69	
	(1.48)		(1.74)		(1.35)	
Children	-10.1	**	-12.2	*	-11.2	*
	(-2.38)		(-3.66)		(-3.02)	
HHsize	-2.03		-2.02		-2.41	
	(-0.794)		(-0.745)		(-1.02)	
A_{iRa}	-1.352E-04	***	-9.022E-05	***	-1.267E-05	***
	(-5.35)		(-6.32)		(-6.14)	
A_{jRa}	6.42E-05	**	4.332E-05	**	1.852E-05	***
	(2.48)		(2.02)		(2.31)	
Commute Duration	0.640***	0.526	***	0.815	***	
	(3.91)		(4.11)		(3.26)	
Number of Work Trips	-148.6	***	-125.0	***	-133.0	***
	(-43.57)		(-25.17)		(-31.5)	
Constant	608.6	***	575.2	***	502.1	***
	(39.64)		(22.0)		(12.3)	
Sample Size	5228		2978		6574	
Adj. R^2	0.2812		0.1255		0.1024	
F	147.1	***	100.2	***	104.1	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.6: Regressions to predict commuting duration by Transit without collinear variables 1

Variable	2010		2000		1990	
Age	Coefficient		Coefficient		Coefficient	
yr	(t-value)		(t-value)		(t-value)	
10	23.21	***	12.78	**	20.34	***
	(5.98)		(8.34)		(4.87)	
20	-1.04	*	-0.72		-0.84	
	(-1.73)		(-0.23)		(-0.17)	
40	-2.51		1.02		-1.64	
	(0.78)		(0.42)		(-1.24)	
50	-3.18		-1.35		-1.75	
	(-2.04)		(-1.02)		(-1.54)	
60	-2.15	**	4.87	*	-0.23	
	(-1.21)		(2.02)		(-1.47)	
Male	0.97		0.87		0.79	
	(0.71)		(0.54)		(0.27)	
SFhome	-0.94		-0.51		-0.75	
	(-1.32)		(-0.79)		(-0.84)	
VPD	-2.47		-2.30		-2.72	
	(-0.36)		(-0.97)		(-0.68)	
Children	-1.72		-3.02		-2.04	
	(-0.983)		(-1.24)		(-1.14)	
HHsize	1.92		2.06		1.87	
	(0.979)		(1.04)		(0.975)	
A_{iEt}	-4.215E-05	***	-4.026E-05	***	-4.521E-05	***
	(-21.42)		(-20.78)		(-19.87)	
A_{jEt}	-3.472E-05	***	-3.788E-05	***	-3.687E-05	***
	(-18.75)		(-21.54)		(-22.45)	
Constant	26.32	***	25.67	***	24.92	***
	(24.72)		(24.17)		(21.49)	
Sample Size	124		106		164	
Adj. R^2	0.123		0.098		0.1111	
F	56.37	***	52.47	***	57.21	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.7: Regressions to predict commuting duration by Transit without collinear variables 2

Variable	2010		2000		1990	
Age	Coefficient		Coefficient		Coefficient	
yr	(t-value)		(t-value)		(t-value)	
10	23.31	***	12.82	**	20.48	***
	(6.02)		(6.24)		(4.74)	
20	-1.08	*	-0.81		-0.87	
	(-1.68)		(-0.21)		(-0.12)	
40	-2.48		1.11		-1.49	
	(0.70)		(0.45)		(-1.34)	
50	-3.24		-1.36		-1.85	
	(-1.97)		(-1.05)		(-1.41)	
60	-2.23	**	4.91	*	-0.31	
	(-1.78)		(1.97)		(-1.42)	
Male	1.02		0.82		0.80	
	(0.78)		(0.51)		(0.15)	
SFhome	-0.89		-0.78		-0.63	
	(-1.18)		(-0.72)		(-0.82)	
VPD	-2.58		-2.19		-2.71	
	(-0.47)		(-1.87)		(-0.71)	
Children	-1.81		-3.13		-1.98	
	(-1.24)		(-1.28)		(-1.42)	
HHsize	1.89		1.97		1.92	
	(0.824)		(1.09)		(1.07)	
A_{iRt}	3.852E-05	***	3.741E-05	***	3.498E-05	***
	(20.47)		(20.89)		(20.47)	
A_{jRt}	3.241E-05	***	2.678E-05	***	2.395E-05	***
	(20.51)		(22.34)		(20.61)	
Constant	28.27	***	28.21	***	27.38	***
	(21.26)		(25.21)		(22.18)	
Sample Size	124		106		164	
Adj. R^2	0.114		0.096		0.1124	
F	54.00	***	51.23	***	56.37	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.8: Regressions to predict commute duration for auto users 2010 resident accessibility 5-30 min

Variable	5 min		10 min		15 min		20 min		25 min		30 min	
Age	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient	
	(t-value)		(t-value)		(t-value)		(t-value)		(t-value)		(t-value)	
Male	1.79E+00	***	1.70E+00	***	1.63E+00	***	1.54E+00	***	1.43E+00	***	1.36E+00	*
	(4.772)		(4.635)		(4.477)		(4.257)		(3.967)		(3.759)	
SFhome	-7.75E-01		-2.37E-01		-4.68E-02		2.28E-02		7.27E-02		-5.38E-03	
	(-1.293)		(-0.411)		(-0.082)		(0.04)		(0.128)		(-0.009)	
VPD	8.43E-01	**	4.94E-01		4.34E-01		3.55E-01		3.02E-01		2.43E-01	
	(2.005)		(1.197)		(1.058)		(0.87)		(0.741)		(0.594)	
Children	-4.44E-01		-4.13E-01		-3.72E-01		-3.66E-01		-3.34E-01		-3.19E-01	
	(-1.183)		(-1.127)		(-1.024)		(-1.013)		(-0.926)		(-0.882)	
HHsize	5.93E-01	***	2.73E-01		2.07E-01		1.99E-01		1.91E-01		2.48E-01	
	(2.651)		(1.241)		(0.945)		(0.916)		(0.882)		(1.144)	
A_{iRa}	6.98E-05	***	3.61E-05	***	1.80E-05	***	1.28E-05	***	1.15E-05	***	1.16E-05	*
	(11.119)		(19.088)		(21.206)		(22.462)		(23.594)		(23.464)	
A_{jRa}	-4.11E-05	***	-2.71E-05	***	-1.51E-05	***	-1.16E-05	***	-1.12E-05	***	-1.18E-05	*
	(-12.812)		(-17.751)		(-19.039)		(-20.397)		(-20.666)		(-19.764)	
Constant	2.06E+01		2.15E+01		2.13E+01		2.07E+01		2.03E+01		1.98E+01	
	(20.688)		(21.335)		(20.805)		(19.764)		(18.387)		(16.388)	
Sample Size	5228		5228		5228		5228		5228		5228	
Adj. R^2	5.88E-02		1.01E-01		1.14E-01		1.24E-01		1.30E-01		1.25E-01	
F	2.82E+01	***	5.00E+01	***	5.69E+01	***	6.28E+01	***	6.59E+01	***	6.32E+01	*

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.9: Regressions to predict commute duration for auto users 2010 resident accessibility 35-60 min

Variable	35 min		40 min		45 min		50 min		55 min		60 min
Age	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient
yr	(t-value)		(t-value)		(t-value)		(t-value)		(t-value)		(t-value)
10	-6.11E+00	***	-6.30E+00	***	-6.63E+00	***	-6.87E+00	***	-6.95E+00	***	-6.73E+00
	(-3.114)		(-3.176)		(-3.306)		(-3.397)		(-3.42)		(-3.326)
20	-1.79E+00	**	-2.02E+00	**	-2.24E+00	***	-2.45E+00	***	-2.60E+00	***	-2.41E+00
	(-2.249)		(-2.511)		(-2.742)		(-2.982)		(-3.145)		(-2.925)
40	6.85E-01		6.64E-01		6.33E-01		5.56E-01		4.88E-01		5.37E-01
	(1.165)		(1.116)		(1.052)		(0.917)		(0.801)		(0.885)
50	-7.03E-01		-6.56E-01		-6.19E-01		-6.96E-01		-7.68E-01		-6.99E-01
	(-1.238)		(-1.142)		(-1.066)		(-1.189)		(-1.304)		(-1.193)
60	-5.97E-01		-5.16E-01		-4.26E-01		-4.36E-01		-4.92E-01		-4.44E-01
	(-0.845)		(-0.722)		(-0.589)		(-0.598)		(-0.67)		(-0.608)
Male	1.34E+00	***	1.36E+00	***	1.43E+00	***	1.52E+00	***	1.58E+00	***	1.55E+00
	(3.67)		(3.672)		(3.841)		(4.041)		(4.17)		(4.112)
SFhome	-9.61E-02		-6.67E-02		-5.98E-02		3.57E-02		9.22E-02		7.35E-02
	(-0.168)		(-0.115)		(-0.102)		(0.06)		(0.155)		(0.124)
VPD	1.70E-01		2.02E-01		2.65E-01		3.24E-01		4.16E-01		3.59E-01
	(0.412)		(0.484)		(0.627)		(0.76)		(0.969)		(0.841)
Children	-2.84E-01		-2.09E-01		-1.58E-01		-1.41E-01		-1.42E-01		-1.28E-01
	(-0.779)		(-0.566)		(-0.424)		(-0.376)		(-0.375)		(-0.341)
HHsize	3.31E-01		4.00E-01	*	4.88E-01	**	5.27E-01	**	5.47E-01	**	5.21E-01
	(1.515)		(1.817)		(2.192)		(2.349)		(2.427)		(2.32)
A_{iRa}	1.25E-05	***	1.38E-05	***	1.57E-05	***	1.83E-05	***	2.28E-05	***	1.67E-05
	(22.085)		(19.836)		(16.969)		(14.417)		(12.619)		(14.15)
A_{jRa}	-1.29E-05	***	-1.46E-05	***	-1.65E-05	***	-1.82E-05	***	-2.12E-05	***	-1.73E-05
	(-17.832)		(-14.989)		(-11.992)		(-9.245)		(-7.054)		(-9.109)
Constant	1.97E+01		1.94E+01		1.93E+01		2.07E+01		2.31E+01		1.90E+01
	(14.241)		(11.355)		(8.458)		(6.453)		(4.724)		(3.411)
Sample Size	5228		5228		5228		5228		5228		5228
Adj. R^2	1.11E-01		9.13E-02		7.06E-02		5.45E-02		4.46E-02		0.05392
F	5.54E+01	***	4.48E+01	***	3.41E+01	***	2.61E+01	***	2.14E+01	***	25.82

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.10: Regressions to predict commute duration for auto users 2010 employment accessibility interval 5-30 min

Variable	5 min		10 min		15 min		20 min		25 min		30 min
	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)
A_{iEa}	-6.98E-05	***	-4.12E-05	***	-2.47E-05	***	-2.01E-05	***	-1.96E-05	***	-1.84E-05
	-11.119		-17.805		-20.067		-20.824		-22.101		-19.199
A_{jEa}	4.11E-05	***	3.55E-05	***	1.96E-05	***	1.93E-05	***	1.82E-05	***	1.79E-05
	12.812		15.346		17.924		18.593		18.409		15.005
Sample Size	5228		5228		5228		5228		5228		5228
Adj. R^2	0.05882		0.08587		0.1057		0.1102		0.115		0.09066
F	28.22	***	41.19	***	52.47	***	54.92	***	57.56	***	44.42

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.11: Regressions to predict commute duration for auto users 2010 employment accessibility interval 35-60 min

