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RESEARCH REPORT

EVALUATING THE EFFECT OF COMPLETE STREETS ON MODE CHOICE, A CASE STUDY IN THE BALTIMORE-WASHINGTON AREA

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16. Abstract

The goal of this project is to enhance regional travel demand modeling capability of MDOT SHA by developing data-driven mode choice models that incorporates bicycling and walking among the modes so that impacts of Complete Street projects and plans can be forecasted in the future. To accomplish the project goals and objectives, a Stated Choice Experiment (SCE) in which respondents are asked to evaluate different alternatives (including walking, biking and other) characterized by attributes related to trips made in a CS context is completed. The data set is used to estimate discrete choice models to explain the preferences for bike and walk modes in a CS context. Considering the implementation of the model in MSTM, we estimated the models by income and trip purposes consistent with MSTM, and we calculated both direct and cross elasticities from the coefficients obtained. We utilized calculated elasticities to update motorized-share table input used in MSTM where each modeling zones are assigned an average LTS value. We developed an Excel spread-sheet tool to update the motorized share input to MSTM and tested it on two scenarios. The scenario results demonstrated that the methods and tools we developed in this project can successfully reflect the potential impacts of CS within a statewide transportation model, i.e., MSTM, albeit requiring further refinement and validation.

17. Key Words	18. Distribution Statement
Complete streets, mode choice, mode shift, non-motorized transportation, benefits evaluation, demand modeling, estimation, level-of-stress, stated-choice experiment	This document is available from the Research Division upon request.

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EXECUTIVE SUMMARY

The Complete Streets concept references roads designed to accommodate: (1) diverse modes, including walking, cycling, public transit, automobile; (2) different users, e.g. affluent and low-income individuals, people with disabilities, senior citizens; (3) and a mix of land uses such as office, retail, businesses, and residential to ensure streets are safe, balanced and inclusively support diverse economic, cultural and environmental uses (AARP, 2009 & 2015; Burden and Litman, 2011; LaPlante and McCann, 2008; Seskin and Gordon-Koven, 2013). Successful Complete Streets projects have prioritized multi-modal transport systems effective in fostering more livable communities, increasing equity and improving public health. Underpinning this model is the intersection of two separate factors: that roads serve diverse functions including mobility, commerce, recreation, and community cohesion; and that road users have multiple mode choice options, including non-motorized modes and well-connected public transit alternatives (Litman, 2015).

Many cities across the country have implemented these Complete Streets transportation plans to guide local transportation agencies on construction and design principles that prioritize pedestrians, cyclists, and transit users. Planning authorities are trying to address the needs of different communities and travelers by supporting legislation that would require prioritizing multi-modal transportation options, providing interconnectivity of all modes and travel options, system preservation and innovation for convenient travel. The Maryland State Highway Administration (MDOT SHA), encouraged by PlanMD legislation enacted in 2012, issued a Complete Streets Policy that same year. The policy aims to strengthen the balance between safety and mobility of all roadway users by developing context sensitive solutions that support pedestrian bicycle, ADA and transit accessibility. Similarly, in November 2018, Baltimore City Council passed a Complete Streets bill that targets improvement of existing legislation and establishing accountability measures for Baltimore City's Department of Transportation (BDOT) to support Baltimore becoming a pioneer for Complete Streets. While these policy efforts are fundamental and necessary, ground truth transit realities in the Baltimore-Washington Metropolitan area are still challenging - not just for motorists but even more so for those relying on transit, cycling and walking.

The planning and implementation of Complete Streets is challenging; the process is best supported by using empirical evidence based on reliable, highly granular data and enhanced modeling tools. The benefits and success of Complete Streets implementation projects depend on future demands for alternative modes to automobiles and on the development of compact, residential/commercial, multi-modal urban neighborhoods. Focusing on the transportation side, it is necessary to forecast the level of demand for these alternative travel options in neighborhoods across the state where Complete Streets are considered the most promising strategies to improve pedestrian and bicycle safety. However, existing models and tools in the modeling tool-box of the MDOT and the MDOT SHA are not sensitive to changes in built environment (to the best of our knowledge - e.g., Complete Streets) to represent the changes in demand for modes such as walking, cycling and public transport in response to such changes in the road infrastructure.

It is important to be able to integrate non-motorized mode choices in the Travel Forecasting and Analysis Division's statewide regional modeling efforts. The goal of this project is to enhance regional travel demand modeling capability of MDOT SHA by developing data-driven mode choice models that incorporates bicycling, walking, transit and multi-modal connections among these modes so that impacts of Complete Street projects and plans can be forecasted in the future. This report summarizes the work done to achieve the project goals and objectives as follows:

Chapter 1. An extensive review of the state of the practice and art on Complete Streets policy and applications, focusing particularly on incorporating non-motorized modes in regional travel demand models is presented in this chapter (Task 1 of the project).

Chapter 2. In this chapter, we report first a review of existing data sources (mainly NHTS 2017) has been conducted to identify useful existing data for this project. The appropriate data source has been identified as a Stated Choice Experiment (SCE) survey on willingness to change mode in presence of Complete Streets - SP data collection. We describe the survey and survey data analysis in this chapter as well as the estimations of models given the new behavioral data collected so that a relationship between Complete Streets projects and demand for non-motorized travel can be built.

Chapter 3. In this chapter, we describe the method used for incorporating behavioral model estimates in the selected regional travel demand model i.e., Maryland Statewide Transportation Model (MSTM) for CS project and policy analysis. Specifically, we developed a Excel Sheet-based tool to update “Motorized-share.xlsx” file input in MSTM to make the model sensitive to non-motorized modes.

Chapter 4. In this chapter, we demonstrate the developed model’s performance on hypothetical CS scenarios: a county level analysis (Prince George’s County) and a statewide level analysis (urban areas in Maryland) where we improved Level of Traffic Stress (LTS) at zone level in these geographies and tested the results. In order to generate scenarios in an automated fashion, we used the *Excel spread-sheet- based tool* described in Chapter 3. This tool can generate new “Motorized-share.xlsx” file input based on SMZ, income, trip purpose and LTS values and associated elasticities obtained from the SCE experiment. The MDOT SHA can use this tool to test many scenarios at SMZ, county or statewide level.

Chapter 5. We conclude the report with a discussion of the project outcomes, recommendations, limitations and further research needs.

CHAPTER 1 LITERATURE REVIEW

The Complete Streets movement emerged to expand the focus of transportation design from automobility to the accommodation of all modes of travel (*McCann, 2013*). Thus, the complete streets policy is broadly defined as a street design framework that can safely accommodate all road users, regardless of mode of travel or ability (*National Complete Streets Coalition, 2011*). In addition to its transportation accommodation and benefits, the policy is expected to have various social, environmental, safety, and economic benefits as well (*Litman, 2015; National Complete Streets Coalition, 2016*). A review of the previous literature was conducted by the UMD research team to investigate how the complete streets policy's impact on transportation systems and travel behavior, safety, health, and economy was studied and measured in the past.

The literary review includes research reports and scientific papers published in peer-reviewed journals, conferences and databases that may contain relevant information in relation to this study. To better present our comprehensive review, this chapter is organized into five sections. First, the conceptual framework, main objectives/expected outcomes, and design requirements of the complete streets policy are summarized, as it has been documented and presented in numerous studies. In the second and third sections, the current state of the practice of the policy, both nationwide and within the state of Maryland is documented and discussed, elaborating on how the policy was implemented and supported in hundreds of cities and jurisdictions across the country within the last few decades and how the design and implementation steps have evolved over time. The last two chapters discuss the expected benefits/outcomes of complete streets policy in terms of transportation, environmental, safety, health, and economic impacts, how they were measured and evaluated in the previous literature, and what are the main research gaps in the existing methods for evaluating Complete Streets performance evaluations, with an emphasis on transportation/travel behavior impacts, specifically mode choice decisions.

The insights provided in this chapter will help the policy makers and planners at the Maryland State Highway Administration and similar agencies to better implement, maintain, and evaluate the statewide complete streets policy as a great tool to promote and achieve sustainable transportation and urban planning.

1.1. Complete Street Policy: Conceptual Framework, Background, and Policy Design Elements/Requirements

The framework for complete streets policies is based on the concept of equity (*Clifton, 2014*). Complete Streets are defined as "streets designed and operated to enable safe access for all users, including pedestrians, bicyclists, motorists and transit riders of all ages and abilities" (*Clifton, 2014; Slotterback and Zerger, 2013*). In fact, communities of color, the poor, older adults, youth, and people with disabilities, are among the transportation disadvantaged groups and thus in greater need for access to convenient, safe, and well-integrated transportation alternatives (*Clifton, 2014; Zaccaro and Atherton, 2017*). Nearly one-third of the U.S. population is transportation disadvantaged, which means that they cannot easily access basic needs such as healthy food choices, medical care, gainful employment, and educational opportunities. Research also shows that millions of Americans who are age 65 and over—and unable to drive due to physical restrictions—stay at home on a given day because they lack access to modes of transportation other than driving (*Burden and Litman, 2011; Handy & McCann, 2011*). Complete Streets is a transportation decision-making approach, which, as a result of integrated thinking and planning and by accommodating all users, can help reduce the environmental barriers which inhibit people from walking, bicycling, or taking transit and optimize/enhance the ability, safety and ease of travel, shopping and other activities in the area. As stated in Litman (2012), "this integrated planning makes travel without a car convenient, comfortable and affordable, while creates communities where households own fewer vehicles, drive less and rely on alternative modes". Many studies focused on the variation of users within the Complete Streets context and stated that complete and walkable streets may attract more people overall and more females and other transportation disadvantaged users in particular (*Jensen et al., 2017*).

The term "Complete Streets" draws together a range of tools, elements and concepts in a package to help achieve better social, economic and environmental outcomes along urban road corridors (*Elias, 2011*). In addition to the term *"Complete Streets"* which is mostly used by transportation professionals, there are other terms used by professionals from different disciplines, such as "*Smart Growth"* used by regional planners, and "T*ransit-oriented Development"* or "*New Urbanism"* used by local planners. All these terms share the same conceptual framework and features and are being used interchangeably. The term *"Complete Streets"* is relatively new, but the main concept and many of its associated elements have been around for a long time.

There are three main focus areas the Complete Streets concept refers to, including: (1) diverse modes, including walking, cycling, public transit, automobile; (2) different users, e.g. affluent and low-income individuals, people with disabilities, senior citizens; and (3) a mix of land uses such as office, retail, businesses, and residential to ensure streets are safe, balanced and inclusively support diverse economic, cultural and environmental uses (*AARP, 2009 & 2015; Burden and Litman, 2011; LaPlante and McCann, 2008; Seskin and Gordon-Koven, 2013; Sousa and Rosales, 2010*). Successful Complete Streets projects have prioritized and encouraged multi-modal transport systems to foster more livable communities, increase equity and support economic development, reduce crashes and injuries, and improve public health. In other words, successful complete street projects need to make sure that first; roads serve diverse functions including mobility, commerce, recreation, and community cohesion, and second; road users have multiple mode choice options, including non-motorized modes and well-connected public transit alternatives (*Litman, 2015; Anderson et al., 2015*).

Efforts to transform streets into Complete Streets (or from mobility-based to accessibility-based designs) with a low-cost approach require cooperation of traffic engineers, planners, policy makers, as well as the general public and communities (*Schlossberg et al., 2013*). Moreover, the concept focuses not just on individual roads but on changing the decision-making and design process so that all users are routinely considered during the planning, designing, construction and operation of all roadways. It is about policy and institutional change (*ITE, 2008; Yusuf et al., 2016*). While there exists no uniform and standardized format for Complete Streets, the following ten factors should be considered in a comprehensive policy framework, according to the National Complete Streets Coalition (2014):

1. Vision: The policy establishes a motivating vision for why the community wants to have complete streets: for improved safety, better health, increased efficiency, convenience of choices, or other reasons.
2. Intent: The policy needs to be clearly written to specify the goals and changes needed to fulfill the policy's intent.
3. All projects and phases: All types of transportation projects are subject to the policy, including design, planning, construction, maintenance, and operations of new and existing streets and facilities.
4. Clear, accountable exceptions: Any exceptions to the policy are specified and approved by a high-level official.
5. Network: The policy recognizes the need to create a comprehensive, integrated, and connected network for all modes and encourages street connectivity.
6. Jurisdiction: All other agencies that govern transportation activities can clearly understand the policy's application and may be involved in the process as appropriate.
7. Design: The policy recommends use of the latest and best design criteria and guidelines, while recognizing the need for flexibility to balance user needs.
8. Context sensitivity: The current and planned context—buildings, land use, and transportation needs—are considered in planning and design solutions for transportation projects.
9. Performance measures: The policy includes performance standards with measurable outcomes.
10. Implementation steps: Specific next steps for implementing the policy are described in the policy.