Variable	35 min		40 min		45 min		50 min		55 min		60 min
	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)
A_{iEa}	-2.04E-05	***	-1.72E-05	***	-1.81E-05	***	-1.41E-05	***	-1.30E-05	***	-6.62E-06
	-18.323		-13.049		-11.053		-7.263		-5.839		-2.693
A$_{jEa}$	1.84E-05	***	1.23E-05	***	1.35E-05	***	2.74E-06	***	7.53E-06	***	-2.44E-06
	13.671		6.97		6.795		1.193		3.112		-0.955
Sample Size	5228		5228		5228		5228		5228		5228
Adj. R^2	0.08199		0.04677		0.04108		0.0227		0.02045		0.01435
F	39.89	***	22.37	***	18.61	***	11.11	***	10.09	***	7.342

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.12: Regressions to predict commute duration for auto users 2010 resident accessibility interval 5-30 min

Variable	5 min		10 min		15 min		20 min		25 min		30 min
	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)
A_{iEa}	1.18E-04	***	4.41E-05	***	2.47E-05	***	1.74E-05	***	1.46E-05	***	1.42E-05
	13.148		19.502		21.358		22.812		22.777		22.971
A_{jEa}	-7.37E-05	***	-3.26E-05	***	-1.99E-05	***	-1.61E-05	***	-1.34E-05	***	-1.42E-05
	-11.809		-17.223		-18.449		-20.203		-19.294		-19.156
Sample Size	5228		5228		5228		5228		5228		5228
Adj. R^2	0.05834		0.1004		0.1126		0.1249		0.1206		0.1206
F	27.98	***	49.63	***	56.24	***	63.16	***	60.74	***	60.73

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.13: Regressions to predict commute duration for auto users 2010 resident accessibility interval 35-60 min

Variable	35 min		40 min		45 min		50 min		55 min		60 min	
	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
A_{iEa}	1.51E-05	***	1.59E-05	***	1.77E-05	***	1.80E-05	***	1.98E-05	***	1.94E-05	*
	21.901		19.693		17.416		13.918		11.858		8.843	
A_{jEa}	-1.49E-05	***	-1.55E-05	***	-1.73E-05	***	-1.45E-05	***	-1.51E-05	***	-7.58E-06	*
	-17.633		-14.425		-12.685		-8.276		-6.991		-2.918	
Sample Size	5228		5228		5228		5228		5228		5228	
Adj. R^2	0.1103		0.09011		0.07517		0.05144		0.04238		0.02787	
F	54.99	***	44.13	***	36.4	***	24.62	***	20.27	***	13.48	*

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.14: Regressions to predict commute duration for auto users 2010 weighted different weights -0.01 - -0.3

Variable	-0.01		-0.01		-0.02		-0.02		-0.03		-0.03	
	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
A_{iEa}, A_{iRa}	-5.17E-06	***	3.20E-06	***	-6.76E-06	***	4.32E-06	***	-8.67E-06	***	5.72E-06	*
	(-24.186)		(23.811)		(-24.289)		(23.902)		(-24.302)		(23.925)	
A_{jEa}, A_{jRa}	5.10E-06	***	-3.15E-06	***	6.54E-06	***	-4.18E-06	***	8.24E-06	***	-2.67E-07	*
	(20.75)		(-20.075)		(21)		(-20.266)		(21.155)		(-20.388)	
Sample Size	5228		5228		5228		5228		5228		5228	
Adj. R^2	0.1328		0.1281		0.1344		0.1294		0.1353		0.1301	
F	67.67	***	64.96	***	68.62	***	65.71	***	69.12	***	66.12	*

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.15: Regressions to predict commute duration for auto users 2010 weighted different weights -0.04 - -0.06

Variable	-0.04		-0.04		-0.05		-0.05		-0.06		-0.06	
	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
A_{iEa}, A_{iRa}	-1.10E-05	***	7.44E-06	***	-1.36E-05	***	9.54E-06	***	-1.68E-05	***	1.21E-05	*
	(-24.243)		(23.892)		(-24.13)		(23.814)		(-23.975)		(23.699)	
A_{jEa}, A_{jRa}	1.02E-05	***	-6.99E-06	***	1.25E-05	***	-8.83E-06	***	1.51E-05	***	-5.38E-07	*
	(21.233)		(-20.451)		(21.251)		(-20.463)		(21.22)		(-20.434)	
Sample Size	5228		5228		5228		5228		5228		5228	
Adj. R^2	0.1355		0.1303		0.1353		0.1301		0.1346		0.1296	
F	69.26	***	66.25	***	69.12	***	66.15	***	68.76	***	65.86	*

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.16: Regressions to predict commute duration for auto users 2010 weighted different weights -0.07 - -0.1

Variable	-0.07		-0.07		-0.09		-0.09		-0.1		-0.1	
	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
A_{iEa}, A_{iRa}	-2.04E-05 (-23.789)	***	1.51E-05 (23.555)	***	-2.92E-05 (-23.354)	***	2.27E-05 (23.207)	***	-3.45E-05 (-23.116)	***	2.74E-05 (23.012)	***
A_{jEa}, A_{jRa}	1.80E-05 (21.151)	***	-1.35E-05 (-20.372)	***	2.48E-05 (20.93)	***	-1.98E-05 (-20.171)	***	2.88E-05 (20.789)	***	-2.36E-05 (-20.042)	***
Sample Size	5228		5228		5228		5228		5228		5228	
Adj. R^2	0.1337		0.1288		0.1313		0.1267		0.1298		0.1254	
F	68.23	***	65.41	***	66.81	***	64.19	***	65.99	***	63.46	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.17: Regressions to predict commute duration for auto users 2010 non-cumulative

Variable	Employment			Resident		
Age (yr)	Coefficient	(t-value)		Coefficient	(t-value)	
10	-5.40E+00	(-2.783)	***	-5.53E+00	(-2.851)	***
20	-1.44E+00	(-1.829)	*	-1.57E+00	(-1.986)	**
40	6.35E-01	(1.096)		5.72E-01	(0.985)	
50	-8.66E-01	(-1.543)		-9.52E-01	(-1.687)	*
60	-6.70E-01	(-0.96)		-7.73E-01	(-1.101)	
Male	1.46E+00	(4.059)	***	1.43E+00	(3.96)	***
SFhome	-2.40E-01	(-0.415)		-1.71E-01	(-0.3)	
VPD	4.55E-02	(0.111)		9.60E-02	(0.234)	
Children	-3.17E-01	(-0.882)		-2.99E-01	(-0.828)	
HHsize	2.33E-01	(1.08)		2.41E-01	(1.111)	
A_{iEa5}, A_{iRa5}	-1.77E-05	(-2.163)	**	3.40E-05	(2.095)	**
A_{iEa10}, A_{iRa10}	-8.73E-06	(-1.544)		-1.21E-05	(-1.699)	*
A_{iEa15}, A_{iRa15}	2.56E-08	(0.006)		-4.81E-06	(-0.811)	
A_{iEa20}, A_{iRa20}	7.66E-07	(0.189)		-3.69E-06	(-0.798)	
A_{iEa25}, A_{iRa25}	-8.98E-06	(-1.984)	**	7.39E-07	(0.154)	
A_{iEa30}, A_{iRa30}	-7.98E-06	(-1.435)		-5.78E-06	(-1.192)	
A_{iEa35}, A_{iRa35}	-8.86E-06	(-1.273)		2.30E-06	(0.41)	
A_{iEa40}, A_{iRa40}	4.91E-06	(0.527)		-1.18E-05	(-1.777)	*
A_{iEa45}, A_{iRa45}	2.47E-05	(2.253)	**	4.44E-06	(0.529)	
A_{iEa50}, A_{iRa50}	-2.02E-05	(-1.167)		1.48E-05	(1.579)	
A_{iEa55}, A_{iRa55}	-2.89E-05	(-2.707)	***	-1.64E-05	(-2.322)	**
A_{iEa60}, A_{iRa60}	4.06E-06	(0.201)		-5.96E-06	(-0.612)	
A_{jEa5}, A_{jRa5}	3.11E-05	(5.187)	***	7.03E-06	(0.572)	
A_{jEa10}, A_{jRa10}	-7.14E-06	(-1.369)		7.95E-07	(0.13)	
A_{jEa15}, A_{jRa15}	-9.22E-06	(-2.209)	**	9.13E-07	(0.154)	
A_{jEa20}, A_{jRa20}	1.08E-05	(2.536)	**	1.25E-05	(2.766)	***
A_{jEa25}, A_{jRa25}	2.30E-05	(3.963)	***	-6.13E-06	(-1.121)	
A_{jEa30}, A_{jRa30}	5.86E-06	(0.9)		1.30E-05	(2.387)	*
A_{jEa35}, A_{jRa35}	-2.36E-05	(-2.288)	**	1.26E-06	(0.175)	
A_{jEa40}, A_{jRa40}	-4.44E-06	(-0.348)		-1.96E-05	(-2.362)	**
A_{jEa45}, A_{jRa45}	1.87E-05	(1.13)		2.55E-05	(2.277)	**
A_{jEa50}, A_{jRa50}	2.55E-05	(0.956)		-1.01E-05	(-0.819)	
A_{jEa55}, A_{jRa55}	-2.03E-05	(-1.21)		-1.76E-05	(-1.754)	*
A_{jEa60}, A_{jRa60}	-3.88E-05	(-1.079)		1.90E-05	(1.462)	
Constant	6.34E+01	(3.095)	***	3.21E+01	(2.799)	***
Sample Size	5228			5228		
Adj. R^2	0.1405			0.1341		
F	26.12 ***			24.8 ***		

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.18: Regressions to predict commute duration for auto users 2010 10 min intervals

Variable	Employment			Resident		
Age (yr)	Coefficient	(t-value)		Coefficient	(t-value)	
10	-5.73E+00	(-2.947)	***	-5.72E+00	(-2.947)	***
20	-1.61E+00	(-2.037)	**	-1.57E+00	(-1.987)	**
40	5.87E-01	(1.009)		5.90E-01	(1.014)	
50	-1.06E+00	(-1.875)	*	-1.03E+00	(-1.819)	*
60	-8.86E-01	(-1.263)		-8.42E-01	(-1.2)	
Male	1.43E+00	(3.944)	***	1.47E+00	(4.053)	***
SFhome	-1.99E-01	(-0.35)		-1.89E-01	(-0.333)	
VPD	1.24E-01	(0.303)		4.25E-02	(0.103)	
Children	-3.39E-01	(-0.938)		-2.86E-01	(-0.793)	
HHsize	2.57E-01	(1.187)		2.36E-01	(1.089)	
A_{iEa10}, A_{iRa10}	-8.85E-06	(-1.661)	*	-1.73E-06	(-0.364)	
A_{iEa20}, A_{iRa20}	-5.57E-06	(-1.536)		-3.98E-06	(-1.353)	
A_{iEa30}, A_{iRa30}	-3.03E-06	(-0.716)		-1.80E-06	(-0.632)	
A_{iEa40}, A_{iRa40}	-8.62E-06	(-1.557)		-4.82E-06	(-1.441)	
A_{iEa50}, A_{iRa50}	-1.37E-06	(-0.189)		6.01E-06	(1.297)	
A_{iEa60}, A_{iRa60}	9.79E-06	(1.602)		-9.14E-06	(-1.986)	**
A_{jEa10}, A_{jRa10}	3.12E-06	(0.742)		3.25E-06	(0.951)	
A_{jEa20}, A_{jRa20}	1.00E-05	(2.88)	***	4.52E-06	(1.626)	
A_{jEa30}, A_{jRa30}	9.09E-06	(2.008)	**	4.55E-06	(1.373)	
A_{jEa40}, A_{jRa40}	-9.02E-06	(-1.301)		-3.00E-06	(-0.689)	
A_{jEa50}, A_{jRa50}	8.23E-06	(0.863)		4.08E-06	(0.653)	
A_{jEa60}, A_{jRa60}	-8.33E-06	(-1.175)		-3.35E-06	(-0.491)	
Constant	2.32E+01	(4.249)	***	4.12E+01	(3.878)	***
Sample Size	5228			5228		
Adj. R^2	0.137			0.1311		
F	38.7 ***			36.83 ***		