Several studies discussed the conceptual framework of complete streets policy and best practices, trying to provide insight for planners and transportation professionals in terms of policy requirements, design elements, evaluation criteria, project costs, etc. for a more efficient design and implementation of this policy (*McCann, 2011; Ferguson et al., 2015; Shapard and Cole, 2013; Dock et al., 2012; McCann and Rynne, 2010*). These studies listed the most common elements used in most complete streets projects as: wide sidewalks, frequent and safe crossings (e.g., median islands, accessible pedestrian signals, curb extensions), bicycle lanes (or wide, paved shoulders) and bicycle parking, shared-use paths, road diets, traffic calming measures to lower automobile speeds and define the edges of automobile travel lanes, greenery design, and public transit accommodations (e.g., accessible transit stops, bus shelters, dedicated bus lanes), and many other features (*Sousa and Rosales, 2010; Slotterback and Zerger, 2013; Ranahan et al., 2014*). *Table 1* lists some of the most significant and common features of complete streets design used in hundreds of projects nationwide. It categorizes the features into four main groups based on the types of users, including pedestrian infrastructure, bicycle infrastructure, traffic calming, and public transit accommodations.

Table 1 The main features of Complete Streets design

Pedestrian/bike infrastructure	Traffic calming	Public transit accommodations
• Sidewalks, or wide paved shoulders • Frequent and safe crossing opportunities • Accessible pedestrian signals • Bike lanes	• Median islands • Narrower travel lanes • Roundabouts • Curb extensions	• Special bus lanes • Comfortable and accessible stops

Knowledge of specific factors related to the growth and expansion of Complete Streets policies is important for communicating with advocates and policy makers about this topic. Using data from 49 community-level policies, Moreland-Russell et al. (2013) identified several factors that had the potential to affect the rate of Complete Streets policy diffusion: rural/urban status, state obesity rate, state funding for transportation, state obesity prevention funding, percentage of people who walk or bike to work in the state, presence of a state Complete Streets policy, and the number of bordering communities with Complete Streets policy. They suggested three variables of state obesity rate, percentage of commuters who bike or walk to work, and presence of a border community with a Complete Streets policy as the most significant factors influencing the adoption of Complete Streets policy.

The estimation of complete streets projects' cost and its comparison to the expected monetary benefits has also received much scholarly attention over the past several years. Shapard and Cole (2013) used the City of Charlotte, North Carolina as a case study to determine the cost range of typical complete streets projects and see if it costs more than building a traditional street. They found that incorporating complete streets elements slightly increases the cost of a project. This increase, for instance, for a four-lane divided street could be as little as 5% of the overall project budget for a four-lane divided street, given the reduced lane width as a result of the complete street design. The addition of a sidewalk increases the cost of a three-lane street by approximately 3.4%, while the additional pavement needed for the bike lanes increases the overall project cost by a little more than 5%. However, as many studies have shown, the additional money spent on complete streets design and implementation is a long-term investment in the financial and physical health of the community and the value added to the cities and residents' quality of life as a result of increased walkability, safety, and congestion relief is very difficult to calculate monetarily (*Shapard and Cole, 2013; LaPlante and McCann, 2011*). Moreover, a typical complete street project costs significantly less than any conventional transportation project (both normal-cost and high-cost per mile specified by the Federal Highway Administration's estimates), while they yield significant safety results (*Anderson et al., 2015; Ferguson et al., 2015*).

The complete street design is highly context-sensitive, as stated by many researchers. This implies that there is no unique way to achieve "completeness". Rather, multiple ways exist for a street to become complete, depending on the environment, location, and many other circumstances. In certain contexts, a complete street may not even require accommodation of every mode (*Sousa & Rosales, 2010; Hui et al., 2017; LaPlante and McCann, 2011*). [1]

1.2. History

For many years, roads and highways have been constructed as if private motor vehicles and freight are the only users. In many cases, urban arterials provide a well-engineered place for cars to travel next to a homemade pedestrian facility—a "goat track" tramped in the grass—with a bus stop that is no more than a pole in the ground uncomfortably close to high-speed traffic (*ITE, 2008*). In contrast, Complete Streets design is a subset of walkable designs, intended to support pedestrians (or other active users) in the presence of automobiles and focuses on making multimodal accommodation routine so that multimodal roads do not require extra funds or extra time to achieve (*Smith et al., 2010; Jensen et al., 2017*). Although the Complete Streets policy has started gaining popularity and recognition very recently, the support for such policy is not new. The first Complete Streets policy was adopted more than 40 years ago. In 1971, the state of Oregon adopted a policy that outlined the infrastructure and support for modes of transportation other than automobiles: "footpaths and bicycle trails, including curb cuts or ramps as part of the project, shall be provided wherever a highway, road or street is being constructed, reconstructed or relocated." Between 1971 and 1999, only 7 additional polices were enacted nationwide. The term "Complete Streets" was first used in December 2003 at a meeting of America Bikes and its partner organizations. The new term, born out of the concept of including bicyclists in transportation planning, was intended to be inclusive of pedestrians, public transit riders, and other road users (*McCann, 2010*). The policy started growing rapidly across the United States, with the number of policies/programs doubled between 2000 and 2003. In 2005, a coalition of advocacy and trade groups including the American Public Transportation Association and the National Association of Realtors founded the National Complete Streets Coalition (NCSC) as a non-profit non-partisan alliance and collaborative effort to promote the policy and procedural changes at the Federal, state and local levels (*ITE, 2008; National Complete Streets Coalition, 2014*). Between 2008 and 2010 the number of Complete Streets policies has doubled per annum. Almost half of States in the United States (23 states) had some form of Complete Streets policy at the community or state level by then (*Moreland-Russell et al., 2013*). As of January 1, 2017, 1232 jurisdictions in the United States, including 955 municipalities, have adopted some form of Complete Streets policy that is intended to support active travel by pedestrians, cyclists, and transit riders by improving built environment and policy supports for walking, cycling, and using transit (*Izenberg and Fullilove, 2016; Moreland-Russell et al., 2013; Smith et al., 2010; Jensen et al., 2017; NCSC, 2017*).

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[1] Complete Street; Nationwide State of the Practice

1.3. Federal and state governments' roles in complete street policy design and implementation

While the Federal government does not legislatively mandate Complete Streets, it actively encourages states and their cities to incorporate the design concepts associated with complete streets. Passing of the Intermodal Surface Transportation Efficiency Act (ISTEA) in 1991, Transportation Equity Act for the 21st Century (TEA-21), Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU), USDOT Policy Statement on Bicycle and Pedestrian Accommodation Regulations and Recommendation in 2010[2], and the Moving Ahead for Progress in the 21st Century Act (MAP-21) passed in July 2012, paved the way towards complete street policies and guidelines within the past few decades (*Yusuf et al., 2016*). In terms of specific complete streets legislation, Federal bills were introduced in Congress as early as 2008 (HR 5951: Safe and Complete Streets Act of 2008; S2686: Complete Streets Act of 2008), but all have failed to pass. In April 2015, a six-year complete streets bill called "Comprehensive Transportation and Consumer Protection Act of 2015" was approved in the House of Representatives. The bill required states and MPOs to incorporate, in all federally funded projects, complete streets principles to accommodate safety and convenience of all users. As a result, the Federal Highway Administration proposed revisions to its rule governing design standards for the National Highway System (NHS) to accommodate the complete streets design standards. That system included interstates and other high-speed, high-volume roads, as well as a lot of routes serving commercial centers, homes, shops, parks, schools, and hospitals—places where people often walk, bike, or take public transportation, in addition to driving. The most recent act called "Transportation funding: active transportation: complete streets" was passed in September 2019 in the senate, requiring the asset management plan to prioritize the implementation of safe and connected facilities for pedestrians, bicyclists, and transit users on all State Highway Operation and Protection Program projects, as specified. The bill would require the USDOT to include complete streets elements in the asset management plan, as specified.

According to the NCSC, more than half of the American states currently have an explicit state-level policy to encourage adoption of complete streets (see Figure 1). States have relied on two different approaches to adopting complete streets policies—a law passed by a state legislature or an executive-level policy such as a DOT regulation or an executive order issued by a governor. Among these, many states have supplemented their first complete streets laws and executive orders with additional laws or orders, which has increased the overall comprehensiveness of their commitment.

Many states have implemented and regulated complete streets policies and plans at their state level decision making levels. For instance, the California Department of Transportation revised its policy directive for bicyclists' and pedestrians' use of state highways, in a suitable local context and with the new policy, entitled Complete Streets—Integrating the Transportation System in October 2008. Complete Streets is also included as one of the strategies in the California Air Resources Board's Climate Change Scoping Report. The goals of these acts and policies are to promote active transportation modes such as walking and cycling, promote

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[2] http://www.fhwa.dot.gov/environment/bicycle_pedestrian/guidance/policy_accom.cfm

economic revitalization through reduced private and public transportation costs, and promote vibrant, livable, and safe communities on a local level (*Geraghty et al., 2009; CalTrans, 2008*). In Hawaii, Complete Streets and Safe Routes to School (SRTS) legislation were introduced January 2009. Advocacy groups monitored bill progress, testified at hearings, and assisted in rewording the bills. The SRTS statute required the Department of Transportation (DOT) to administer the federal SRTS funds and the complete streets law tasked the state and county DOTs to adopt complete streets policies and review existing highway design standards and guidelines. Both bills were signed into law June 2009 (*Heinrich et al., 2011).* Illinois also passed a law in 2008, requiring the state department of transportation to accommodate bicycle and pedestrian travel on all its roads in urbanized areas. Other places have been building complete streets for several years, including Oregon, Florida, Arlington, VA, and Boulder, CO. In Charlotte, North Carolina, transportation planners have been using a six-step Complete Streets planning process that systematically evaluates the needs of all modes. The National Complete Streets Coalition offers a Local Implementation Assistance Program to help jurisdictions with this task (*ITE, 2008*). Figure 1 shows the states with a Complete Street policy designed/implemented, highlighted in gray. As it indicates, more than 30 states have adapted some form of the policy and have implemented cases of complete streets through their local agencies.

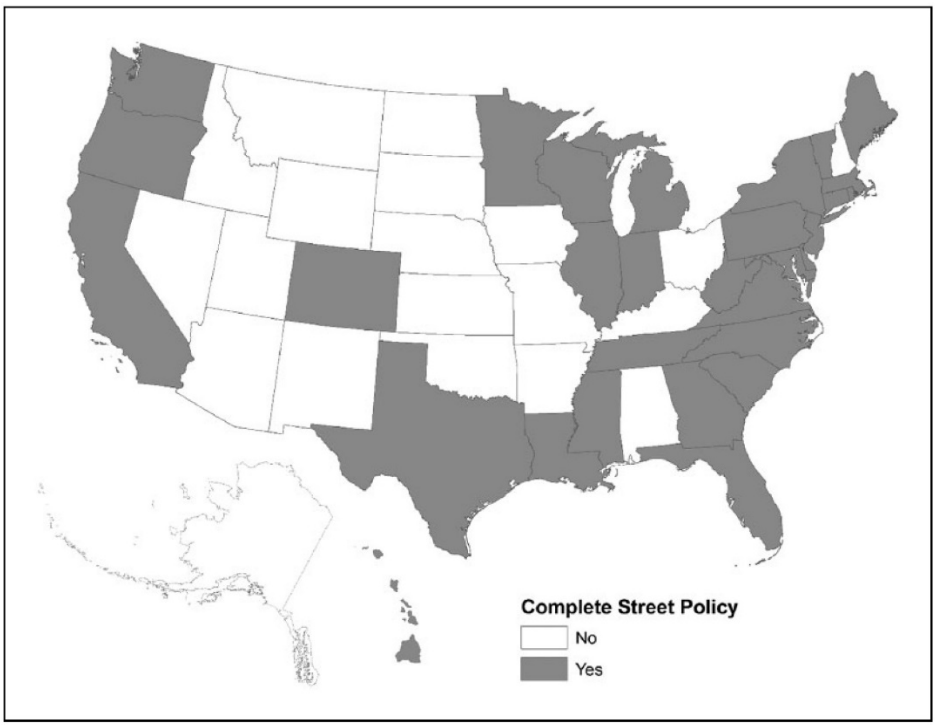

Figure 1 Nationwide State of the practice-Complete Street Policy

In summary, many cities/states across the country have implemented various Complete Streets transportation projects and plans to guide local transportation agencies on construction and design principles that prioritize pedestrians, cyclists, and transit users. Carlson et al. (2017)

estimated the prevalence of Complete Streets policies in the United States using data from the National Survey of Community-Based Policy and Environmental Supports for Healthy Eating and Active Living (CBS HEAL) and reported that in the United States, 25.2% of municipalities have Complete Streets policies reported by a local official. They also suggested that the prevalence increases as population increases, from 16.1% in municipalities with < 2500 people to 49.6% in those with >=50,000 people. Planning authorities are trying to address the needs of different communities and travelers by supporting legislation that would require prioritizing multi-modal transportation options, providing interconnectivity of all modes and travel options, system preservation and innovation for convenient travel.