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.19: Regressions to predict commute duration for auto users 20 min intervals

	2010				2000				1990		
	Employment		Resident		Employment		Resident		Employment		Re
	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coeff
Variable	(t-value)		(t-value)		(t-value)		(t-value)		(t-value)		(t-v
A_{iEa20}, A_{iRa20}	-5.40E-06	***	3.78E-06	***	-5.95E-06	***	4.14E-06	***	-5.23E-06	***	4.1
	(-6.032)		(3.407)		(-6.650)		(3.730)		(-5.840)		(3
A_{iEa40}, A_{iRa40}	-3.22E-06	***	2.08E-06	***	-2.52E-06	***	2.48E-06	**	-2.37E-06	**	2.0
	(-4.072)		(2.867)		(-3.182)		(3.409)		(-2.997)		(2
A_{iEa60}, A_{iRa60}	-2.78E-06	*	1.31E-06	*	-2.17E-06	*	1.55E-06	*	-2.21E-06	*	1.9
	(-1.914)		(1.49)		(-1.450)		(1.771)		(-1.520)		(2
A_{jEa20}, A_{jRa20}	6.74E-06	***	-4.95E-06	***	5.26E-06	***	-5.88E-06	***	4.96E-06	***	-3.8
	(8.366)		(-5.099)		(6.537)		(-6.062)		(6.157)		(-3
A_{jEa40}, A_{jRa40}	2.68E-06	***	-1.80E-06	**	2.10E-06	***	-2.14E-06	**	2.93E-06	**	-2.4
	(2.767)		(-2.193)		(2.162)		(-2.607)		(3.025)		(-3
A_{jEa60}, A_{jRa60}	-2.11E-06		-7.23E-07		-1.65E-06	*	-8.60E-07		-2.79E-06		-5.4
	(-0.912)		(-0.56)		(-0.713)		(-0.665)		(-1.208)		(-0
Constant	35.4	***	31.29	***	15.672	***	20.765	***	19.212	***	2
	(5.64)		(5.606)		(12.504)		(16.426)		(17.360)		(17
Sample Size	5228		5228		2978		2978		6574		
Adj. R^2	0.136		0.1312		0.1368		0.1327		0.1301		0
F	52.4	***	50.34	***	48.21	***	52.31	***	48.75	***	

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.20: Regressions to predict commute duration for auto users 2010 30 min intervals

Variable	Employment			Resident		
Age (yr)	Coefficient	(t-value)		Coefficient	(t-value)	
10	-5.53E+00	(-2.857)	***	-5.69E+00	(-2.934)	***
20	-1.47E+00	(-1.862)	*	-1.56E+00	(-1.975)	**
40	6.39E-01	(1.102)		5.89E-01	(1.013)	
50	-9.30E-01	(-1.658)	*	-1.03E+00	(-1.831)	*
60	-7.63E-01	(-1.093)		-8.62E-01	(-1.231)	
Male	1.47E+00	(4.081)	***	1.46E+00	(4.033)	***
SFhome	-1.40E-01	(-0.247)		-1.97E-01	(-0.349)	
VPD	3.98E-02	(0.098)		6.09E-02	(0.149)	
Children	-3.10E-01	(-0.862)		-3.01E-01	(-0.836)	
HHsize	2.38E-01	(1.101)		2.47E-01	(1.14)	
A_{iEa30}, A_{iRa30}	-4.66E-06	(-14.118)	***	-3.13E-06	(-10.679)	***
A_{iEa60}, A_{iRa60}	-2.44E-06	(-4.459)	***	-1.39E-06	(-4.148)	***
A_{jEa30}, A_{jRa30}	5.73E-06	(16.317)	***	3.96E-06	(12.881)	***
A_{jEa60}, A_{jRa60}	-9.27E-07	(-1.159)		-2.28E-07	(-0.495)	
Constant	3.31E+01	(9.68)	***	3.06E+01	(9.36)	***
Sample Size	5228			5228		
Adj. R^2	0.1365			0.1317		
F	60.02 ***			57.62 ***		

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.21: Regressions to predict commute duration for auto users 2010 10 min intervals

Regression	Adjusted R^2	Regression	Adjusted R^2
DC	0.1398	Interval Resident 35	0.1103
Non-colinear Employment	0.1347	Interval Resident 40	0.0901
Non-colinear Resident	0.1299	Interval Resident 45	0.0752
Cumulative Resident 5	0.0588	Interval Resident 50	0.0514
Cumulative Resident 10	0.1010	Interval Resident 55	0.0424
Cumulative Resident 15	0.1140	Interval Resident 60	0.0279
Cumulative Resident 20	0.1240	Weights Employment -0.01	0.1328
Cumulative Resident 25	0.1300	Weights Employment -0.02	0.1344
Cumulative Resident 30	0.1250	Weights Employment -0.03	0.1353
Cumulative Resident 35	0.1110	Weights Employment -0.04	0.1355
Cumulative Resident 40	0.0913	Weights Employment -0.05	0.1353
Cumulative Resident 45	0.0706	Weights Employment -0.06	0.1346
Cumulative Resident 50	0.0545	Weights Employment -0.07	0.1337
Cumulative Resident 55	0.0446	Weights Employment -0.08	0.1347
Cumulative Resident 60	0.0539	Weights Employment -0.09	0.1313
Interval Employment 5	0.0588	Weights Employment -0.1	0.1298
Interval Employment 10	0.0859	Weights Resident -0.01	0.1281
Interval Employment 15	0.1057	Weights Resident -0.02	0.1294
Interval Employment 20	0.1102	Weights Resident -0.03	0.1301
Interval Employment 25	0.1150	Weights Resident -0.04	0.1303
Interval Employment 30	0.0907	Weights Resident -0.05	0.1301
Interval Employment 35	0.0820	Weights Resident -0.06	0.1296
Interval Employment 40	0.0468	Weights Resident -0.07	0.1288
Interval Employment 45	0.0411	Weights Resident -0.08	0.1299
Interval Employment 50	0.0227	Weights Resident -0.09	0.1267
Interval Employment 55	0.0205	Weights Resident -0.1	0.1254
Interval Employment 60	0.0144	Total Interval Employment	0.1405
Interval Resident 5	0.0583	Total Interval Resident	0.1341
Interval Resident 10	0.1004	10 min Interval Employment	0.1370
Interval Resident 15	0.1126	10 min Interval Resident	0.1311
Interval Resident 20	0.1249	20 min Interval Employment	0.1360
Interval Resident 25	0.1206	30 min Interval Employment	0.1365
Interval Resident 30	0.1206	30 min Interval Resident	0.1317

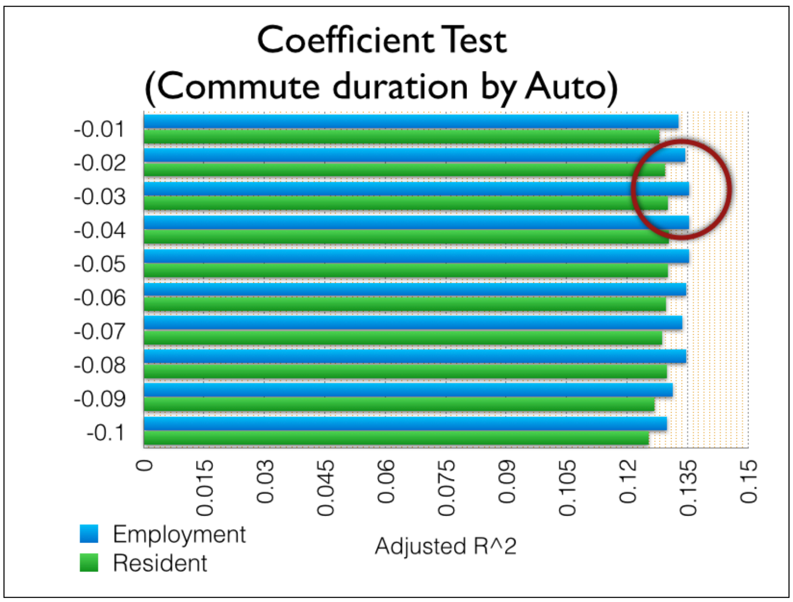

Figure B.4: Coefficient Test

Table B.22: Regressions to predict time spent at work for auto users

Variable	2010		2000		1990	
Age	Coefficient		Coefficient		Coefficient	
yr	(t-value)		(t-value)		(t-value)	
10	-118.3	***	-102.8	***	-115.6	***
	(-5.151)		(-3.83)		(-7.29)	
20	-21.96	**	-20.38	**	-20.24	**
	(-2.354)		(-3.214)		(-2.31)	
40	1.436		1.16		1.231	
	(0.209)		(0.215)		(0.312)	
50	4.359		4.514		4.621	
	(0.656)		(0.721)		(0.771)	
60	-9.73		-8.24		-9.21	
	(-1.174)		(-1.75)		(-1.54)	
Male	18.87	***	20.12	***	21.24	***
	(4.409)		(5.34)		(6.47)	
SFhome	-6.454		-5.791		-5.244	
	(-0.964)		(-0.214)		(-0.781)	
VPD	7.056		8.516		7.945	
	(1.464)		(1.742)		(1.24)	
Children	-10.06	*	-12.4	**	-11.54	*
	(-2.364)		(-3.64)		(-2.98)	
HHsize	-2.121		-2.021		-2.397	
	(-0.829)		(-0.744)		(-0.926)	
A_{iEa}	-1.085E-04		-8.952E-05		-1.463E-04	
	(-1.129)		(-1.541)		(-1.394)	
A_{iRa}	5.673E-05		4.287E-05		5.021E-05	
	(0.364)		(0.495)		(0.528)	
A_{jEa}	1.093E-04		2.157E-04		1.487E-04	
	(1.241)		(1.648)		(1.349)	
A_{jRa}	-9.7E-05		-1.512E-04		-1.021E-04	
	(-0.643)		(-0.785)		(-0.324)	
D_{io}	4.469E-02		4.384E-02		4.524	
	(0.371)		(0.215)		(0.202)	
D_{jo}	5.677E-02		5.894E-02		6.058	
	(0.395)		(0.541)		(0.247)	
Commute Duration	0.6264	***	0.5247	***	0.779	***
	(3.807)		(4.026)		(3.264)	
Number of Work Trips	-148.5	***	-124.3	***	-137.2	***
	(-43.503)		(-26.97)		(-34.67)	
Constant	592.5	***	534.7	***	499.6	***
	(19.57)		(21.13)		(18.54)	
Sample Size	5228		2978		6574	
Adj. R^2	0.2811		0.134		0.2671	
F	114.5	***	98.4	***	117.9	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.23: Regressions to predict time at work for auto users using predicted travel times 2010