1.4. State of the Practice in Maryland

The Maryland State Highway Administration (MDOT SHA) adopted complete streets policies on three occasions. In 2000, their policy had a total comprehensiveness score of 21.6. That legislation was subsequently updated in 2010, then updated with a more comprehensive statutes from 2000 to 2012 influenced by PlanMD legislation enacted the same year, increasing the total comprehensiveness score to 77.6. Maryland has supplemented their initial complete streets laws with executive-type complete streets policies, which has increased the overall comprehensiveness of their commitment to complete streets. The current policy specifies coverage of all users and modes, with a greater emphasis on performance measures, jurisdictions, and exceptions. (*Yusuf et al., 2016*).

The 2012 policy aims to strengthen the balance between safety and mobility of all roadway users by developing context sensitive solutions that support pedestrian bicycle, ADA and transit accessibility. Similarly, in November 2018, Baltimore City Council passed a Complete Streets bill that targeted improvement of existing legislation and establishing accountability measures for Baltimore City's Department of Transportation (BDOT) to support Baltimore becoming a pioneer for Complete Streets.

While these policy efforts are fundamental and necessary, ground-truth transit realities in the Baltimore-Washington Metropolitan area are still challenging - not just for motorists but even more so for those relying on transit, cycling and walking. As of now, despite these initiatives, plans, and policies in effect both statewide and county-wide, Maryland's transportation demand models—similar to other statewide transportation demand models across the nation—lack the ability to evaluate the success of complete streets policy and quantitatively measure its various outcomes, especially with regards to travel behavior and mode choice changes.

1.5. Complete Street Implementation, Benefits and Evaluation of Success

Complete streets offer many benefits, both for individual users and for the area at large. Assessing the completeness of all the streets and its various impacts on transportation systems, community development, and economy yields useful insights as to how to prioritize infrastructure investment and develop planning policy, as has already been proven in many previous studies (*Kingsbury et al., 2011; Jones and Boujenko, 2009; Hui et al., 2017*). A context-sensitive framework with which to quantitatively define the completeness of a complete street by measuring its various impacts has useful applications in planning and design. The various benefits of complete streets policy should be analyzed from transportation (multimodal LOS, behavior, and safety), environment, economic, and health perspectives (*Hui et al., 2017; Ranahan et al., 2014*). Most of the complete streets literature addresses and evaluates the qualitative goals of complete streets and the array of different complete street design elements through analyzing case studies of complete streets projects all around the country and elaboration of how the policy was implemented in terms of street design, construction, traffic and parking regulations, community engagement processes, and lessons learned from the process of passing the Complete Streets resolution in several communities (*Hui et al., 2017; Dodson et al., 2014; Carter et al., 2013; Geraghty et al., 2009*). Less scholarly attention has been paid to quantitatively assess and measure the performance of the existing projects and analyze their various before-and-after effects, especially on transportation and travel behavior. The extensive body of literature on the interaction between the built environment and travel behavior is not a literature that deals specifically with the impacts of complete streets implementations, and there has been practically no comprehensive and rigorous research focused on the social, behavioral, economic, and environmental impacts of complete streets. However, some detailed research has been done on a "street-by-street"/link-by-link" basis focused on the travel behavior and safety benefits of more "livable" streets (*Ferguson et al., 2015).* The Smart Growth America (2011) has emphasized on the need to continuously evaluate the success of complete streets projects and their proper implementation through the following performance measures:

- User data -- bike, pedestrian, transit and traffic
- Crash data
- Use of new projects by mode
- Compliments and complaints
- Linear feet of pedestrian accommodations built
- Number of ADA accommodations built
- Miles of bike lanes/trails built or striped
- Number of transit accessibility accommodations built
- Number of street trees planted

Although every design or redesign is different, complete streets have been shown to share some key outcomes/benefits and these benefits such as social, environmental, health, and economic benefits are to some degree intertwined (*Ferguson et al., 2015*). For example, the travel behavior changes as a result of the implementation of the policy could lead to an increased level of physical activity, which is associated with many public health benefits as highlighted in numerous previous studies (*Blair and Morris, 2009; Warburton & Bredin, 2016 and 2017*).

These health impacts would then potentially lead to significant economic benefits through cost savings. On the other hand, complete streets are also associated with increased safety for motorists and other users, primarily through reduced vehicular travel speeds and reduced air and noise pollution (*Litman, 2014; Shu et al., 2014*). By supporting more active, accessible, and attractive areas, complete streets are expected to also improve livability and economic activity and encourage more healthy lifestyles for residents (*LaPlante and McCann, 2011; Babb and Watkins, 2016*). One study examined dozens of individual complete streets projects from across the country and found that when rates from before and after their completion were compared, the vast majority of projects saw decreases in crash rates and increases in pedestrian, bicycle, and public transit trips made. These projects were also much lower in cost on a per mile basis than typical arterial projects (*Smart Growth America, 2015a*). Another study of many complete streets redesign projects, found instances of economic development, reduced crashes, and increased cycling rates (*Smart Growth America, 2015b*). Complete streets modifications to roadways have been shown to be desired by roadway users of different modes, including drivers (*Schlossberg et al., 2015*). Table 2 lists the potential benefits vs. costs of complete streets projects in terms of improved transport options and use of alternative modes, reduced automobile dependency, and enhanced smart growth development. As it indicates, the potential benefits of complete streets project outweigh the costs and would eventually aim for more sustainable and livable transportation systems and communities. In the following sub-sections, the benefits/impacts of complete streets policy as studied in the previous literature has been summarized in terms of transportation and travel behavior, safety, economic development, environmental, and public health.

Table 2. Potential Benefits and Costs of Complete Streets

	Improved transport options	Increased use of alternative modes	Reduced automobile travel	Smart growth development
Potential benefits	-Improved user convenience & comfort -Improved accessibility, particularly for non-drivers -Option value -Increased local property values	-User enjoyment -Improved public fitness and health -Increased community cohesion (positive interactions among neighbors due to more walking on local streets)	-Reduced congestion -Road and parking savings -Consumer savings -Reduced crashes -Reduced chauffeuring burdens -Energy conservation -Reduced air & noise pollution	-Improved land use accessibility -Transport cost savings -Infrastructure savings -Open space preservation -Improved aesthetics -Urban redevelopment -Support for local businesses
Potential costs	-Planning and implementation -Lower traffic speeds	-Additional user costs (shoes, bikes, fares, etc.)	-Reduced travel speeds -Reduced parking convenience	-Increases in some development costs -Transition costs

Source: Litman, Todd, Evaluating Complete Streets, The Value of Designing Roads for Diverse Modes, Users and Activities, Victoria Transport Policy Institute, May 2014, p.10.

Transportation and travel behavior impacts

Complete streets can provide many direct and indirect transport and community development impacts including improved accessibility and safety for non-drivers, increase economic activity and local property values, energy conservation and emission reductions, lower traffic speeds, improved community livability and aesthetics, improved public transit service and mode shifts, improved public fitness and health, and support for strategic development such as urban redevelopment and reduced sprawl (*Litman, 2012; Hui et al., 2017; Ranahan et al., 2014*). Despite all the transportation and behavioral impacts of complete streets policy, to date, little research has been done to quantitatively measure and confirm these benefits and outcomes. Much of the relevant literature only focuses on descriptive analysis of improvements to the accessibility, travel speeds, and overall safety of all users (*Perk et al., 2015*). Many studies tried to evaluate the performance of complete streets projects through completeness scores (*Kingsbury et al., 2011; Jones & Boujenko, 2009*). Kingsbury et al., (2011) presented a four-dimensional audit for automobiles, transit users, bicyclists, and pedestrians to assess completeness and compare the balance between the modes. The National Complete Streets Coalition also emphasized on the uniqueness of every street which makes it almost impossible to give a single description of completeness. As mentioned above, most of these analyses were more of qualitative and planning-oriented ones and thus encouraged proactive complete street assessment rather than a quantitative assessment of impacts.

Sugiyama et al. (2012) also performed a qualitative analysis of the transportation impacts of complete streets policy and found that utilitarian walking (walking to destinations) is consistently associated with the presence and proximity of utilitarian destinations, such as local shops, services, and transit stops, and to sidewalks, while recreational walking was associated with recreational destinations and route aesthetics. Also, Slotterback and Zerger (2013) provided a guidebook on the various ways of complete streets policy conceptualization and implementation through studying several best practices in Minnesota, Virginia, Colorado, North Carolina, Ohio, Iowa, North Dakota, Wisconsin, and Connecticut. Their qualitative approach includes investigation and documentation of framing and positioning, institutionalizing complete streets, analysis and evaluation, project delivery and construction, promotion and education, and funding.

Elias (2011) tested several different designs features of the complete streets and the impact on pedestrian and bicycle LOS scores within the context of a complete street vs. an auto-oriented street and showed that a complete street design can improve bicycle and pedestrian LOS while minimally affecting auto LOS. Later, Schlossberg et al. (2013) documents the redesign of 25 streets across the United States and some of their measurable outcomes the redesign had on traffic, safety, and economic measures, to help communities better visualize new ways to use streets with multiple purposes and multiple modes of transportation. They found that cycling increased and the cycling behavior was improved significantly across all the cases. They also suggested that as a result of street redesign projects, safety was improved with fewer—and less severe—accidents and crimes, auto travel times were declined, and transit ridership was promoted significantly. More recently, Ferguson et al. (2015) examined 15 street cases in the City of Hamilton to assess the extent to which Complete Street concepts and practices can be effective in shaping the development of Hamilton in the future. Brown et al. (2016) examined the influence of Complete Streets with a light rail extension, more complete bike paths, and wider sidewalks on transit-related walking and non-transit walking and found that residents living near Complete Streets were more likely to have higher transit-related walking and non-transit walking than those living in other areas.

There is abundance of previous research on the effect of various pedestrian- and transit-friendly transportation policies and programs on mode choice using advanced mode choice models. These studies suggest that providing a better access to alternative modes of transportation and improve their attractiveness, safety, and efficiency through various pedestrian- and transit-friendly policies would result in a mode choice towards less driving and more non-motorized and transit mode choice (*Nasri and Zhang, 2019;* Faghri & Venigalla, 2016; Liu et al., 2016; June*, 2008*).

However, the literature is limited regarding studies specifically modeling mode choice changes as a result of complete streets interventions. Studies focused on various design elements of complete streets and their impact on mode choice suggest that the influence is not uniform across all design elements, with some specific elements heavily influencing mode choice while some others have small or negligible influence on mode choice in the context of complete streets implementation (*Tracz, 2015*).

Safety impacts

The impact of complete street policy on safety of pedestrian and bicyclists has been studied in many previous studies, who suggested that implementation of complete streets policies is associated with a substantial increase in the pedestrian and cycling population while it improves safety by reducing the fatality rate per population unit due to many design intervention such as road diets and reduced speed limits (*Mooney et al., 2018; Anderson et al., 2015; Marshall and Garrick, 2011; Laplante and McCann,2008; McCann and Rynne,2010; National Complete Streets Coalition, 2015; Smart Growth America, 2015a*). Huang et al. (2002) examined the pre-post impact of Complete Streets on motor vehicle crashes and injuries in several California and Washington cities and found that the percentage of crashes dropped by 6% after Complete Streets interventions. Anderson et al. (2015) evaluated complete streets from the pedestrian safety point of view and suggested that about 70 percent of the projects had fewer collisions and fewer injuries after their redesigns. The New York City Department of Transportation found that total crash rates (pedestrians, cyclists and motorists) declined 40-50% after bike lanes were installed on the city's arterials (*NYCDOT, 2011*). Narrower streets with lower design speeds tend to have fewer and less severe accidents (*Frith, 2012*), and per capita traffic accident rates tend to decline in communities with more connected streets, more multi-modal transportation systems, and more accessible land use development (*Wei and Lovegrove, 2010*). Marshall and Garrick (2011) also highlighted that more connected, multi-modal street design can significantly reduce traffic injury and fatality rates in U.S. cities. Stout, et al. (2006) found that conversion of four-lane undivided roadways to three-lane cross-sections in typical Iowa towns reduced crash frequency by 25% and crash injuries by 34%. Collision frequency is the most common measure of safety in complete streets projects (*Anderson et al., 2015).* However, collision rates alone do not reveal the mechanisms of safety improvements: in a study of the before-and-after effects of 37 complete streets projects in the United States, Anderson et al. (2015) was unable to identify the specific causes for collision and injury reduction in any case. Collisions may also be underreported in multimodal situations (*Loukaitou-Sideris et al., 2014*), leading to inaccurate reports of safety improvements on a street. Tolford et al. (2014) proposed a low-cost methodology piloted in New Orleans, Louisiana for evaluating pedestrian safety within the complete streets policy implementation context. They used a spatial tool to identify areas where a statistically significant number of crashes have occurred and showed that in many pedestrian crash clusters, the pedestrian traffic is relatively low, while there are serious accessibility issues such as lack of curb ramps, street furniture, and transit shelters, as well as narrow sidewalks. They suggested that a systematic change towards complete streets design, such as consideration of road diets, would enhance pedestrian, transit, and bicycle accessibility and ultimately would result in lower pedestrian crash rate. Mooney et al., (2018) investigated the effect of complete streets policies on overall numbers of cyclist fatalities while accounting for potential policy effects on the size of the cycling population using cyclist fatality data between January 2000 and December 2015. They found that complete streets policies made cycling safer overall, averting 0.6 fatalities per 100,000 cyclist-years by encouraging a 2.4% increase in cycling but producing only a 0.7% increase in cyclist fatalities.