Variable	20 min Interval		Weighted		Reported Trip Time	
Age	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
10	-1.54E+02 (-6.363)	***	-6.48E+01 (-2.14)	**	-1.17E+02 (-5.091)	***
20	-3.47E+01 (-3.652)	***	-1.07E+01 (-0.982)		-2.46E+01 (-2.641)	***
40	1.20E+00 (0.174)		1.74E+00 (0.252)		1.12E+00 (0.163)	
50	-1.99E+00 (-0.291)		1.48E+01 (1.975)	**	5.39E+00 (0.812)	
60	-1.13E+01 (-1.359)		-8.74E+00 (-1.053)		-8.70E+00 (-1.051)	
Male	2.76E+01 (5.907)	***	2.50E+01 (4.78)	***	1.86E+01 (4.331)	***
SFhome	-4.45E+00 (-0.663)		-3.94E+00 (-0.587)		-4.45E+00 (-0.665)	
VPD	1.09E+01 (2.283)	**	1.13E+01 (2.367)	**	1.02E+01 (2.15)	**
Children	-1.09E+01 (-2.559)	**	-1.04E+01 (-2.432)	**	-1.01E+01 (-2.363)	**
HHsize	-1.05E+00 (-0.409)		-4.55E-01 (-0.178)		-7.64E-01 (-0.3)	
Number of Work Trips	-1.50E+02 (-44.017)	***	-1.50E+02 (-43.759)	***	-1.48E+02 (-43.457)	***
Predicted/Reported Commute Duration	5.06E+00 (3.99)	***	1.05E+01 (3.001)	***	9.12E+01 (5.915)	***
Constant	7.10E+02 (23.604)	***	7.72E+02 (23.43)	*	5.79E+02 (48.455)	***
Sample Size	5228		5228		5228	
Adj. R^2	0.275		0.274		0.2776	
F	166.1	***	165.4	***	168.3	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.24: Regressions to predict time at work for auto users using predicted travel times 2000

Variable	20 min Interval		Weighted		Reported Trip Time	
Age	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
10	-180.72	***	-57.770	**	-97.861	***
	(-7.46)		(-1.90)		(-4.25)	
20	-36.96	***	-12.278		-26.178	**
	(-3.89)		(-1.12)		(-2.81)	
40	1.12		1.818		1.279	
	(0.16)		(0.26)		(0.18)	
50	-2.17		13.745	**	5.303	
	(-0.31)		(1.83)		(0.79)	
60	-9.79		-10.191		-7.983	
	(-1.17)		(-1.22)		(-0.96)	
Male	23.50	**	4.184		19.046	***
	(5.03)		(0.63)		(4.43)	
SFhome	-4.17		-3.959		-3.920	
	(-0.62')		(-0.58)		(-0.58)	
VPD	11.89	*	12.377	**	8.393	**
	(2.49)		(2.59)		(1.76)	
Children	-11.54	**	-12.197	*	-10.820	**
	(-2.71)		(-2.85)		(-2.53)	
HHsize	-1.03		-0.380		-0.824	
	(-0.40)		(-0.14)		(-0.32)	
Number of Work Trips	-169.18	***	-146.634	***	-124.380	***
	(-49.64)		(-42.77)		(-36.52)	
Predicted/Reported Commute Duration	5.99	***	9.15	***	8.85	***
	(4.72)		(2.61)		(5.52)	
Constant	828.84	***	266.388	*	545.894	***
	(27.55)		(2.13)		(45.68)	
Sample Size	2978		2978		2978	
Adj. R^2	0.3121		0.2987		0.2546	
F	158.7	***	162.1	***	163.7	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.25: Regressions to predict time at work for auto users using predicted travel times 1990

Variable	20 min Interval		Weighted		Reported Trip Time	
Age	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
10	-166.88	***	-48.320	**	-114.839	***
	(-6.89)		(-1.59)		(-4.99)	
20	-38.76	***	-13.066		-27.885	***
	(-4.07)		(-1.19)		(-2.99)	
40	1.18		2.077		1.193	
	(0.17)		(0.30)		(0.17)	
50	-1.85		13.523	*	5.770	
	(-0.27)		(1.80)		(0.86)	
60	-10.91		-9.351		-6.920	
	(-1.31)		(-1.12)		(-0.83)	
Male	27.63	**	4.284		16.218	***
	(5.91)		(0.64)		(3.77)	
SFhome	-4.58		-3.487		-3.675	
	(-0.68)		(-0.51)		(-0.54)	
VPD	12.92	**	10.185	**	9.158	**
	(2.70)		(2.13)		(1.93)	
Children	-9.88	**	-13.067	**	-11.459	**
	(-2.32)		(-3.05)		(-2.68)	
HHsize	-0.96		-0.410		-0.806	
	(-0.37)		(-0.16)		(-0.31)	
Number of Work Trips	-143.785 (-42.19)	***	-123.232 (-35.9)	***	-140.284 (-41.19)	***
Predicted/Reported Commute Duration	6.34 (4.99)	***	8.55 (2.44)	***	10.1 (6.54)	***
Constant	773.86	***	251.157	*	637.266	***
	(25.72)		(2.01)		(53.33)	
Sample Size	6574		6574		6574	
Adj. R^2	0.2876		0.2964		0.3145	
F	159.3	***	164.5	***	162.3	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.26: Regressions to predict commute duration for transit users 20 min intervals

	2010				2000				1990		
	Employment		Resident		Employment		Resident		Employment		Re
	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coeff
Variable	(t-value)		(t-value)		(t-value)		(t-value)		(t-value)		(t-
A_{iEa20}, A_{iRa20}	-0.0000452	**	4.21E-05	**	-4.91E-05	**	3.92E-05	**	-4.58E-05	**	3.6
	(-1.34)		(0.78)		(-1.455)		(0.727)		(-1.356)		(0
A_{iEa40}, A_{iRa40}	-0.0000421	**	2.16E-05	*	-3.60E-05	***	2.35E-05	**	-3.92E-05	**	2.5
	(-1.13)		(0.59)		(-0.967)		(0.641)		(-1.052)		(0
A_{iEa60}, A_{iRa60}	-0.0000262		1.23E-05		-2.44E-05		1.07E-05		-2.11E-05		9.2
	(-0.86)		(1.23)		(-0.800)		(1.066)		(-0.693)		(0
A_{jEa20}, A_{jRa20}	-3.95E-05	*	3.68E-06	**	-3.36E-05	*	3.45E-06	**	-3.15E-05	***	3.2
	(-0.63)		(0.92)		(-0.535)		(0.862)		(-0.501)		(0
A_{jEa40}, A_{jRa40}	-3.22E-05	*	1.22E-06		-3.41E-05	*	1.33E-06	*	-3.72E-05	*	1.4
	(-0.61)		(0.84)		(-0.645)		(0.916)		(-0.703)		
A_{jEa60}, A_{jRa60}	-9.86E-06		9.78E-08		-9.24E-06		1.04E-07		-9.79E-06		1.1
	(-0.59)		(0.57)		(-0.553)		(0.6042)		(-0.586)		(0
Constant	46.14		48.79		35.04		32.74		36.683		4
	(7.599)		(8.036)		(6.703)		(6.263)		(4.944)		(5
Sample Size	124		124		106		106		164		
Adj. R^2	0.114		0.132		0.125		0.146		0.134		
F	4.092	***	4.53	***	5.68	***	6.02	***	4.86	***	

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.27: Regressions to predict time at work for transit users using predicted travel times 2010

Variable	20 min Interval		Weighted		Reported Trip Time	
Age	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
10	-270.97	***	-228.30	***	-257.77	***
	(-11.41)		(-9.61)		(-10.85)	
20	-27.47	**	-26.98		-23.92	***
	(-2.88)		(-2.82)		(-2.50)	
40	0.83		0.74		0.74	
	(0.11)		(0.10)		(0.10)	
50	-1.57		-1.70		-1.58	
	(-0.23)		(-0.25)		(-0.23)	
60	-13.38		-12.80		-14.29	
	(-1.14)		(-1.09)		(-1.21)	
Male	4.41	**	4.05	*	4.18	*
	(8.29)		(7.63)		(7.88)	
SFhome	-7.39		-7.54		-8.05	
	(-1.10)		(-1.12)		(-1.19)	
VPD	7.83		7.60		6.35	
	(1.47)		(1.43)		(1.19)	
Children	-19.05	**	-16.40	**	-16.90	*
	(-4.97)		(-4.28)		(-4.41)	
HHsize	-0.61		-0.60		-0.56	
	(-0.22)		(-0.21)		(-0.20)	
Number of Work Trips	-15.83 (-5.48)	**	-15.2 (-5.26)	**	-17.0 (-5.89)	**
Predicted/Reported Commute Duration	7.66 (2.21	***	8.30 (2.40)	***	6.31 (1.83)	***
Constant	541.33	***	508.20	***	476.23	***
	(33.59)		(31.534)		(29.55)	
Sample Size	124		124		124	
Adj. R^2	0.187		0.201		0.192	
F	142.1	***	146.3	***	185.6	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.28: Regressions to predict time at work for transit users using predicted travel times 2000

Variable	20 min Interval		Weighted		Reported Trip Time	
Age	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
10	-291.64 (-12.28)	***	-300.77 (-12.66)	***	-314.01 (-13.22)	***
20	-72.93 (-7.63)	*	-60.47 (-6.33)	**	-61.42 (-6.43)	**
40	1.14 (0.15)		1.24 (0.17)		0.98 (0.13)	
50	-2.18 (-0.32)		-2.03 (-0.30)		-1.82 (-0.27)	
60	-31.41 (-2.67)		-29.44 (-2.50)		-33.04 (-2.81)	
Male	3.60 (6.77)	*	3.79 (7.13)	**	3.23 (6.07)	**
SFhome	-8.21 (-1.22)		-8.78 (-1.30)		-7.59 (-1.13)	
VPD	16.78 (3.15)		13.74 (2.58)		18.23 (3.42)	
Children	-19.76 (-5.16)	***	-19.08 (-4.98)	**	-20.05 (-5.24)	***
HHsize	-1.17 (-0.41)		-1.11 (-0.39)		-1.20 (-0.42)	
Number of Work Trips	-20.30 (-7.03)	***	-20.0 (-6.93)	**	-17.6 -6.09	**
Predicted/Reported Commute Duration	4.18 (1.21	***	4.56 (1.32)	***	3.42 (0.99)	***
Constant	229.23 (14.22)	***	241.88 (15.008)	***	234.22 (14.53)	***
Sample Size	106		106		106	
Adj. R^2	0.195		0.214		0.187	
F	154.3	***	162.3	***	149.6	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

Table B.29: Regressions to predict time at work for transit users using predicted travel times 1990

Variable	20 min Interval		Weighted		Reported Trip Time	
Age	Coefficient (t-value)		Coefficient (t-value)		Coefficient (t-value)	
10	-157.36	***	-134.11	***	-142.91	***
	(-6.62)		(-5.65)		(-6.02)	
20	-56.57	**	-52.97	**	-59.92	*
	(-5.92)		(-5.54)		(-6.27)	
40	0.72		0.68		0.76	
	(0.10)		(0.09)		(0.10)	
50	-0.94		-1.00		-0.78	
	(-0.14)		(-0.15)		(-0.12)	
60	-14.84		-15.96		-15.58	
	(-1.26)		(-1.36)		(-1.32)	
Male	5.23	*	5.58	**	5.59	*
	(9.85)		(10.51)		(10.52)	
SFhome	-7.95		-6.85		-6.82	
	(-1.18)		(-1.02)		(-1.01)	
VPD	9.28		8.87		8.78	
	(1.74)		(1.67)		(1.65)	
Children	-18.29	***	-18.49	**	-15.88	**
	(-4.78)		(-4.83)		(-4.15)	
HHsize	-1.55		-1.25		-1.55	
	(-0.55)		(-0.44)		(-0.55)	
Number of Work Trips	-7.34 (-2.54)	***	-7.33 (-2.54)	**	-6.70 (-2.32)	***
Predicted/Reported Commute Duration	9.17 (2.65	***	8.84 (2.56)	***	9.93 (2.87)	***
Constant	582.96	***	560.15	***	569.83	***
	(36.17)		(34.76)		(35.36)	
Sample Size	164		164		164	
Adj. R^2	0.199		0.194		0.203	
F	154.3	***	162.3	***	149.6	***

* indicates $P < 0.10$, ** indicates $P < 0.05$, *** indicates $P < 0.01$

B.0.5 Household Table

The household tables contained information at the household level, such as number of vehicles, number of people, etc. Numeric variables such as these are generally easy to compare from year to year. Some variables were modified to account for numeric data from one survey year and ordinal categories from another (e.g., ten or more people in the household). The largest source of complexity was managing income across four decades. This is described in greater detail in Section B.0.5.