Economic development impacts

In addition to the potential transportation and safety benefits of complete streets, many economic development benefits can be envisioned as well. Although limited attention has been paid investigating economic benefits related to Complete Streets, research showed that Complete Streets interventions could potentially bring many economic benefits, including creation of new businesses and employment and increased property values and retail sales (*Schlossberg et al., 2013; Guzman, 2014; Smart Growth America, 2012; Litman, 2014, 2015, 2016; New York City Department of Transportation; National Complete Streets Coalition, 2015*) through changes of the travel behavior. If users of different modes and capabilities (such as pedestrians, bicyclists, and transit users; children, elderly, women; and disabled citizens) feel an increased sense of safety along a corridor, more of them might use the corridor more often and that would potentially bring a boost to the surrounding businesses, increases surrounding property values—both commercial and residential, and bring new businesses to the corridor- all resulting in economic development to the area. Moreover, the policy's impact on land/property values and housing sale prices would result in generating more revenue from property taxes to be used into improvement of transit and public services and promotion of transit usage as well (*Yu et al., 2018*).

While the evaluation of the economic effects of Complete Streets is very limited in the literature. In terms of the methodology, the hedonic price approach has been mostly used to explore the effects of various community designs on economic development and housing prices (*Dong, 2015; Li et al., 2015*). Also, propensity score matching (PSM) is used to address the selection bias within a natural experiment design and distribute observed confounding equally between the intervention and control groups (*Steiner and Cook, 2013; Austin, 2011; Nasri et al., 2018*). Many studied have shown that the Complete Streets policy influenced an increased housing prices when, in fact, a series of community characteristics or price trends are causing both the higher house prices and the adoption of a Complete Streets policy. For instance, along a complete street project done in Lancaster, California, employment grew by 64 percent between 2008 and 2011, while employment grew by less than 3 percent citywide (*Perk et al., 2015; Anderson et al., 2015*). Perk et al. (2015) investigated the effects of complete streets on economic development, specifically on increased property values, tax collections, and increased business activities (such as new businesses, retail sales, and new jobs creation), and suggested that, despite the overall economic downturn, the Complete Streets promoted and maintained local economic activities, often outperforming other nearby areas and the cities. A more recent study by Yu et al. (2018) explored the before-and-after property value appreciation as a result of implementation of the Complete Streets policy during the housing market boom (from 2000 to 2007), using a natural experiment approach and propensity score matching in Orlando, Florida. They suggested that on average, single-family homes exposed to Complete Streets had 8.2% and 4.3% higher home value appreciation and home value resilience than their counterparts in the adjacent non-exposed control area during housing market boom.

Moreover, several studies focused on evaluating/measuring the economic effects of some of complete streets design elements, both directly and indirectly, without explicitly referring to the term itself. Studies that assess the impact of transit-oriented development (TOD) on housing prices suggest that the effect is mediated by other design elements. Bowes and Ihlanfeldt (2001) find that transit stations built with parking lots (i.e., park and ride) decrease residential property prices about 1.4% for homes located in within one-half to a mile of the station (relative to stations without lots, i.e., walk and ride). Similarly, Kahn (2007) finds that walk-and-ride stations show a 3% increase in home prices while park-and-ride stations show no significant effect.

Overall, the Complete Streets projects can potentially increase property values and job growth along the respective corridors, and much of the previous research confirms these improvements as a result of many complete street projects across the country, despite a few studies suggesting these effects are minor and not statistically significant, if any (*Vandegrift and Zanoni, 2018*).

Environmental impacts

According to the 2008 and 2017 National Household Travel Survey (NHTS), around 50 percent of all trips in the United States are three miles or less, and 28 percent of all trips are one mile or less—distances easily accessible by walking, biking, or taking a bus or train. Yet, a high percentage of the shortest trips are now made by automobile (NHTS 2008 & 2017). In part, this is because of incomplete streets that make it unsafe or unpleasant for other modes of travel. Complete streets can potentially convert many of these short automobile trips to multimodal travel, which would save millions of gallons of gasoline each year and would eventually improve the environmental air quality substantially (*Burden and Litman, 2011).* Despite many studies which highlighted and emphasized on the potential role complete streets policy can play to improve environmental air quality and reduce emissions, the potential environmental impacts of complete streets policy are not extensively analyzed and quantified in the previous literature. A few studies tried to measure the environmental impacts of the policy and reported mix findings regarding the impact of complete streets policy's implementation on air quality and emission reduction. For instance, Shu et al. (2014) investigated the effect of a complete street retrofit in Santa Monica, California, in terms of the street use by different transportation modes and the on-roadway air quality and found that the air quality improved and the number of pedestrians increased by 37% compared to pre-retrofit conditions while the number of cyclists remained approximately the same. On the other hand, Peiravian and Derrible (2014) conducted research to quantify vehicle emission impacts of Complete Streets and found that if a project design allows for less space for vehicles, depending on the characteristics of the corridor, congestion can increase along with emissions. These mixed findings indicate the research gap in this area and that there is a need to investigate and measure the significance and magnitude of the environmental impacts of complete streets policy.

Health impacts

Another expected benefit of complete streets policy and other pedestrian-friendly policies as indicated in many previous studies and policy guidebooks is to provide an opportunity of developing a healthier, more active lifestyle for the individuals with an improved access to safer streets in a long term. When streets are transformed into safe, comfortable, and convenient places for people walking, bicycling, riding public transportation, and driving, people of all ages and abilities have more opportunities to be active when they go from place to place, or when they exercise for recreation (*National Complete Streets Coalition, 2013*). Advocates of complete streets policy endorse it for its potential to support physical activity, obesity prevention, social equity, youth and elderly mobility, less automobile dependency and sprawl, open space preservation, and transit-oriented development (*Brown et al., 2015*). The Centers for Disease Control and other public health organizations recommend Complete Streets policy adoption as an important element in the fight against the obesity epidemic (*Carr, 2011; LaPlante and McCann, 2011*).

In the previous literature, the health impact of complete street has mostly been evaluated through its impact on the level of physical activity (*Sanders et al., 2011; Carr, 2011; Peiravian and Derrible, 2014; Yamarone, 2012; Kingsbury et al., 2011; Schlossberg et al., 2015; Moreland-Russell et al., 2013*). For example, Schlossberg et al. (2015) showed that after a "road diet" (where a roadway is modified to reduce the amount of space devoted to automobiles and allow more space for bike lanes and pedestrians) of a minor arterial roadway in Seattle, Washington, the volume of cyclists increased by 35% from 2007 to 2010. Another case study reported that introducing bike lanes to a busy street in Long Beach, California, nearly doubled the rate of cycling (*Schlossberg et al., 2015*). Brown et al. (2015) assessed the effects on physical activity and weight among participants in a complete street intervention in Salt Lake City, Utah and found that use of transit associated with a complete street intervention yields beneficial physical activity and BMI outcomes for those who begin to use transit. Similarly, individuals who stopped using transit gained sedentary activity and BMI and lost MVPA minutes. Later, Jensen et al. (2017) used a decision tree technique to understand how perceived walkability within complete streets is related to active transportation and demonstrated that residents living closer to the complete street corridors are more likely to have active transportation trips compared to more distant residents. A review of mostly cross-sectional studies worldwide found 9 studies that showed that transit use was associated with between 8 and 33 minutes of physical activity per day of transit use; 4 of these were limited to self-reported physical activity. In the United States, according to the National Household Travel Survey, walking to and from transit is increasingly popular, with a 28% increase from 2001 to 2009. Transit walking is especially likely in cities with rail systems, and rail riders have been found to walk more than either car drivers or bus riders. Also, past studies indicated that nearby residents of the complete streets projects used more transit, and more people were counted at transit stops than before the construction and implementation of the policy (*Brown et al., 2015; Werner et al., 2016*). They suggested that overall, the complete street renovations resulted in an increased use of the streets by pedestrians, especially for the section of the street that was less busy before the renovation (*Jensen et al., 2017; Shu et al., 2014*).

Despite many benefits of complete streets and other pedestrian-friendly policies discussed above, a few studies reported opposite findings for the true impacts of the policy. For instance, California's complete streets renovation project did not follow with an increase in the number of cyclists, but a 37% increase in pedestrians (*Shu et al., 2014*). These mixed findings, however, are difficult to interpret because the potential shifting of transportation practices over time was not controlled in many of these previous studies (*Jensen et al., 2017*). Additional research is needed to understand the mixed findings and better examine/evaluate the various impacts with additional data and more advanced methods.

1.6. Research Gaps in Policy Regulation and Implementation, Evaluation, and Performance of the Complete Streets Policy

Much of the existing literature on Complete Streets focuses on policy and design implications, implementation guidelines, policy objectives/goals and elements, and safety improvements as a result of Complete Streets for all user groups including auto and transit riders as well as pedestrian/bicyclists and emphasized the strength of this policy content and used case examples of various projects across the country to illustrate the state-of-practice in complete streets implementation (*McCann and Rynne, 2010; McCann, 2013; Ranahan et al., 2014*). To date, little research has been done to confirm and quantify the various benefits of complete streets such as mode shifts towards sustainable modes of transportation, property value increase, economic development, and environmental impacts (*Perk et al, 2015*). Although research on the impacts of transit-oriented and pedestrian-friendly design on travel behavior is extensive, there is very limited research focused specifically on modeling the travel behavior changes as a result of complete street interventions using statewide travel demand models and other approaches. Future research can address this issue and examine how complete streets policy (both policy presence and comprehensiveness of content) may be related to transportation performance issues such as pedestrian or bicycle fatalities, investment in public transit, modal shifts, and vehicle miles traveled.

Measuring the "completeness" of a complete street is significantly important for policy makers, stakeholders, and city planners. However, most of the previously developed frameworks for this purpose are unsuitable for evaluating complete streets because, with few exceptions, they guide street design by specifying the design elements for inclusion on the street. Secondly, the performance of a street can be assessed according to transportation, environmental, and place criteria, and compared to the target performance levels specified by the street's classification. As there are many different impacts to consider on a street, additional work is required to define the priorities and performance objectives for different types of streets (*Hui et al., 2017*).

Babb and Watkins (2016) compared complete streets programs of different types from different levels of government across the United States revealed a dramatic gap in complete streets programs regarding transit and calls for future attention and guidance of agencies adopting complete streets programs. They highlighted the disparity between the treatment of transit in complete streets policies compared with other modes and indicated that many implemented programs across the country did not even list transit vehicles, passengers, or operators as part of "all users" in their plans and implementation processes.

Ranahan et al. (2014) interviewed representatives from 13 municipalities with active Complete Streets programs and found that none are comprehensively gathering data that measure the impact of their Complete Streets projects. The lack of required data for evaluation and quantification of the various impacts of complete streets policy remains a big challenge for researchers and policy makers.

A few studies provided a list of performance measures such as safety, mobility, delivery, stewardship, and service to evaluate the success of complete street policies (CalTrans, 2008). However, the majority of these studies are heavily focused on motorized transportation and the measures concerned with the safety and mobility of non-motorized travelers, and environmental quality are somehow overlooked and neglected (Sanders et al., 2011). Sanders et al., 2011 proposes a *Complete, Green Streets Performance Measure Framework* to fill in this gap for pedestrian and bicycle safety and mobility and contributes to evaluating environmental stewardship.

The lack of work on the impacts of complete streets may also reflect a shortage of the data required to do such analysis. However, there is a large body of research offering insight into the various inputs of the complete streets design's framework individually. It thus seems logical that taken together, the effects of these individual parts can shape the outcomes of the concept (Ferguson et al., 2015). Little research has been done that directly links complete streets as a package to such outcomes. Instead, researchers have assessed the expected outcomes and benefits from a body of evidence that considers the outcomes of complete street elements individually. The present research tries to fill in this gap in the previous literature by investigating the effect of complete streets policy on travel behavior and specifically on mode choice. Past research has suggested that perceived traffic safety, crime safety, land use mix, pleasantness of walking (e.g., lots of shade from trees on paths, sidewalks in good condition), proximity of utilitarian destinations—such as local shops, services, and transit stops—and attractiveness significantly influence the amount of walking for both traveling and recreational purposes (*Van Cauwenberg et al., 2011; Saelens and Handy, 2008; Duncan et al., 2005; Jensen et al., 2018; Sugiyama et al., 2012*).

CHAPTER 2 THE STATED CHOICE EXPERIMENT (SCE) AND BEHAVIORAL MODEL ESTIMATION

The main idea underlying the Complete Streets (CS) concept is that the implementation of a certain urbanistic layout as well as specific traffic measures –such as dedicated lanes, paved shoulders, speed reduction, etc. make travel by non-motorized means safer. Consequently, safer roads for cyclists and pedestrians helps in integrating different modes of transportation. However, this urban disposition also has its controversies, basically, longer travel times and costs for private cars and possibly for public transportation. In fact, space for motorized modes is reduced and drivers need to interact with pedestrians, bikers and public transportation users. How these interactions and street layout affect people's travel behavior in choosing non-motorized modes is the purpose of this survey. We designed a Stated Choice Experiment (SCE) in which respondents are asked to evaluate different alternatives (including walking and biking) characterized by attributes related to trips made in a CS context. The aim is to elicit the preference of individuals towards motorized and non-motorized modes. These preferences will be materialized in discrete choice models that will allow the numerical evaluation of the influence of certain aspects of these means of transportation, as well as the sensitivity of individuals to changes in them.

Based on our discussions with MDOT SHA staff members, we have decided that the suitable approach for collecting data is from a Stated Preference (SP) survey that is designed to study non-motorized trips for different CS configurations. The motivation behind this decision was that the data we collect from this survey would be applicable to CS projects across the state rather than to a specific project as it would require selecting a specific project which was not available at the time of this study. A SCE is especially appropriate when analysts are required to elicit individuals' preferences in hypothetical contexts. For example, a researcher might want to explore the inclination towards an alternative or service that does not exist yet — like a new metro line to be built or the introduction of a new fare scheme. The case at hand is similar since we are asking users to make choices in a hypothetical CS setting.

In the following sections, we proceed with the description of the survey explicitly designed to study individual's behavior and preferences towards CS. We also outline the questionnaire and show a descriptive analysis of the data collected. Then, after a brief technical section we proceed with a description of the results.

2.1. Survey design

Technical aspects

The purpose of stated choice experiments is to determine the influence of the characteristics of a set of alternatives on the probability of choosing them. A study of this type normally consists of an individual making a choice in a hypothetical scenario in which different levels of attributes related to the set of alternatives are presented. It is common practice to make the respondent face a number of these choice situations and pool the responses. The reasons are the difficulty (economic or technical) of counting with a high number of individuals, but also, counting with *panel* observations helps in behavior identification.

Since users' choices are dependent on the attribute levels shown in the scenarios, these become the main decision element and, therefore, their careful predefinition is very important. Frequently, the levels are obtained from; i) some other previous experiment; ii) real information obtained from the market; iii) existing literature. However, in most cases, the best approach is to combine information that comes from all these sources and apply modifications to fit the case at hand and to overcome potential problems such as lexicographic biases.

Conceptually, a design consists of a series of values to be displayed in each scenario. The fundamental question is how to distribute them throughout all the situations of choice that will appear in the questionnaire. This is not a trivial matter, and requires a great deal of preliminary work, as the number of attributes, their levels, and the number of alternatives exponentially increase the combinations needed for a correct design. In addition, other complexities such as the type of design and the underlying discrete choice model also come into play. Regarding the former, there are three main approaches: *Full factorial*, *Orthogonal*, and *Efficient* designs. Full factorial designs are infeasible, except in the case of a small number of alternatives, attributes, and attribute levels, as this type of designs considers all possible attribute combinations. In the case, for example, of three attributes with 2, 2, and 3 levels, there would exist 12 choice situations, as shown in **Table 3** (each column represents a variable, while each row represents a choice situation).

Table 3: Example of full factorial design.

Scenario	A	B	C
1	-1	-1	-1
2	-1	-1	0
3	-1	-1	1
4	-1	1	-1
5	-1	1	0
6	-1	1	1
7	1	-1	-1
8	1	-1	0
9	1	-1	1
10	1	1	-1
11	1	1	0
12	1	1	1

The total number of choice situations in a full factorial design can increase rapidly, e.g., for two alternatives with 3 attributes and with 4 levels each, the combinations are $(4 \times 4 \times 4) \times (4 \times 4 \times 4) = 4096$. Therefore, the practical application of the full factorial is almost non-existent.

Orthogonal designs, widely used for many years, are another option to populate choice situations. However, there are arguments against its use since orthogonality does not meet some desired properties of the econometric models estimated afterwards. Orthogonality means, in statistical terms, that the attribute levels of the designed structure are not correlated. While this is a very desirable property in linear models, discrete choice models (DCM) are non-linear and therefore it is less relevant. In fact, what is important is the correlation of the differences in attributes. Therefore, Efficient designs are positioned in contrast to orthogonal ones. This methodology tries to minimize the standard error of the estimated parameters using prior information about them (estimations available in the literature, or in previous studies, for instance). These standard errors can be predicted by determining the asymptotic variance–covariance (AVC) matrix based on the underlying experiment and information about the parameter estimates obtained beforehand, technically called priors.

Various measures are used to assess the efficiency of a design. They are usually expressed as an error; thus, the objective is to minimize the error. The most used type is the D-error, which is derived from the determinant of the AVC matrix. Practically, it is very difficult to find a design with the lowest D-error, and the researcher is usually satisfied if it is small enough. For the purpose of finding a design with minimum error, we used the Modified Federov algorithm ([32]), illustrated in **Figure 2**.

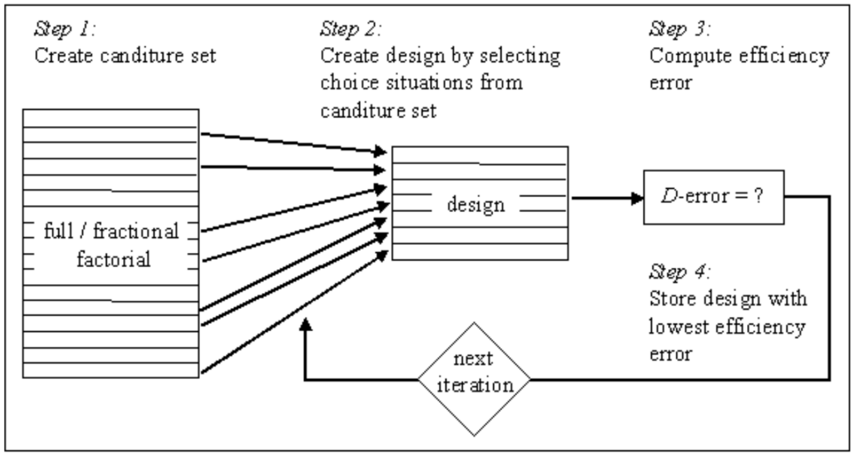

Figure 2 Modified Federov algorithm. Source: [24].

The algorithm starts by selecting a candidate design that can be the full factorial or a fractional factorial. Then, a new design is created by selecting choice situations from the candidate set and the efficiency measure is computed. If it is lower than the efficiency measure of the candidate, the new design is kept as the most efficient so far, and continues with the next iteration, repeating the process. The algorithm terminates if all possible combinations of choice situations have been evaluated (which in general is an enormous number of situations) or after a pre-defined number of iterations.

One last consideration refers to the number of choice situations. It does not seem to have an important impact on the efficiency of the design if the number of choice situations is not smaller than $K/(J-1)$. Obviously, the more scenarios are presented to the respondent, the more data available. However, too many choice situations may lead to another kind of problem such as inaccurate or incoherent answers due to user fatigue. Therefore, it is important to find a balance between the data amount and efficiency, and fidelity in responses. In general, the number of choice tasks depends on the intuition of the researcher as well as how many tasks the user can handle.

For this study, we opted for the orthogonal rather than an efficient design because of the difficulty of finding reliable priors for our case, and after performing tests with some. We defined three different designs for *short* (1 mile)*, medium* (3 miles) and *long* (5 miles) trips. Note that we consider trips up to 5 miles long as we are interested in modeling choice of non-motorized modes compared to driving. The reasoning behind this decision is discussed in section 2.3. Each of them contained 24 scenarios divided into 4 blocks randomly assign to the respondents, as described in the following section. We ran the Modified Federov algorithm with 30,000 iterations using the software *Ngene* ([24]). Figure 3 shows the output of the software, to be mapped into the questionnaire.

The decision of performing three designs (and, therefore, three *subsurveys*) was a relevant one, and proved to be a good choice. On the first hand, we believed that a residual number of users would select non-motorized modes on long trips, especially the *Walk* mode, which would have invalidated any trade-off analysis among modes. On the other hand, we also thought that the impact of the trip characteristics (travel time, specially) would be much different for short 1-mile trips than for 5-mile trips; again, especially for the *Walk* alternative. In other words, 8 minutes of walking may be comparable to 4 minutes of driving (*ceteris paribus* other aspects of the trip), but 50 minutes compared to 20 minutes, not so much. The same applies, analogously, to the rest of the trip characteristics considered, which are detailed in the following section.

MNL efficiency measures								
D error	0.121123							
A error	2.524287							
B estimate	100							
S estimate	0							
Prior	b1	b2	b3	b4	b5	b6	b7	
Fixed prior value	0	0	0	0	0	0	0	
Sp estimates	Undefined	Undefined	Undefined	Undefined	Undefined	Undefined	Undefined	
Sp t-ratios	0	0	0	0	0	0	0	
Design								
Choice situation	car.tt_car	car.tc_car	car.pc_car	bike.tt_bike	bike.lts_bike	walk.tt_walk	walk.lts_walk	Block
1	4	0.5	1	6	1	9	2	3
2	4	0.5	3	5	2	8	1	1
3	4	0.5	0	4	1	10	1	4
4	4	0.5	1	6	3	10	2	2
5	6	0.5	1	6	4	14	4	2
6	6	0.5	0	6	1	12	1	4
7	8	0.5	0	10	4	20	3	4
8	8	0.5	3	12	3	20	3	2
9	6	0.5	1	9	1	14	2	1
10	8	0.5	1	12	4	18	4	3
11	8	0.5	3	8	1	18	1	2
12	8	0.5	3	10	2	18	1	3
13	6	0.5	0	9	3	12	2	3
14	8	0.5	0	8	2	20	2	1
15	8	0.5	3	12	2	16	2	4
16	4	0.5	3	5	3	10	3	1
17	4	0.5	1	5	4	9	3	3
18	6	0.5	0	9	1	15	2	1
19	4	0.5	3	4	3	8	4	3
20	6	0.5	0	8	4	12	4	1
21	6	0.5	3	6	3	15	4	4
22	4	0.5	1	6	2	8	3	4
23	4	0.5	1	4	4	9	3	2
24	8	0.5	0	10	2	16	3	2

Figure 3 Output of Federov algorithm to be mapped into survey questionnaire.

Attributes, levels, and alternatives.
The selection of the attributes to be considered in the survey design was based on a comprehensive literature review related to travel behavior on non-motorized alternatives, as well as on previous research experience and knowledge of the field. Four key attributes were retained to define the choice experiment scenarios: *travel time, travel cost, parking cost, and Level of Traffic Stress* (LTS). It is worth mentioning that other trip or mode characteristics were considered (e.g., pollution, landscape) but finally discarded. They presented difficulties in their definition that would hinder the subsequent estimation of the impact of the attributes in the choices and could potentially dilute the effect the major variables of interest, i.e., those related to Complete Streets (LTS). LTS can be considered as a composite variable which includes impacts of attributes such as safety and built environment which are important factors in CS context.