Household Vehicles

Vehicles were recorded as numeric values in all four survey years. In 2010, respondents with 10 or more vehicles reported a "Ten or more" category instead of a value, so all vehicle numbers over 10 in previous years were recoded to "Ten or more". The 2010 and 2000 surveys asked about bicycle availability.

Household Size

People over age 5 are recorded in the person table, so the household variables are largely tabulations those records. Notably, in 1990, the survey asked about household members "under 5", whereas the other years asked about "5 or under".

Household Members

The number of students or workers in each household was provided. No variable existed for 1990, though it may be possible to construct this variable from the person table. The 1980 survey did not ask about student status.

Income

The income variable changed considerably from year to year - both in the numeric ranges provided as response categories, and the value of those categories due to inflation.

Variable `income_asis` contains the numeric category for income according to whatever it was in that year. This variable is *not* consistent across years (e.g., a '1' in 2010 is unrelated to a '1' in 1990, except for the fact that they're both the lowest income bracket.)

Four variables were created to provide a consistent measure of income over time. The first two (`inc_lbCY` and `inc_ubCY`) represent the upper and lower bounds of the income category *in the year the survey was completed*. For example, a person who chose income category 4 in the 2010 survey would have `inc_lbCY`$= 15,001$ and `inc_ubCY`$= 20,000$. A person who chose income category 4 in the 1980 survey would also have `inc_lbCY`$= 15,001$ and `inc_ubCY`$= 20,000$, even though the value of the 1980 respondent's income today would be worth considerably more than the 2010 respondent's income.

Variables `inc_lb2011` and `inc_ub2011` account for this inflation effect by recoding `inc_lbCY` and `inc_ubCY` to their 2011 dollar value. Table B.38 shows the rates indicated by the Bureau of

Table B.30: Household Vehicles

Final: `totveh`	2010: `totveh`	2000: `TOTVEH`	1990: `vehicles`	1980: `novehcl`
#: Label	#: Label	#: Label	#: Label	#: Label
1-9: 1 to 9 vehicles	1-9: 1 to 9 vehicles	1-9: 1 to 9 vehicles	1-9: 1 to 9 vehicles	1-9: 1 to 9 vehicles
10: 10+ vehicles	10: 10+ vehicles	*: $10 \leq$ `TOTVEH` ≤ 999	*: $10 \leq$ `vehicles` ≤ 999	*: $10 \leq$ `novehcl` ≤ 99
Labeled Missing Values				
.e: Not yet retrieved	-1: Not yet retrieved			

Table B.31: Bicycles

Final: `bicyc`	2010: `bicyc`	2000: `BIKES`	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
1-9: Number of bikes	1-9: Number of bikes	1-9: Number of bikes		
10: 10+ bikes	10: 10+ bikes	*: $10 \leq$ `BIKES` ≤ 99		
Labeled Missing Values				
.a: Don't Know	98: Don't Know			
.b: Refused	99: Refused	99: Refused		

Table B.32: People Over Age 5

Final: `hhpeople`	2010: `hhpeople`	2000: `HHPART`	1990: `peoplege_5`	1980: overfiv
#: Label	#: Label	#: Label	#: Label	#: Label
#: Number of people	#: Number of people	#: Number of people	#: Number of people	#: Number of people

Table B.33: People Over Age 5 (tenormore)

Final: `hhsize6`	2010: `hhsize6`	2000: `HHPART*`	1990: `PEOPLEGE_5*`	1980: `overfiv*`
#: Label	#: Label	#: Label	#: Label	#: Label
1-9: Number of people	1-9: Number of people	1-9: Number of people	1-9: Number of people	1-9: Number of people
10: 10+ people	10: 10+ people	*: 10 ≤ `HHPART` ≤ 99	*: 10 ≤ `PEOPLEGE_5` ≤ 99	*: 10 ≤ `overfiv` ≤ 99

Table B.34: People Age 5 and Under

Final: under6	2010: under6	2000: HHSIZE* HHPART*	1990: CHILDLT_5	1980: underfiv
#: Label	#: Label	#: Label	#: Label	#: Label
#: Number of people under 6	#: Number of people under 6	*: HHSIZE−HHPART	#: Number of people under 5	#: Number of people under 5

NOTE: 1990 asked about under 5, whereas 2010 and 2000 asked about under 6.

Table B.35: Household Size

Final: `thhsize`	2010: `thhsize`	2000: `HHSIZE*`	1990: `size*`	1980: `hhsize`
#: Label	#: Label	#: Label	#: Label	#: Label
1-9: Number of people	1-9: Number of people	1-9: Number of people	1-9: Number of people	1-9: Number of people
10: 10+ people	10: 10+ people	*: $10 \leq \texttt{HHSIZE} \leq 99$	*: $10 \leq \texttt{size} \leq 99$	*: $10 \leq \texttt{hhsize} \leq 99$

Table B.36: Students

Final: `students`	2010: `students`	2000: `NSTUD`	1990: N/A	1980: N/A
Final: `hhcurrstudent`	2010: `hhcurrstudent`	2000: `NSTUD`	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
#: Number of students	#: Number of students	#: Number of students		

Table B.37: Workers

Final: `workers` Final: `hhworker`	2010: `workers` 2010: `hhworker`	2000: `NWORK` 2000: `NWORK`	1990: N/A 1990: N/A	1980: N/A 1980: N/A
#: Label	#: Label	#: Label		
#: Number of workers	#: Number of workers	#: Number of workers		

Table B.38: Inflation Rates for Income Variables

$1,000 in year:	2011	2001	1990	1982
Is equivalent to this much in year:				
2011	$1,000.00	$1,270.12	$1,721.03	$2,330.97
2001	$ 787.32	$1,000.00	$1,355.01	$1,835.23
1990	$ 581.05	$ 738.00	$1,000.00	$1,354.40
1982	$ 429.01	$ 545.89	$ 738.33	$1,000.00
http://www.bls.gov/data/inflation_calculator.htm				

Labor Statistics for inflating each survey year's categories to their 2011 value. Since the 2010 TBI was administered from November 2010 through March 2012, the income categories for the 2010 survey have not been inflated. Thus for 2010 respondents, `inc_lbCY=inc_lb2011` and `inc_ubCY=inc_ub2011`. Previous years were inflated based on when the survey was administered. The 2000 survey was administered in 2001, so the rate of inflation between 2001 and 2011 is used to adjust those values. The upper bound values for the highest income category of each survey (e.g., "$250,000 or more" in 2010) is represented as missing in the data.

The 2010, 2000, and 1990 surveys provided respondents who refused to provide or didn't know their household income an opportunity to indicate whether their income was above or below a specified threshold: $50,000 in 2010, $45,000 in 2000, and $35,000 in 1990. This information fits into the upper and lower bound variable structure easily. Respondents who do not have a specified income range but reported that their income was below the threshold have a lower bound equal to 0 and an upper bound equal to the threshold value (both current year and inflated). Respondents whose incomes are above the threshold have a lower bound equal to the threshold, and a missing value for the upper bound.

Housing

The 2000 and 2010 surveys asked about what type of housing structure the respondent lives in. The 2010 survey provided many more response categories, particularly for discerning between types of multifamily housing (apartment, duplex, etc.). The surveys also asked about owning or renting, which has been converted into a binary indicator variable with a value of "1" indicating renter.

Table B.39: Income - As Is

Final: `income_asis`	2010: `income`	2000: `INCOME, INCAT*`	1990: `income`	1980: `hhincm`
#: Label	#: Label	#: Label	#: Label	#: Label
0:		0: Less than $5,000		
1:	1: Less than $5,000	1: $5,000 - $10,000	1: Less than $7,500	1: Less than $7,500
2:	2: $5,000 - $10,000	2: $10,000 - $15,000	2: $7,501 - $15,000	2: $7,501 - $10,000
3:	3: $10,000 - $15,000	3: $15,000 - $20,000	3: $15,001 - $25,000	3: $10,001 - $15,000
4:	4: $15,000 - $20,000	4: $20,000 - $25,000	4: $25,001 - $35,000	4: $15,001 - $20,000
5:	5: $20,000 - $25,000	5: $25,000 - $30,000	5: $35,001 - $45,000	5: $20,001 - $30,000
6:	6: $25,000 - $30,000	6: $30,000 - $35,000	6: $45,001 - $55,000	6: $30,001 - $40,000
7:	7: $30,000 - $35,000	7: $35,000 - $40,000	7: $55,001 - $75,000	7: More than $40,000
8:	8: $35,000 - $40,000	8: $40,000 - $45,000	8: Over $75,000	
9:	9: $40,000 - $45,000	9: $45,000 - $50,000		
10:	10: $45,000 - $50,000	10: $50,000 - $60,000		
11:	11: $50,000 - $60,000	11: $60,000 - $75,000		
12:	12: $60,000 - $75,000	12: $75,000 - $100,000		
13:	13: $75,000 - $100,000	13: $100,000 - $150,000		
14:	14: $100,000 - $125,000	14: $150,000 or more		
15:	15: $125,000 - $150,000			
16:	16: $150,000 - $200,000			
17:	17: $200,000 - $250,000			
18:	18: $250,000 or more			
Labeled Missing Values				
.f: Below $50,000	96: Below $50,000	*: Below $45,000 (`INCAT`)	0: Below $35,000	
.g: Above $50,000	97: Above $50,000	*: Above $45,000 (`INCAT`)	10: Above $35,000	
.a: Don't Know	98: Don't Know	98: Don't Know		
.b: Refused	99: Refused	99: Refused		
.c: DK/RF			9: RF/DK	8: RF/DK

Table B.40: Examples of Income - Lower Bound (Survey Year)

Final: inc_lbCY	2010: income*	2000: INCOME*, INCAT*	1990: income*	1980: hhincm*
#: Label	#: Label	#: Label	#: Label	#: Label
0: $0	1: Less than $5,000	0: Less than $5,000	1: Less than $7,500	1: Less than $7,500
0: $0	96: Below $50,000	*: Below $45,000 (INCAT)	10: Below $35,000	
5000: $5,000	2: $5,000 - $10,000	1: $5,000 - $10,000		
15001: $15,001	4: $15,000 - $20,000		3: $15,001 - $25,000	4: $15,001 - $20,000
50000: $50,000	97: More than $50,000	*: More than $45,000 (INCAT)		
250000: $250,000	18: $250,000 or more			

Table B.41: Examples of Income - Upper Bound (Survey Year)

Final: inc_ubCY	2010: income*	2000: INCOME*, INCAT*	1990: income*	1980: income*
#: Label	#: Label	#: Label	#: Label	#: Label
4999: $4,999	1: Less than $5,000	0: Less than $5,000		
9999: $9,999	2: $5,000 - $10,000	1: $5,000 - $10,000		
25000: $25,000			3: $15,001 - $25,000	
49999: $49,999	96: Below $50,000			
249999: $249,999	17: $200,000 - $250,000			
'.': (Missing)	18: $250,000 or more	14: $150,000 or more	8: $75,000 or more	7: More than $40,000
'.': (Missing)	97: Above $50,000	*: Above $45,000 (INCAT)	0: Over $35,000	