Travel time
Since presenting realistic trips was a priority, a segment of Route 1 was taken as the basis for calculating possible travel times by car. Namely, Google Maps was used to explore travel times from College Park to destinations 1, 3 and 5 miles away, under normal traffic conditions. With these references, a time range was built to be used in the design. It follows naturally that travel times by bicycle and walking should be proportional to those of car. However, such a design is expected to generate fully correlated values that would invalidate any further estimates. Therefore, for each car trip time, a range needs to be defined for the cycling and walking trip time. To take this into consideration in practical terms, it is necessary to adjust the algorithm that performs the statistical design to first select a combination of car travel times and then choose the travel times for non-motorized alternatives accordingly, all maximizing the efficiency. Table 4 shows the travel times defined for this design.

Table 4. Travel times for 1, 3, 5 miles trips

Destination	Length	Actual travel time car	Survey travel time car	Survey travel time bike	Survey travel time walk
Graduate Gardens	1	5	[4,6,8]	4: [4,5,6] 6: [6,8,9] 8: [8,10,12]	4: [8,9,10] 6: [12,14,15] 8: [16,18,20]
Greenbelt	3	9	[10,14,18]	10: [10,13,15] 14: [14,18,21] 18: [18,23,27]	10: [20,23,25] 14: [28,32,35] 18: [36,41,45]
Beltsville	5	12	[13,18,23]	13: [13,17,21] 18: [18,23,27] 23: [23,29,35]	13: [26,30,33] 18: [36,41,45] 23: [45,52,58]

As can be seen, bike travel times may be, in the best scenario, equal to car travel times, thanks to CS streets elements such as dedicated lanes or safer conditions that make the cyclists ride faster. In the worst case, they are up to 50% longer. Although it may seem that a car is more than a 50% faster than a bike, again, this hypothetical trip happens in a CS context, in which vehicle traffic calming measures or other elements of the same nature that slow down automobiles apply. Regarding walking times, they at least double car travel times in all cases, and they might be as high as 150% longer.

Travel cost

Consistent with the assumptions in mode choice modeling, in this study travel cost includes fuel cost only. Travel cost was calculated as cost per mile[3] times trip miles. Although we considered to differentiate among types of vehicles –bigger vehicles usually consume more implying higher costs per mile– we finally discarded this option because the trips considered were so short that such difference would have been negligible. On the other hand, Bike and Walk travel costs were defined as zero. We evaluated to include maintenance or insurance costs but, again, computing these costs per mile, for trips up to five miles, have resulted in an insignificant amount.

In a similar vein, we decided to slightly increase the travel cost by car to highlight the difference between this mode and the non-motorized ones. Discrete choice models are all about differences in the perception of the utility that an alternative provides. In this case, if the travel cost had not been noticeably superior, users would not have given it any importance. However, it is fair to say that even in this case, this attribute was not statistically significant in any of the models estimated.

Parking cost

For the sake of simplicity, and without detriment to the results of this project, we decided to simply include fixed parking costs on three levels of variation: $0, $1, and $3.

Level of Traffic Stress

Level of Traffic Stress is usually measured on a rating scale for a particular road segment based on the traffic stress imposed to users. Levels of traffic stress for bicyclists are defined on a scale ranging from 1 to 4 as follows (Mekiura et al., 2012) (Figure 4). We did not use MDOT SHA's

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[3] Fuel costs are based on average prices for the 12 months ending May 31, 2019, as reported by AAA Gas Prices at www.GasPrices.AAA.com. During this period, regular grade gasoline averaged $2.679 per gallon.

https://exchange.aaa.com/automotive/driving-costs/#.XwRMNudS9hE

https://exchange.aaa.com/automotive/driving-costs/#.Xw2l2edS-Ht

https://exchange.aaa.com/wp-content/uploads/2019/09/AAA-Your-Driving-Costs-2019.pdf

LTS level definitions 0 to 5, since lowest value zero (trails, separated bike lanes) and highest values 5 (freeways where bikes and pedestrians are not allowed) were not relevant in our comparative experiment context. We decided to use LTS levels from 1-4 in the survey questionnaire according to the following definitions.

- **LTS 1**: Represents little traffic stress and requires little attention, so is suitable for all cyclists. This includes children that are trained to safely cross intersections alone and supervising riding parents. Traffic speeds are low and there is no more than one lane in each direction. Intersections are easily crossed by children and adults. Typical locations include residential local streets and separated bike paths/cycle tracks.
- **LTS 2**: Represents little traffic stress but requires more attention than young children would be expected to deal with, so is suitable for teen and adult cyclists with adequate bike handling skills. Traffic speeds are slightly higher, but speed differentials are still low, and roadways can be up to three lanes wide for both directions. Intersections are not difficult to cross for most teenagers and adults. Typical locations include collector-level streets with bike lanes or a central business district.
- **LTS 3**: Represents moderate stress and is suitable for most observant adult cyclists. Traffic speeds are moderate but can be on roadways up to five lanes wide in both directions. Intersections are still perceived to be safe by most adults. Typical locations include low-speed arterials with bike lanes or moderate speed non-multilane roadways.
- **LTS 4**: Represents high stress and suitable for experienced and skilled cyclists. Traffic speeds are moderate to high and can be on roadways from two to over five lanes wide for both directions. Intersections can be complex, wide, and or high volume/speed that can be perceived as unsafe by adults and are difficult to cross. Typical locations include high-speed or multilane roadways with narrow or no bike lanes.

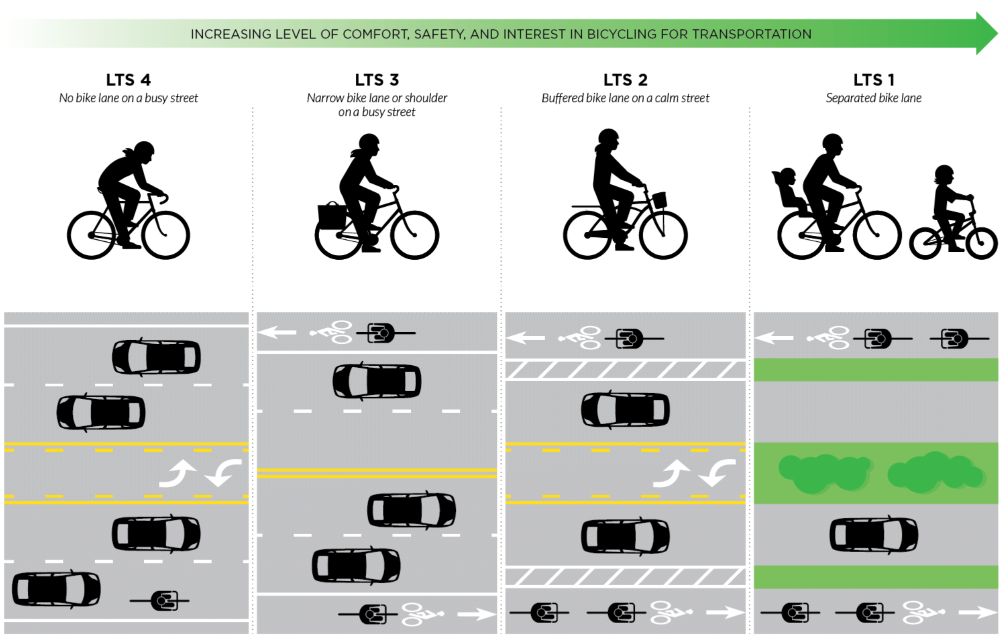

Figure 4. Level of Traffic stress for bicyclists

Similarly, it was necessary to analyze the effect that better infrastructure for pedestrians has on users' choice to walk. In this regard, we found that the city of Boulder Colorado performed a *Low Stress Walk and Bike Network Plan*[4] that performs a LTS classification for pedestrians that is conceptually in line with that of bike (see Figure 5).

Figure 5. Level of Traffic stress for pedestrians

Now, since users would be choosing among the three alternatives (Car, Bike, Walk) in a hypothetical situation occurring in the same road segment, we believed that it would be logical to assume that cyclists and pedestrians should experience similar LTS. In other words, a road prepared for cyclists (LTS 1) is also likely to be safe, to some extent, for pedestrians. Following this rationale, we only allowed for a variation of 1 level, up or down, of the LTS for the Walk alternative, with respect to the LTS for the Bike alternative. For instance, if LTS Bike was defined as 2 in the design of a scenario, the LTS Walk could only be 1, 2, or 3, but never 4. Finally, we followed a color scheme to inform the user of the LTS levels, as shown in the questionnaire section.

2.2. Questionnaire

As mentioned above, the statistical design described takes the form of several scenarios that are presented to the users to make their choices. However, this is only one of the sections comprising the questionnaire. There are others that are intended to collect information of a different nature

[4] https://www-static.bouldercolorado.gov/docs/Low Stress_Walk_and_Bike_Network_Plan_(modified_4.1.20)-1 202004011307.pdf?_ga=2.129065615.2045802425.1594119846-832671723.1594119846

that can help identify the behavior underlying the choices. In this case, the following sections were included in the questionnaire (please see Appendix A1 for the complete questionnaire):

1. **Purpose and Consent.** Short introduction to the study that explains the concept of CS, the scope of the survey, and the privacy rules. Finally, consent to participate is asked, plus confirmation of being over 18.
2. **Last trip.** Information on the last short trip made by the user is asked, including its length and duration, the possibility of having used non-motorized means to complete the trip, the safety of the road, and the existence of CS elements.
3. **Control questions for experiment logic.** Since mode choice may differ significantly depending on the purpose of the trip, the scenarios presented in the SCE refer to one of the following trip purposes: *Work, School, Shop, Social or Recreational*, and *Other*. In order to make these scenarios more realistic, we ask the user if s/he is retired or have any condition that prevents her/him from working, if s/he has school-age children, and if s/he is a student. Depending on the responses, some purposes are discarded from the random assignment made on the SCE –for instance, W*ork* does not appear if s/he is retired.
4. **Information about CS.** Information on Complete Streets, including external links, real pictures, and Figures 6 (a) and (b) on LTS are presented. In this section we also asked if the information provided is enough to understand what a Complete Street is and its purpose and directed respondents to sources to learn more if the CS concept is not understood clearly.

Information about Complete Streets

We now provide you the following public information about *Complete Streets*; what they are and what are their purposes and advantages over regular street designs.

Please take a few minutes to read the materials. If you want to learn more, we invite you to visit the following links and read the information provided by the U.S. Department of Transportation, and the Maryland Department of Transportation

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Complete Streets

Complete Streets are streets designed and operated to enable safe use and support mobility for all users, regardless of whether they are travelling as drivers, pedestrians, bicyclists, or public transportation riders. The concept of Complete Streets encompasses many approaches to planning, designing, and operating roadways with all users in mind to make the transportation network safer and more efficient.
These designs may address a wide range of elements, such as sidewalks, bicycle lanes, bus lanes, public transportation stops, crossing opportunities, median islands, accessible pedestrian signals, curb extensions, modified vehicle travel lanes, streetscape, and landscape treatments.

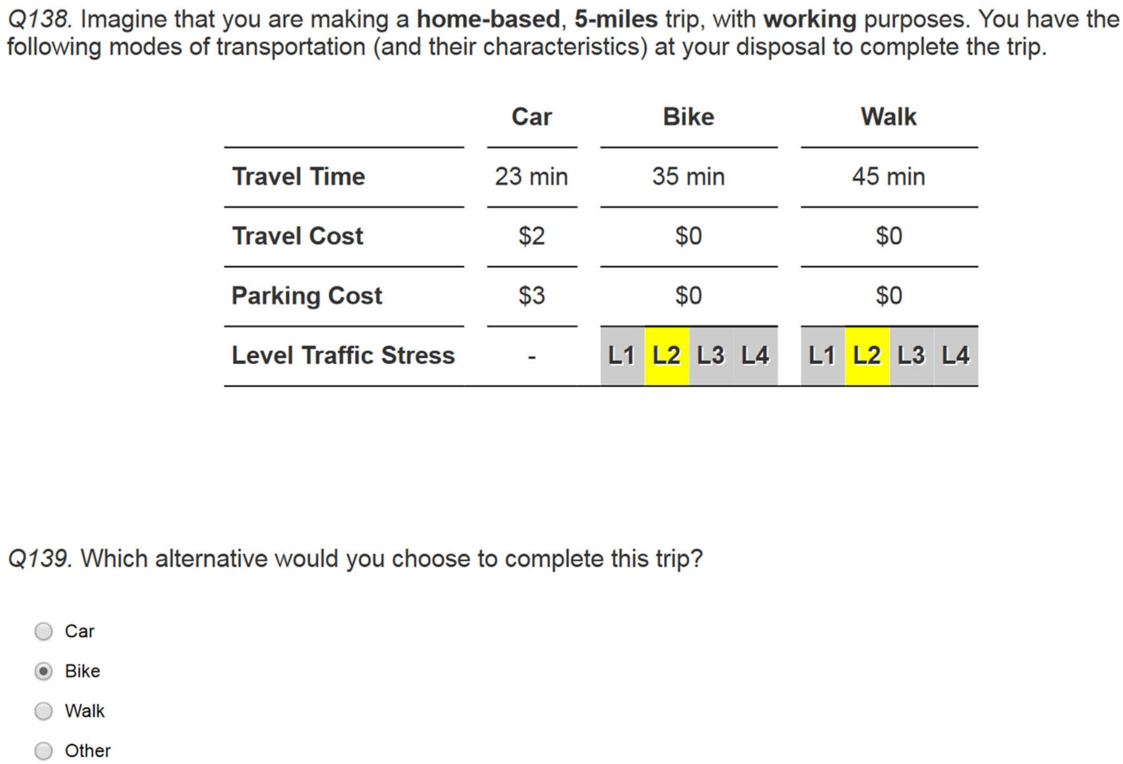
(a)

The State of Maryland adopted new legislation in 2018 to promote the adoption of Complete Streets policies at the state and local level. The definition of policy and guidelines for underserved and under invested communities is part of the short-term schedule of the Maryland Department of Transportation.

(b)

Figure 6. CS information provided before SCE

5. **Pre-scenarios information.** A descriptive text where the SCE are introduced.
6. **Stated Choice Experiment.** The SCE is dynamic, following certain rules to assign the user to the proper logic branch. First, when the respondent enters the survey, it is randomly decided if the trips of the scenarios s/he will face in the SCE are home-based or non-home based. Likewise, a trip length (1, 3, or 5 miles) is also automatically designated. Secondly, six purposes are randomly generated as well, considering the filters set on point 3 of this list. Then, one of the 4 blocks of 6 scenarios created in the statistical design is shown to the respondent. Each of them maps the purpose, the home/non-home-based indicator, the length, and the attribute values. Figure 7 shows an example of one of these hypothetical situations.


Q138. Imagine that you are making a **home-based**, **5-miles** trip, with **working** purposes. You have the following modes of transportation (and their characteristics) at your disposal to complete the trip.

	Car	Bike	Walk
Travel Time	23 min	35 min	45 min
Travel Cost	$2	$0	$0
Parking Cost	$3	$0	$0
Level Traffic Stress	-	L1 L2 L3 L4	L1 L2 L3 L4

Q139. Which alternative would you choose to complete this trip?

- Car
- Bike
- Walk
- Other

Figure 7. Example of a home-based, 5-miles trip with working purposes

7. **Attitudes towards Complete Streets.** The first question in this section presents a list of CS elements and ask the user to state how important each of them is for her/him. The second question presents a list of statements to show the level of agreement. These statements are related to Environmental Concern and Urban Design concepts.
8. **Bicycle ownership.** Questions to gather information on bike ownership and usage.
9. **Car-sharing usage.** Questions to gather information on the use of ride hailing services (see Appendix A1).
10. **Socioeconomic information.** Individual and household socioeconomic information such as age, gender, income, vehicle ownership, etc.

2.3. Data analysis

2017 National Household Travel Survey

To check for consistency with the rationale of our survey, and to set a baseline for comparison of our results, we analyzed non-motorized behavioral patterns using real/experienced data extracted from the 2017 National Household Travel Survey add-on data relative to the State of Maryland. We focus our analyses on modal share, modal share by trip purpose, and modal share by trip length.

As expected, most of the trips were made by Car/SUV/Truck and Van; Walk and Bike were the selected mode of travel for respectively 8.5% and 0.6% of the overall trips made in the State of Maryland (Figure 4.1). Most of the trips made by Walk were less than one mile long (85.5%), while the Bike trips were more equally distributed across the distance categories considered (Figure 8).

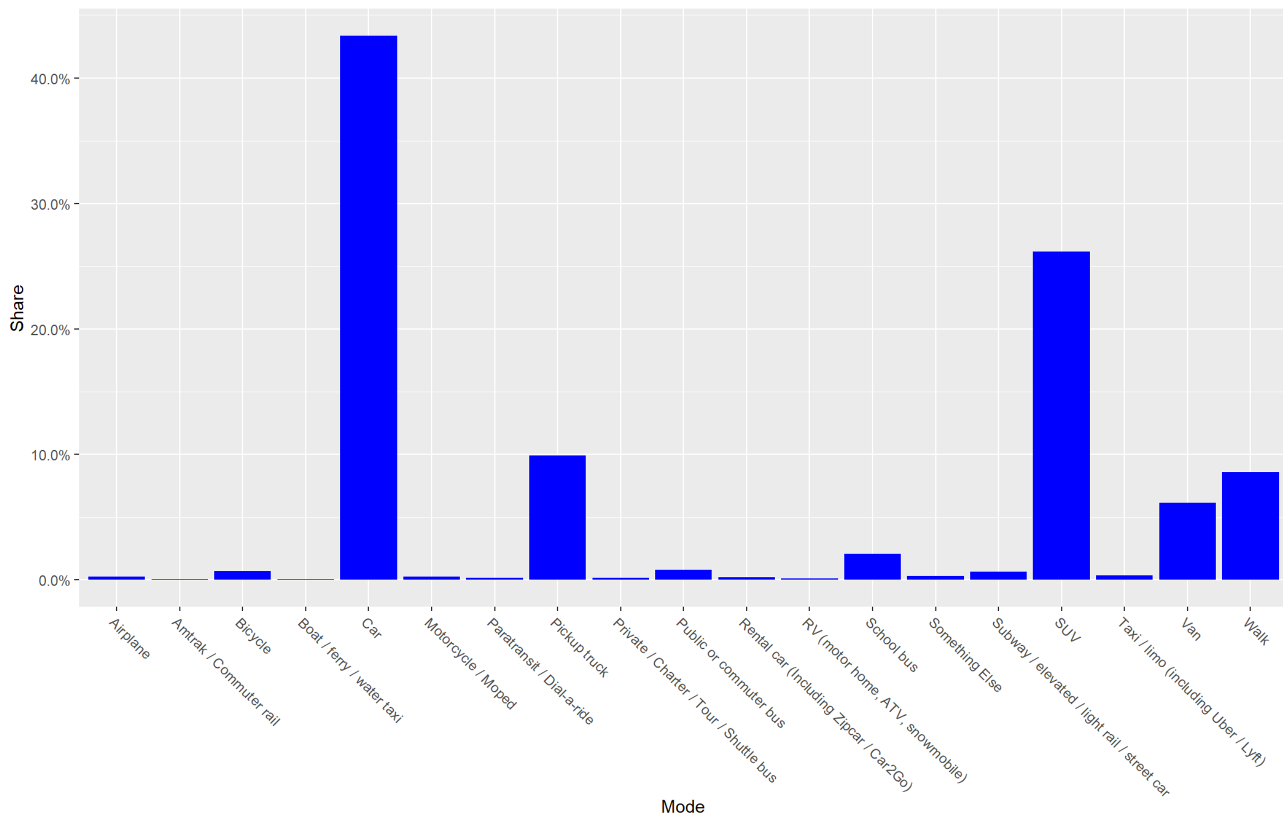


Figure 8. Mode choice shares in Maryland

Table 5 and Figure 9 show that half of the home-based trips with working purpose at the destination were made by *Car.* The same is observed for shopping purposes. Social and Other purposes had lower percentages, around 40%. Regarding non-home-based trips, car is still the most utilized mean (43%) of travel. Walk shows higher percentages of use for home-based social or recreational purposes, with almost 20% share. The use of *Bicycle* is marginal for all the purposes considered.

Table 5. Mode share by trip purpose

Mode	HBW	HBSHOP	HBSOCREC	HBO	NHB
Walk	2.21%	4.18%	19.76%	12.10%	6.63%
Bicycle	0.71%	0.37%	1.75%	0.79%	0.32%
Car	49.96%	46.19%	40.71%	38.49%	43.18%
SUV	22.21%	29.28%	23.81%	24.75%	27.76%
Van	5.38%	6.09%	4.47%	7.33%	6.54%
Pickup truck	13.68%	12.13%	6.98%	6.68%	10.39%
Motorcycle / Moped	0.40%	0.19%	0.35%	0.09%	0.28%
RV (motor home, ATV, snowmobile)	0.00%	0.00%	0.28%	0.09%	0.06%
School bus	0.32%	0.00%	0.00%	6.91%	1.67%
Public or commuter bus	1.42%	0.56%	0.42%	1.35%	0.47%
Paratransit / Dial-a-ride	0.08%	0.14%	0.00%	0.33%	0.09%
Private / Charter / Tour / Shuttle bus	0.16%	0.05%	0.35%	0.09%	0.16%
Amtrak / Commuter rail	0.32%	0.00%	0.00%	0.05%	0.03%
Subway / elevated / light rail / streetcar	2.61%	0.19%	0.42%	0.23%	0.47%
Taxi / limo (including Uber / Lyft)	0.08%	0.33%	0.28%	0.37%	0.41%
Rental car (Including Zipcar / Car2Go)	0.00%	0.09%	0.07%	0.05%	0.47%
Airplane	0.00%	0.00%	0.00%	0.00%	0.73%
Boat / ferry / water taxi	0.00%	0.00%	0.00%	0.05%	0.09%
Something Else	0.47%	0.23%	0.35%	0.23%	0.22%

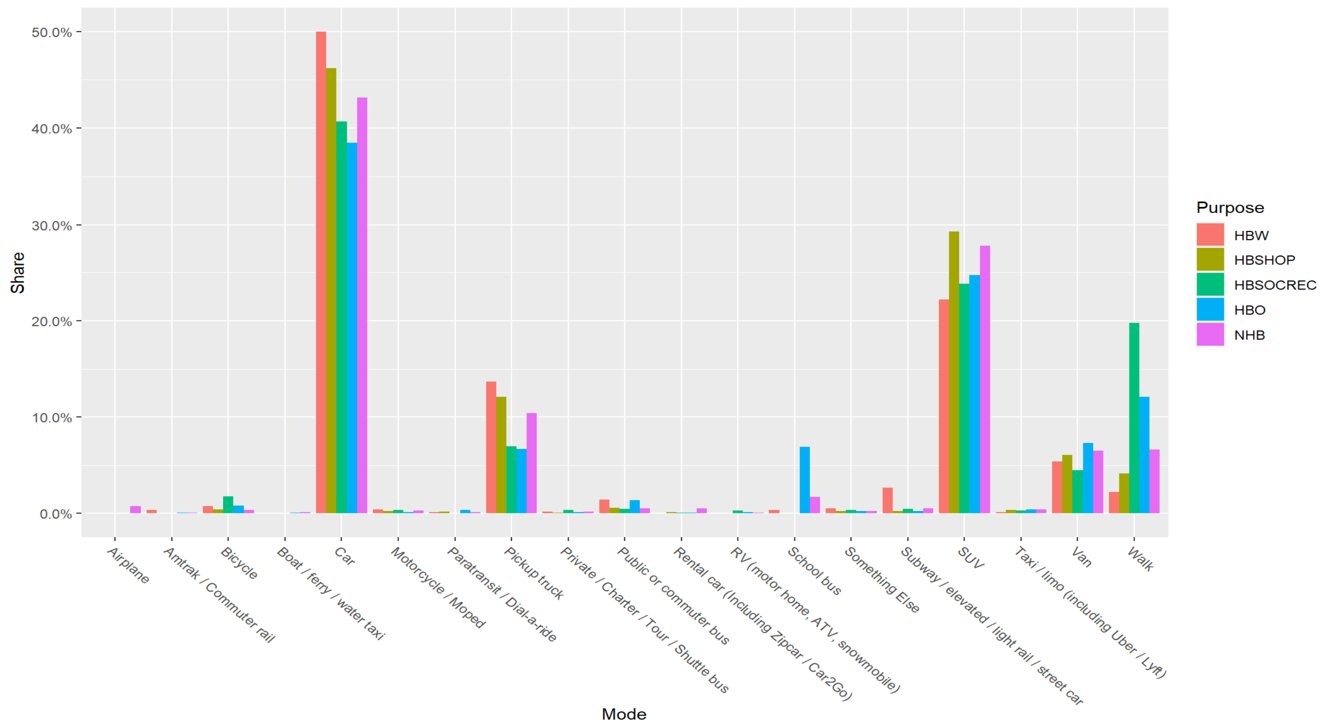


Figure 9. Mode share by trip purpose

Regarding the declared trip length, Table 6 and Figure 10 show length by mode choice. As expected, trips made walking are mainly up to 1 mile in length; while those made biking are up to 4 miles, principally. The trend reverses for motorized means, being more frequent 5+ miles trip, although it can be appreciated that some of these modes are also used for very short trips.