Table B.42: Housing Type

Final: hometyp_2	2010: hometyp	2000: RESTYPE	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
1: Single family/Mobile		1: Single family/Mobile		
1: Single family/Mobile	1: Single family home			
1: Single family/Mobile	2: Mobile/Manufactured			
2: Multi family		2: Duplex/Condo/Apt./Townhome		
2: Multi family	3: Townhome			
2: Multi family	4: 2/3/4-plex			
2: Multi family	5: Apartment			
2: Multi family	6: Condo/Co-op			
3: Group/Assisted	7: Group/Assisted	3: Group Housing		
7: Other	96: Other	7: Other		
Labeled Missing Values				
.a: Don't Know	98: Don't Know			
.b: Refused	99: Refused	9: Refused		

Table B.43: Owner or Renter

Final: `renter`	2010: `ownrent`	2000: `OWN`	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
0: Owner	1: Owner	1: Owner		
1: Renter	2: Renter	2: Renter		
Labeled Missing Values				
.a: Don't Know	8: Don't Know			
.b: Refused	9: Refused			
.c: DK/RF		9: DK/RF		
.d: Inapplicable	-1: Inapplicable			
.i: Other	7: Other	7: Other		

Table B.44: Tenure at Current Residence

Final: `tenure`	2010: `tenure`	2000: `ADDLIVE`	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
1: Less than 2 years	1: Less than 2 years	1: Less than 2 years		
2: 2-5 years	2: 2-5 years	2: 2-5 years		
3: 6-10 years	3: 6-10 years	3: 6-10 years		
4: More than 10 years	4: More than 10 years	4: More than 10 years		
Labeled Missing Values				
.a: Don't Know	98: Don't Know			
.b: Refused	99: Refused			
.c: DK/RF		9: DK/RF		

B.0.6 Person Table

Age

Age was reported as a numeric value in 2010, 2000, and 1990. In 1980, age was collected as a binary indicator of older or younger than 15. Two age variables are included in the person table: one containing the actual person age for the three most recent surveys, and a binary indicator consistent with 1980.

B.0.7 Gender

Gender was collected in 2010, 2000, and 1990. For consistency and ease of use, this variable has been transformed into a binary indicator variables called “female” and “male” with a response of 1 indicating that the respondent identifies as the gender of the variable title.

Driver License

Driver License was collected in 2010, 2000, and 1990.

B.0.8 Multiple Jobs

Multiple jobs was collected in 2010, 2000, and 1990. In 2000, the response indicated the number of jobs (1, 2, or 3+). These values were recoded into a binary indicator of having 2 or more jobs.

Education Level

Highest level of education attained was collected in 2010 and 2000.

Student Status

Student status was collected for 2010, 2000, and 1990 as an indicator variable of being a current student.

In 2010 and 2000, the TBI also collected the type of school at which the student is currently enrolled. Graduate versus undergraduate college student is inferred based on current school type and highest level of education completed. Students who are full or part time college or university students who have already earned a bachelor’s degree or higher are assumed to be graduate students. This mapping is shown in Table B.54.

An attempt was made to infer 2010 elementary versus middle/high school enrollment based on age and an assumption that the age distribution in 2010 would mirror 2000 enrollment. The age distributions for elementary and middle/high school in 2000 are shown in Table B.52. Students identified as K-12 in 2010 are randomly assigned to either the “Elementary” or “Middle/High School” brackets using a a single draw per respondent from a binomial distribution, using the percentage of that age group that is enrolled in elementary school in 2000 as the probability. Since

Table B.45: Age

Final: age	2010: age	2000: AGE	1990: age	1980: N/A
#: Label	#: Label	#: Label	#: Label	
1-96: Age 1 to 96	1-96: Age 1 to 96	1-96: Age 1 to 96	1-96: Age 1 to 96	
97: Age 97+	97: Age 97+	*: $97 \leq \texttt{AGE} \leq 150$	*: $97 \leq \texttt{age} \leq 150$	
Labeled Missing Values				
.a: Don't Know	98: Don't Know			
.b: Refused	99: Refused			

Table B.46: Age >15

Final: age_15	2010: age*	2000: AGE*	1990: age*	1980: age
#: Label	#: Label	#: Label	#: Label	#: Label
0: Age 5-15	*: 5 ≤ age ≤ 15	*: 5 ≤ AGE ≤ 15	*: 5 ≤ age ≤ 15	1: Age 5 to 15
1: Age 16+	*: age >15	*: AGE >15	*: age >15	2: Age Over 15

Table B.47: Gender (Female)

Final: `female`	2010: `gender`	2000: `GENDER`	1990: `gender`	1980: N/A
#: Label	#: Label	#: Label	#: Label	
0: Male	1: Male	1: Male	1: Male	
1: Female	2: Female	2: Female	2: Female	
Labeled Missing Values				
.b: Refused	9: Refused	9: Refused		

Table B.48: Gender (Male)

Final: `male`	2010: `gender`	2000: `GENDER`	1990: `gender`	1980: N/A
#: Label	#: Label	#: Label	#: Label	
0: Female	2: Female	2: Female	2: Female	
1: Male	1: Male	1: Male	1: Male	
Labeled Missing Values				
.b: Refused	9: Refused	9: Refused		

Table B.49: Driver License

Final: `license`	2010: `license`	2000: `LIC`	1990: `licensed`	1980: N/A
#: Label	#: Label	#: Label	#: Label	
0: No	2: No	2: No	2: No	
1: Yes	1: Yes	1: Yes	1: Yes	
Labeled Missing Values				
.a: Don't Know	8: Don't Know			
.b: Refused	9: Refused	9: Refused		
.c: Don't Know/ Refused			3: Don't Know/ Refused	
.d: Ineligible/ Inapplicable	0: Ineligible/ Inapplicable	*: `AGE` $\leq$ 15	0: Ineligible/ Inapplicable	

Table B.50: Multiple Jobs

Final: `multijob`	2010: `multijob`	2000: `JOBS`	1990: `anotherjob`	1980: N/A
#: Label	#: Label	#: Label	#: Label	
0: No	2: No	1: No	1: No	
1: Yes	1: Yes	2: 2 jobs	2: Yes	
1: Yes		3: 3+ jobs		
Labeled Missing Values				
.a: Don't Know	8: Don't Know			
.b: Refused	9: Refused	9: Refused		
.c: DK/RF			3: DK/RF	
.d: Ineligible/ Inapplicable	-1: Ineligible/ Inapplicable			

Table B.51: Education Level

Final: educ_2	2010: educ	2000: EDUCA	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
2: Less than high school	1: Daycare/Preschool			
2: Less than high school	2: Less than high school	1: 11th grade or less		
3: High school graduate	3: High school graduate	2: High school graduate		
6: Associates degree	4: Some college			
6: Associates degree	6: Associates degree	3: 2 years of college/Associate's		
7: Bachelors degree	7: Bachelors degree	4: 4 years of college/Bachelor's		
8: Graduate/Post-graduate	8: Graduate/Post-graduate	5: Post-Graduate		
9: Other	5: Vocational/Technical	7: Other		
Labeled Missing Values				
.a: Don't Know	98: Don't Know			
.b: Refused	99: Refused	9: Refused		

Table B.52: Distribution of Ages For K-12 Students

Age	Elementary School	Middle/High School	P(Elementary)
5-9	100%	0%	1.00
10	94%	6%	0.94
11	62%	38%	0.62
12	21%	79%	0.21
13-18	0%	100%	0.00

these K-12 school types are synthetic, not actual records, they are saved in a separate school type variable: schtype_3, shown in Table B.55, rather than overwriting the responses.

Worker Status

A binary indicator of currently employed or not is available for all years, shown in Table B.56. A finer-resolution worker status variable is available for more recent years. The 2010 survey collected a broad range of non-employed response categories. The first worker status variable collapses these categories into three: full time, part time, or not employed/missing. The second variable infers some of these categories for 2000 using other variables. For example, non-employed volunteer (response category "3" in 2010) is inferred in 2000 to be anyone who is not working AND volunteers with a regular schedule. The assumptions used to calculate each category are described in Table B.58.

Average Hours Worked

Average hours worked was collected for 2010, 2000, and 1990 as a numeric value. Second job hours were collected in categories for 2010 ("Full-time", "Part-time", and "Varies"), but with numeric values in 2000. The 2000 values were mapped to 2010 categories by classifying second jobs with 1 to 34 hours as "Part-time" and 35 or more hours as "Full-time". The 2000 survey provided a response option for "Varies" to map to the 2010 version.

Disability Status

Disability status and type were collected in 2010 and 2000. Status was collected separately as a binary indicator variable. In 2010, disability type was collected using five categories, including "Other (Do Not Specify)". In 2000, slightly different categories were used, and the "Other" option included "Please Specify". The three mobility categories in 2000 were collapsed into 2010's mobility/walking category. "General Health" in 2010 and "Mentally Disabled" in 2000 were consolidated into an "Other" category because neither has a compatible category in the other year.

Additionally, the 2000 survey provided respondents the option to list up to three disabilities. However, only three people listed a second type of disability, and nobody listed a third type, so these variables are ignored.

Table B.53: Student Status

Final: `currstudent`	2010: `currstudent`	2000: `STUDE`	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
0: No	0: No	2: No		
1: Yes	1: Yes	1: Yes		
Labeled Missing Values				
.a: Don’t Know	8: Don’t Know			
.b: Refused	9: Refused	9: Refused		
.c: DK/RF				
.d: Ineligible/ Inapplicable	-1: Ineligible/ Inapplicable			

Table B.54: Type of School

Final: schtype_2	2010: schtype*	2000: SCHOL	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
1: Preschool/Nursery School	1: Preschool/Nursery School	1: Daycare/Preschool		
2: K-12	2: K-12	2: Elementary SChool		
2: K-12		3: Middle/High School		
3: Vocational/Technical	3: Vocational/Technical	5: Trade/Vocational		
4: College Student	*: educ $\leq$ 6 & schtype = 4 or 5	4: College/University		
6: Graduate Student	*: educ = 7 or 8 & schtype = 4 or 5	6: Post Graduate		
7: Other		7: Other		
Labeled Missing Values				
.a: Don't Know	98: Don't Know			
.b: Refused	99: Refused	9: Refused		

Table B.55: Type of School (Imputed K-12 Status)

Final: schtype_3	2010: schtype*	2000: SCHOL	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
1: Preschool/Nursery School	1: Preschool/Nursery School	1: Daycare/Preschool		
7: Elementary School	*: $binom(1, p)$ if schtype_2 = 2	2: Elementary SChool		
8: K-12	*: $binom(1, 1-p)$ if schtype_2 = 2	3: Middle/High School		
3: Vocational/Technical	3: Vocational/Technical	5: Trade/Vocational		
4: College Student	*: educ $\leq$ 6 & schtype = 4 or 5	4: College/University		
6: Graduate Student	*: educ = 7 or 8 & schtype = 4 or 5	6: Post Graduate		
7: Other		7: Other		
Labeled Missing Values				
.a: Don't Know	98: Don't Know			
.b: Refused	99: Refused	9: Refused		

Table B.56: Currently Working

Final: `worker`	2010: `worker`	2000: `EMPLY`	1990: `employed`	1980: `employed`
#: Label	#: Label	#: Label	#: Label	#: Label
0: No	0: No	2: No	0: No	97: Not Employed
1: Yes	1: Yes	1: Yes	1: Yes	
1: Yes				1: Part-Time
1: Yes				2: Full-Time
Labeled Missing Values				
.b: Refused		9: Refused		

Table B.57: Worker Status: Few Assumptions

Final: wrkr_1	2010: wrkr*	2000: EMPLY* FTPT*	1990: N/A	1980: employed
#: Label	#: Label	#: Label		#: Label
1: Paid FT	1: Paid FT	*: EMPLY = 1 and FTPT = 1		2: Paid FT
2: Paid PT	2: Paid PT	*: EMPLY = 1 and FTPT = 2		1: Paid PT
97: Other/Not Employed	3: Volunteer			
97: Other/Not Employed	4: Homemaker			
97: Other/Not Employed	5: Retired			
97: Other/Not Employed	6: Unemp/Looking			
97: Other/Not Employed	7: Unemp/Not Looking			
97: Other/Not Employed	8: Disabled non-worker			
97: Other/Not Employed	9: Student			
97: Other/Not Employed	96: Other			3: Not Employed
Labeled Missing Values				
.c: DK/RF	98: Don't Know			
.c: DK/RF	99: Refused	9: Refused		
.d: Ineligible		*: AGE $\leq$ 15		
Inapplicable				:

Table B.58: Worker Status - Many Assumptions

Final: wrkr_2	2010: wrkr	2000: EMPLY, SCHED, FTPT	1990: N/A	1980: employed
#: Label	#: Label	#: Label		#: Label
1: Paid FT	1: Paid FT	*: EMPLY = 1 & FTPT = 1		2: Paid FT
2: Paid PT	2: Paid PT	*: EMPLY = 1 & FTPT = 2		1: Paid PT
3: Volunteer	3: Volunteer	*: SCHED = 1 & wrkr_1 = .		
97: Other/Not Employed	4: Homemaker			
5: Retired	5: Retired	*: wrkr_1 = . & AGE $\geq$ 65		
97: Other/Not Employed	6: Unemp/Looking			
97: Other/Not Employed	7: Unemp/Not Looking			
8: Disabled non-worker	8: Disabled non-worker	*: DISAB = 1 & wrkr_1 = .		
9: Student	9: Student	*: currstudent = 1 & wrkr_1 = .		
97: Other/Not Employed	96: Other			3: Not Employed
Labeled Missing Values				
.c: DK/RF	98: Don't Know			
.c: DK/RF	99: Refused	9: Refused		
.d: Ineligible Inapplicable		*: AGE $\leq$ 15		

Table B.59: Average Hours Worked

Final: `wrkhrs`	2010: `wrkhrs`	2000: `HWORK`	1990: `hrsworked`	1980: N/A
#: Label	#: Label	#: Label	#: Label	
#: Hours Worked	#: Hours Worked	#: Hours Worked	#: Hours Worked	
Labeled Missing Values				
.a: Don't Know	998: Don't Know			
.b: Refused	999: Refused	99: Refused		
.d: Ineligible/ Inapplicable	0: Ineligible/ Inapplicable			:
.e: Not Yet Retrieved	-1: Not Yet Retrieved			
.f: Not Yet Retrieved				

Table B.60: Second Job Hours Worked

Final: secjob	2010: secjob	2000: MJOBS*	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
1: Full-time	1: Full-time	*: 35 $\leq$ MJOBS $\leq$ 90		
2: Part-time	2: Part-time	*: 1 $\leq$ MJOBS $\leq$ 34		
3: Varies	3: Varies	97: Varies		
Labeled Missing Values				
.a: Don't Know	8: Don't Know			
.b: Refused	9: Refused			
.c: Refused		99: DK/RF		
.d: Ineligible/ Inapplicable	-1: Ineligible/ Inapplicable	9: Refused		

Table B.61: Disability Status

Final: `disable`	2010: `disable`	2000: `DISAB`	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
0: No	2: No	2: No		
1: Yes	1: Yes	1: Yes		
Labeled Missing Values				
.a: Don’t Know	98: Don’t Know			
.b: Refused	99: Refused	9: Refused		

Table B.62: Disability Type

Final: typdisable_2	2010: typdisable	2000: DISTY1	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
1: Eye or Vision	1: Eye or Vision	1: Eye or Vision		
2: Hearing	2: Hearing	4: Deaf/Hearing Impaired		
3: Walking	3: Walking			
3: Walking		2: Transferable Wheelchair		
3: Walking		3: Non-transferable Wheelchair		
3: Walking		6: Cane/Walker		
6: General/Other	4: General Health			
6: General/Other		5: Mentally Disabled		
6: General/Other	5: Other	7: Other		
Labeled Missing Values				
.a: Don't Know	98: Don't Know			
.b: Refused	99: Refused	9: Refused		

Telework

Telework behavior is collected in 2010 and 2000 both as an indicator and a frequency. The "Work from home only" category in 2010 was collapsed into "Yes" for consistency with 2000, shown in Table B.63. This information can be inferred from the telework frequency category "Almost every day", shown in Table B.64. The company telework policy variable is a binary indicator.

Table B.63: Telework

Final: `telcom`	2010: `telcom`	2000: `TELE`	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
0: No	2: No	2: No		
1: Yes	1: Yes	1: Yes		
1: Yes	3: Works from home only			
Labeled Missing Values				
.a: Don’t Know	8: Don’t Know			
.b: Refused	9: Refused	9: Refused		
.d: Ineligible/ Inapplicable	0: Ineligible/ Inapplicable	*: `WORKER` <> 1		

Table B.64: Telework Frequency

Final: `telfreq`	2010: `telfreq`	2000: `TELETIME`	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
1: Almost every day	1: Almost every day	1: Almost every day		
2: Once a week or more	2: Once a week or more	2: Once a week or more		
3: Once a month or more	3: Once a month or more	3: Once a month or more		
4: A few times a year or more	4: A few times a year or more	4: A few times a year or more		
5: Once a year	5: Once a year	5: Once a year		
Labeled Missing Values				
.a: Don't Know	8: Don't Know			
.b: Refused	9: Refused	9: Refused		
.d: Ineligible/ Inapplicable	-1: Ineligible/ Inapplicable			

Table B.65: Telework Policy

Final: `telpolicy`	2010: `telpolicy`	2000: `TPOLICY`	1990: N/A	1980: N/A
#: Label	#: Label	#: Label		
0: No	2: No	2: No		
1: Yes	1: Yes	1: Yes		
Labeled Missing Values				
.a: Don’t Know	98: Don’t Know			
.b: Refused	99: Refused	9: Refused		
.d: Ineligible/ Inapplicable	0: Ineligible/ Inapplicable	-1: Ineligible/ Inapplicable		

B.0.9 Trip Table

Modes

The travel diary format changed several times between 1980 and 2010. In 1980 and 1990, the diary asked respondents to record each trip from starting place to destination place. In 2000 and 2010, the record was structured around the place itself, with arrival time and departure time on either side.

Additionally, the handling of multimodal trips changed. In 1980, there was no option for recording multimodal trips. In 1990 and 2000, respondents were instructed to indicate each modal segment as an individual trip, with a time threshold defining walking trips. For example, if a person walked seven minutes from their home to a bus stop, rode the bus, and then walked one minute from their stop to their destination, this would be recorded as two trips: one walking trip from home to the bus stop, and one bus trip from stop to stop. The final trip is too short so it is not counted as a walking trip. The destination activity or trip purpose for the walking segment is "change modes" or "go on to other transportation". In 2010, the travel diary provided the option to list up to three modes: an access mode, a primary mode, and an egress mode.

Each survey year used different options for auto travel to record whether the person is the driver or a passenger, and how many others are in the vehicle. The mode and trip structure variables are summarized in Table B.66.

Due to these and other variations in response options from year to year, several mode variables were created with different levels of aggregation so that researchers can decide how to balance the trade-offs between detail and legacy for their specific research questions. Tables with a year in the title, such as "Table B.68: Modes 1980", indicate the oldest year with which they are compatible. The "Modes 1980" table is compatible across all years, while the "Modes 2000" is only compatible between 2010 and 2000.

Between the 2000 and 2010 surveys, two new modes became available in the Twin Cities: the Hiawatha LRT and North Star Commuter Rail. These modes were not available to TBI respondents before 2010, so naturally they were not mentioned in those surveys. A "Public Transit" value was created by collapsing "Public Bus", "Hiawatha LRT", and "Northstar Commuter Rail" in the 2010 survey for comparison to the "Public Bus" modes in 2000, 1990, and 1980. Alternate recoding options are listed at the bottom of each table.

Some modes, such as walking or biking, clearly existed in all four survey years, but were not asked about during the trip log portion of the survey before 2000. These modes were collapsed into the "other" categories where needed to ensure compatibility over time.

Activity/Purpose

The activity and trip purpose response options grew in detail and complexity over the years. The 1980 travel diary was the most simple, with only three trip purpose options (shown in Table B.74. Notably, the types of trip purposes recorded in 1980 provide information about both the origin and the destination of the trip (e.g., home-based work), rather than the destination activity alone (e.g., went to work). Thus 1980 trip purposes are managed separately from the other years.

Table B.66: Mode and Trip Structure Variables

2010:	2000:	1990:	1980:
#: Label	#: Label	#: Label	#: Label
Mode(s)			
`mode*`	`MODE`	`mode`	`vehtype`
(See Tables B.67-B.73 for mode values)			
Multimodal Trips			
`mode1, mode2, mode3`	`DACT`= 16	`purpose`= 6	N/A
Single trip has up to 3 modes	Activity=Change Mode	Purpose=Went to other transportation	*(multimodal trips not recorded)*
Number of people on trip			
`autotype`	`OTHTR`	*(separate modes)*	*(not asked)*
1: Drive alone	1: Drive alone		
2: One passenger	2: One passenger		
3: Two or more	*: $3 \leq$ `OTHTR` ≤ 98		
Driver or Passenger			
`trvlocdr`	*(separate modes)*	*(separate modes)*	*(separate modes)*
1: Driver			
2: Passenger			

Table B.67: Modes - Original Values

Final:	2010:	2000:	1990:	1980:
#: Label	#: Label	#: Label	#: Label	#: Label
	1: Car, van, or truck			
		3: Drove		1: Drove
			1: Drove alone	
			1: Drove with passenger	
		4: Rode as passenger	3: Rode as passenger	2: Rode as passenger
	6: Walk	1: Walk		
	7: School Bus	6: School Bus	5: School Bus	4: School Bus
	2: Public Bus	5: Public Bus	4: Public Bus	3: Public Bus
	3: Light Rail			
	4: Commuter Rail			
	5: Bicycle	2: Bike		
		8: Motorcycle/Moped	7: Motorcycle	
	8: Taxi/Shuttle	7: Taxi/Shuttle/Limo	6: Taxi	
	9: Other	97: Other	8: Other	5: Other

Table B.68: Modes 1980

Final:	2010:	2000:	1990:	1980:
#: Label	#: Label	#: Label	#: Label	#: Label
1: Drove	*: Mode = 1 & Driver	3: Drove	*: Mode = 1, 2	1: Drove
4: Rode as passenger	*: Mode = 1 & Driver = 0	4: Passenger	3: Rode as passenger	2: Rode as passenger
6: School Bus	3: School Bus	6: School Bus ("Private Bus")	5: School bus	4: School bus
16: Public Transit	*: 4, 5, 6	5: Public Bus	4: Public bus	3: Public bus
17: Other (1980)	*: 2, 5 – 12	*: 1, 2, 7 – 9	*: 6 – 8	5: Other
Alternate Possible Recodings				
7: Public Bus	4: Public Bus	5: Public Bus	4: Public bus	3: Public bus
15: Other	12: Other	97: Other	8: Other	5: Other

Table B.69: Modes 1990

Final:	2010:	2000:	1990:
#: Label	#: Label	#: Label	#: Label
2: Drove alone	*: Mode = 1, Drv. = 1, Ppl. = 1	*: Mode = 3 & People = 1	1: Drove Alone
3: Drove w/ passenger(s)	*: Mode = 1 & Driver = 1 & # People ≥ 2	*: Mode = 3 & People ≥ 2	2: Drove w/ passenger(s)
4: Rode as passenger	*: Mode = 1 & Driver = 0	4: Passenger	3: Rode as passenger
6: School Bus	3: School Bus	6: School Bus ("Private Bus")	5: School bus
16: Public Transit	*: 4, 5, 6	5: Public Bus	4: Public bus
12: Motorcycle	9: Moped	8: Motorcycle/Moped	7: Motorcycle
13: Taxi/Shuttle	10: Taxi/Shuttle	7: Taxi/Shuttle/Limo	6: Taxi
18: Other (1990)	*: 2, 5, 6, 7, 8, 11, 12	*: 1, 2, 9	8: Other
Alternate Possible Recodings			
7: Public Bus	4: Public Bus	5: Public Bus	4: Public bus
15: Other	12: Other	97: Other	8: Other

Table B.70: Modes 2000

Final:	2010:	2000:
#: Label	#: Label	#: Label
2: Drove alone	*: Mode = 1, Drv. = 1, Ppl. = 1	*: Mode = 3 & People = 1
3: Drove w/ passenger(s)	*: Mode = 1 & Driver = 1 & # People ≥ 2	*: Mode = 3 & People ≥ 2
4: Rode as passenger	*: Mode = 1 & Driver = 0 & # People ≥ 2	4: Passenger
5: Walk	2: Walk	1: Walk
6: School Bus	3: School Bus	6: School Bus (”Private Bus”)
16: Public Transit	*: 4, 5, 6	5: Public Bus
11: Bicycle	8: Bicycle	2: Bicycle
12: Motorcycle	9: Motorcycle/Moped	8: Motorcycle/Moped
13: Taxi/Shuttle	10: Taxi/Shuttle	7: Taxi/Shuttle/Limo
19: Other (2000)	*: 5, 6, 7, 11, 12, 15	97: Other
Alternate Possible Recodings		
15: Other	12: Other	97: Other
7: Public Bus	4: Public Bus	5: Public Bus

Table B.71: Modes 2000 (Simple)

Final:	2010:	2000:
#: Label	#: Label	#: Label
1: Auto	1: Auto	*: 3, 4
2: Public Transit	*: 2, 3, 4	5: Public Bus
5: Walk	5: Walk	1: Walk
6: Bicycle	6: Bicycle	2: Bicycle
7: School Bus	7: School Bus	6: School Bus
9: Other	*: 8, 9	*: 8, 97

Table B.72: Primary Mode Hierarchy: 2000 Simple Recoding

Rank	Label	Primary Mode	Decision Rule(s) In Order Applied
1	7	School Bus	Any trip for which mode 1, mode 2, or mode 3 is school bus
2	2	Public Transit	Any trip where primary mode is not school bus Any trip for which mode 1, mode 2, and/or mode 3 is public transit
3	1	Auto	Any trip where primary mode is not school bus or public transit Any trip for which mode 1, mode 2, and/or mode 3 is auto
4	5	Bicycle	Any trip where primary mode is not school bus, transit, or auto Any trip for which mode 1, mode 2, and/or mode 3 is bicycle
5	6	Walking	Any trip where primary mode is not school bus, transit, auto, or bike Any trip for which mode 1, mode 2, and/or mode 3 is walk
6	9	Other	Any trip where primary mode is not school bus, transit, auto, bike, or walk Any trip for which mode 1, mode 2, and/or mode 3 is other
N/A	N/A	Missing	Any trip with missing values for mode 1, mode 2, AND mode 3

Table B.73: Modes - All Possible Recodings

Final:	2010:	2000:	1990:	1980:
#: Label	#: Label	#: Label	#: Label	#: Label
1: Drove	*: Mode = 1 & Driver	3: Drove	*: Mode = 1, 2	1: Drove
2: Drove alone	*: Mode = 1, Drv. = 1, Ppl. = 1	*: Mode = 3 & People = 1	1: Drove Alone	
3: Drove w/ passenger(s)	*: Mode = 1 & Driver = 1 & # People ≥ 2	*: Mode = 3 & People ≥ 2	2: Drove w/ passenger(s)	
4: Rode as passenger	*: Mode = 1 & Driver = 0	4: Passenger	3: Rode as passenger	
5: Walk	2: Walk	1: Walk		
6: School Bus	3: School Bus	6: School Bus (”Private Bus”)	5: School bus	4: School bus
7: Public Bus	4: Public Bus	5: Public Bus	4: Public bus	3: Public bus
8: LRT	5: Light Rail (Hiawatha)			
9: Commuter Rail	6: Commuter Rail (North Star)			
10: Amtrak	7: Amtrak			
11: Bicycle	8: Bicycle	2: Bicycle		
12: Motorcycle	9: Moped	8: Motorcycle/Moped	7: Motorcycle	
13: Taxi/Shuttle	10: Taxi/Shuttle	7: Taxi/Shuttle/Limo	6: Taxi	
14: Dial-a-ride	11: Dial-a-ride			
15: Other	12: Other	97: Other	8: Other	5: Other
16: Public Transit	*: 4, 5, 6	5: Public Bus	4: Public bus	3: Public bus
17: Other (1980)	*: 2, 5, 6, 7, 8, 9, 10, 11, 12	*: 1, 2, 7, 8, 9	*: 6, 7, 8	5: Other
18: Other (1990)	*: 2, 5, 6, 7, 8, 11, 12	*: 1, 2, 9	8: Other	
19: Other (2000)	*: 5, 6, 7, 11, 12, 15	97: Other		

Table B.74: 1980 Trip Activities

1980: `purpose`
#: Label
1: Home-based Work
2: Home-based Other
3: Non-Home based

Table B.75: Activity/Purpose - Original Values

2010: `destact`	2000: `DACT`	1990: `purpose`
#: Label	#: Label	#: Label
1: Home - Paid Work	18: Work at Home	
2: Home - Unpaid Work		
3: Home - Other	17: Home Activities	
		1: Went Home
4: Work	1: Work	2: Work
	2: Work-Related	3: Work-Related
5: Attend Childcare	5: Childcare	
6: Attend School	3: Attend School	4: Attend School
7: Attend College		
8: School Activities	4: School Activities	
9: Quick Stops	6: Quick Stops	
10: Personal Business	9: Personal Business	
11: Major Shopping		
12: Everyday Shopping		
	7: Shopping	7: Shopping
13: Social	8: Visit Friends/Relatives	
14: Recreation-Participate		
15: Recreation-Watch		
	11: Entertain/Rec/Fitness	
16: Eat Out	10: Eat out	
17: Religious/Community	12: Civic/Religious	
18: Accompany another	14: Accompany another	
19: Pick-Up Passenger		
20: Drop-Off Passenger		
	13: Pickup/Drop off	5: Pickup/Drop off
21: Turn Around		
	16: Change Mode	6: Change Mode
	97: Other Outside of Home	8: Other

Table B.76: Activities 1990

Final:	2010:	2000:	1990:
#: Label	#: Label	#: Label	#: Label
1: Shopping	*: 11, 12	7: Shopping	7: Shopping
2: Attend School/College	*: 6, 7	3: School	4: School
12: Change Mode	*: (has multiple modes)	16: Change mode	6: Went to other transportation
15: Pickup/Drop Off	*: 19, 20	13: Pickup/Drop Off	5: Drop off/Pickup
28: Work & Related	4: Work	*: 1, 2	*: 2, 3
30: Home	*: 1, 2, 3 *	17, 18: *	Went home:
35: Other (1990)	*: 5, 8 – 10, 13, 15 – 18, 21	*: 4 – 6, 8 – 12, 14, 15	8: Other
Alternate Possible Recodings			
2: Attend School	6: School	3: School	4: School
29: Work	4: Work 1	Work: 2	Went to work:

Table B.77: Activities 2000

Final:	2010:	2000:
#: Label	#: Label	#: Label
1: Shopping	*: 11, 12	7: Shopping
2: Attend School/College	*: 6, 7	3: School
3: Childcare	5: Childcare	5: Childcare
4: School Activities	8: School Activities	4: School Activities
5: Quick Stops	9: Quick Stops	6: Quick Stops
6: Personal Business	10: Personal Business	9: Personal Business
12: Change Mode	*: (has multiple modes)	16: Change mode
15: Pickup/Drop Off	*: 19, 20	13: Pickup/Drop Off
18: Accompany Another	18: Accompany Another	14: With Another Person
19: Religious/Civic	17: Religious/Community	12: Civic/Religious
20: Dining Out	16: Eat out	10: Eat outside of home
24: Visit Friends/Relatives	13: Social	8: Visit friends/relatives
28: Work & Related	4: Work	*: 1, 2
31: Telework	1: Home - Paid work	18: Working at home
32: Home - Non-telework	*: 2, 3	17: At home activities
37: Entertainment/Recreation	*: 14, 15	11: Entertainment/Recreation/Fitness
Alternate Possible Recodings		
30: Home	*: 1, 2, 3	*: 17, 18

Appendix C

Glossary and Acronyms

This appendix defines jargon terms in a glossary, and contains a table of variables and a table of acronyms and their meaning.

C.1 Glossary

- **Accessibility** – The ability to reach a destination within a certain cost parameter (typically travel time).
- **Auto** – Automobile
- **Commute** – A trip that had home as the origin and work or work-related as the destination and was the first of such of the travel day.
- **Destination** – The location that a trip ends.
- **Metropolitan Council** – Regional government agency responsible for transportation and planning policy in the Minneapolis/Saint Paul metropolitan region.
- **Origin** – The location that a trip begins.
- **Work Trip** – A trip where the destination was work or work-related, not necessarily the first of such of the travel day.

C.2 Acronyms

Table C.1: Variables used in regressions

Demographic and socio-economic variables	
Age 10[0,1]	1 if individual aged 10-20. 0 otherwise
Age 20[0,1]	1 if individual aged 20-30, 0 otherwise
Age 30[0,1]	1 if individual aged 30-40, 0 otherwise
Age 40[0,1]	1 if individual aged 40-50, 0 otherwise
Age 50[0,1]	1 if individual aged 50-60, 0 otherwise
Age 60[0,1]	1 if individual aged 60+, 0 otherwise
Children	Number of children 0 - I6 in the household
HHsize	Number of persons in household
Male[0,1]	1 if individual is male, 0 otherwise
SFhome[0,1]	1 if individual lives in single family home, 0 otherwise
VPD	Number of vehicles per licensed driver
Accessibility variables	
A_{iEa}, A_{iEt}	Origin (home-end) accessibility to employment, by auto, transit
A_{iRa}, A_{iRt}	Origin (home-end) accessibility to population (housing for DC), by auto, transit
A_{jEa}, A_{jEt}	Destination (work-end) accessibility to employment, by auto, transit
A_{jRa}, A_{jRt}	Destination (work-end) accessibility to population (housing for DC), by auto, transit
D_{io}	Distance (Km) between origin (home-end) and IDS Tower (miles, White House)
D_{jo}	Distance (Km) between destination (workplace) and IDS Tower (miles, White House)
T_W	Time spent at work
T_E	Travel time to work
WT	Number of work trips (a trip that had work or work-related as its destination)

Table C.2: Acronyms used

Acronym	**Meaning**
CBD	Central Business District
GLM	Generalized Linear Model
OLS	Ordinary Least-Squares Regression
TAZ	Transportation Analysis Zone
TBI	Travel Behavior Index