Table 6. Trip length share by mode

Mode	<1	1-2	2-3	3-4	4-5	5+
Walk	85.48%	9.22%	2.76%	1.15%	0.46%	0.92%
Bicycle	34.78%	24.64%	11.59%	10.14%	2.90%	15.94%
Car	12.27%	13.50%	11.39%	8.30%	6.59%	47.95%
SUV	12.63%	16.57%	10.11%	9.43%	5.56%	45.70%
Van	13.40%	13.40%	9.89%	6.70%	5.90%	50.72%
Pickup truck	10.04%	12.03%	12.23%	9.64%	6.06%	50.00%
Motorcycle / Moped	12.00%	16.00%	4.00%	4.00%	4.00%	60.00%
RV (motor home, ATV, snowmobile)	25.00%	12.50%	12.50%	0.00%	0.00%	50.00%
School bus	8.37%	21.18%	14.78%	8.87%	7.88%	38.92%
Public or commuter bus	2.50%	17.50%	12.50%	6.25%	7.50%	53.75%
Paratransit / Dial-a-ride	0.00%	21.43%	14.29%	0.00%	14.29%	50.00%
Private / Charter / Tour / Shuttle bus	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
Amtrak / Commuter rail	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
Subway / elevated / light rail / streetcar	1.64%	1.64%	3.28%	0.00%	0.00%	93.44%
Taxi / limo (including Uber / Lyft)	18.18%	21.21%	9.09%	6.06%	6.06%	39.39%
Rental car (Including Zipcar / Car2Go)	0.00%	5.26%	0.00%	10.53%	0.00%	84.21%
Airplane	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
Boat / ferry / water taxi	25.00%	0.00%	0.00%	25.00%	0.00%	50.00%
Something Else	25.93%	18.52%	14.81%	0.00%	0.00%	40.74%

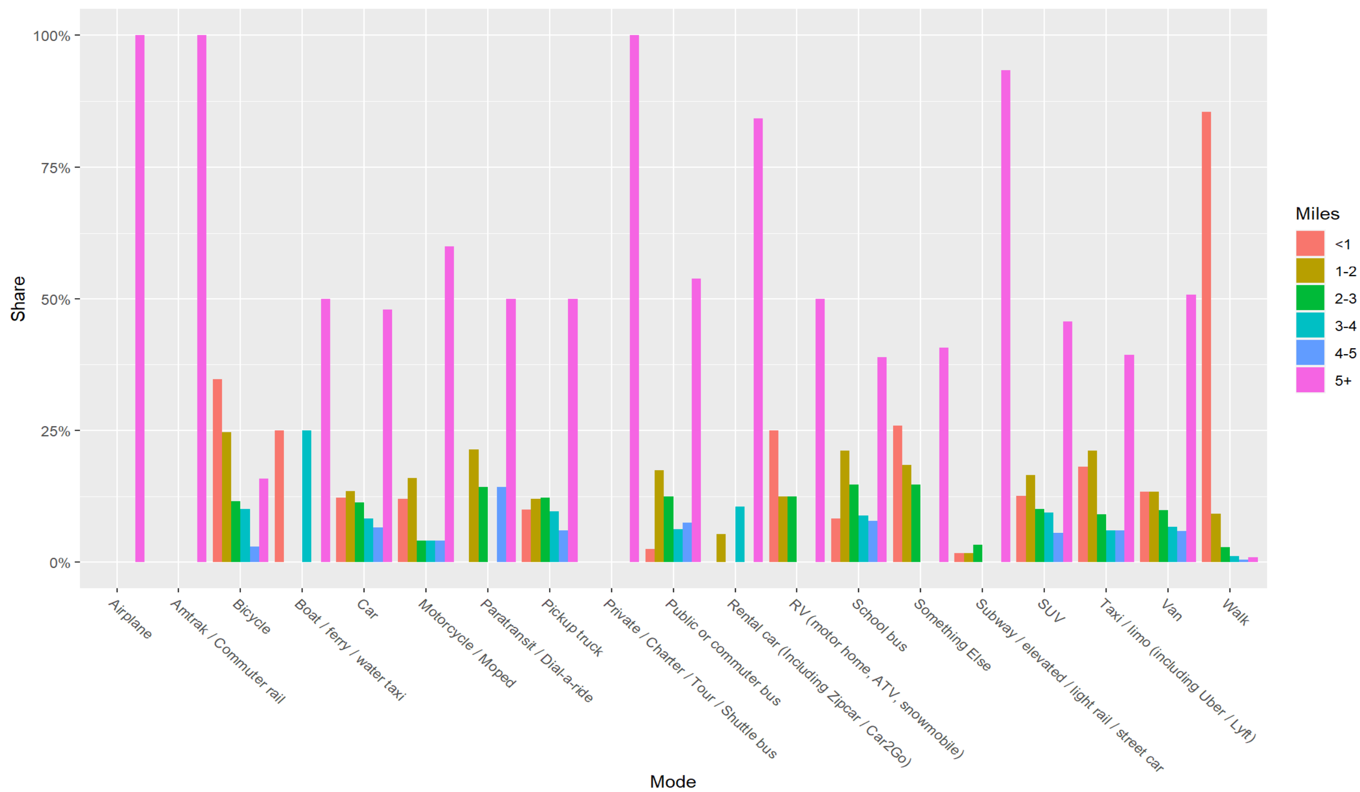


Figure 10. Trip length share by mode

These findings helped in taking the decision of constraining the study to trips of length 5 miles or shorter. We believe that trips over 5 miles cannot be realistically done by walking, at least in a significant amount. We also restrict Bike trips to the same 5-mile threshold, given their very limited modal share in NHTS. We decided to define trip purposes in our survey design according to the MSTM specification and to consider all of them in our study for consistency.

Survey data analysis

The data for this study was collected in two phases: a pilot (100 completes collected) and a *release* or final launch (766 completes). First, a pilot was launched, with a two-fold aim. First, to check questionnaire consistency, which comprises verifying of technical aspects such as logic among questions, required responses, display logic, or correct logic branching. Minor errors were identified during this phase that did not require any significant modification of the structure of the questionnaire or its flow (navigation among sections following pre-defined logic). The second objective of carrying out a pilot was the estimation of preliminary models, similar to those that would ultimately be calculated. This is a capital step on studies of this nature since any identification problem, non-significant result or, in general, results that deviate of what is reasonably expected, must be addressed before full data collection. Precisely, in our case, we decided to adjust some of the levels of the alternative's attributes, to highlight the differences among alternatives[5]. It was not necessary to modify the LTS levels as they were highly significant from the outset.

After a thorough analysis of the responses, the pilot and launch data were merged, and some observations removed due to inconsistencies, yielding a total of 862 completes. The complete data set is embedded into this document in Appendix A2 along with a codebook describing the variables (Appendix A3). Table 7 shows the statistics of the most important variables, as well as the graphical distribution of some specific variables (we refer the reader to the codebook to have a full description of each variable and its levels). The first part of the table relates to socioeconomic characteristics, which reasonably match census information for the State of Maryland. There is an outlier in the household income of $5M that increases the average, but it is the only observation, and the median income is correct. The second section of the table refers to trip revealed preferences. Length, duration, and other characteristics about the last trip made by the interviewee. Average travel time was 17.9, while average length, was 3.5 miles. In general, users felt that those trips were safe since the mean of this variable is 3.9 over a maximum safety of 5. Interestingly, to the question *Would you say that the road infrastructure allowed for this trip to be made by non-motorized means such as walking or biking?* they declared 3.1, on average, in the same scale 1-5 (*definitely not* - *definitely yes*).

Of special interest is the third part of the table, which shows the importance of several CS elements. All of them present relative importance (higher than 3), being the most relevant one for users the existence of wide sidewalks, paved shoulders, medians, and traffic calming measures. On the contrary, bicycle parking, landscaping or truck mountable curbs in roundabouts are features to which users state that they do not attach much importance.

The variables about attitudes reflect agreement with sentences in favor of both motorized and non-motorized means of transportation, as well as with pro-environmental or pro-ridesharing statements (ATT_EC2 is expressed in negative terms, so disagreement to it means environmentally friendly). Finally, the variables about bike ownership show that 50% of the sample own a bike. Among these individuals, many of them use it to get to work (frequency of 3.6 over 5), but only to get to another main mean of transportation (commute to bus or metro), since 1.5 is the answer to the use of the bicycle as the main mean of transportation to go to work.

[5] It is worth mentioning in this regard that Table 7 presents the final levels appearing in the full launch of the survey, and not those intermediate that are mentioned here.

Table 7. Descriptive statistics of the main variables in the dataset.

Variable	Mean	Std. dev.	Min.	25%	Median	75%	Max.
AGE	42.3	17.5	18	27	40	58	87
GENDER	1.6	0.5	1	1	2	2	3
MARRIED	1.5	0.5	1	1	2	2	2
EMPLSTAT	4.0	2.8	1	1	3	7	9
EDUDGR	3.4	1.1	1	3	3	4	5
HHINC	75,202.1	239,441.7			38,000	100,000	5,000,000
ONLYWORKER	1.7	0.5	1	1	2	2	2
INDINC	32,070.3	56,805.3			3,000	50,000	600,000
RETORCOND	1.7	0.4	1	1	2	2	2
SCHOOLCH	1.7	0.4	1	1	2	2	2
STUDENT	1.8	0.4	1	2	2	2	2
TRIPLONG	17.9	50.0	1	5	10	15	1,000
TRIPMILES	3.5	1.5	0	2	4	5	5
TRIPHB	1.2	0.4	1	1	1	1	2
TRIPSAFETY	3.9	1.1	1	3	4	5	5
TRIPPOSOTHERMEAN	3.1	1.3	1	2	3	4	5
TRIPNUMWORKING	2.8	1.4	1	2	2	3	7
TRIPNUMWEEKEND	3.0	1.4	1	2	3	4	7
IMPCSPASHO	3.5	1.1	1	3	4	4	5
IMPCSWSIDE	3.6	1.1	1	3	4	4	5
IMPCSDEDBILA	3.4	1.2	1	3	4	4	5
IMPCSDEDBUSLA	3.1	1.3	1	2	3	4	5
IMPCSPMEDIANS	3.5	1.1	1	3	4	4	5
IMPCSCALM	3.5	1.1	1	3	4	4	5
IMPCSTRUCKCURBS	3.0	1.2	1	2	3	4	5
IMPCSBUSSTOPACC	3.4	1.2	1	3	4	4	5
IMPCSBUSSTOSHEL	3.4	1.3	1	3	4	4	5
IMPCSONSTPARK	3.2	1.2	1	2	3	4	5
IMPCSBIKEPARK	3.1	1.3	1	2	3	4	5
IMPCSLANDSCAPE	3.1	1.2	1	2	3	4	5
ATT_CAR1	3.9	1.1	1	3	4	5	5
ATT_CAR2	3.7	1.1	1	3	4	5	5
ATT_CAR3	3.2	1.2	1	2	3	4	5
ATT_NOMOT1	3.7	1.0	1	3	4	4	5
ATT_NOMOT2	3.9	1.0	1	3	4	5	5
ATT_SHARED	3.4	1.2	1	3	4	4	5
ATT_EC1	3.5	1.1	1	3	4	4	5
ATT_EC2	2.8	1.3	1	2	3	4	5
OWNBIKE	1.5	0.5	1	1	1	2	2
FREQUSEBIKEWORK	3.6	1.4	1	3	4	5	5
FREQUSEBIKEOTHER	3.1	1.1	1	2	3	4	5
USEBIKEWORKMAIN	1.5	0.5	1	1	1	2	2
USEBIKEOTHERMAIN	1.5	0.5	1	1	1	2	2

More specific information is shown below about the revealed preferences, which served to confirm the preliminary assumptions.

Table 8. Average trip length by purpose

Purpose	Average trip length
HBOther	3.35
HBSchool	3.96
HBShop	3.31
HBSocial	3.42
HBWork	4
NHB	3.49

Table 9. Share of home-based/non home-based trips

H/NH Based	Count	Share
Home-based	690	79.95
Non-Home-based	173	20.05

Table 10. Share of purposes for home-based trips

Purpose	Count	Share
Other	116	16.81
Recreational	150	21.74
School	25	3.62
Shopping	322	46.67
Work	77	11.16

Graphical visualization of some variables may also be useful to understand the travel behavior of this sample (Figure 11 and 12). Figure 11 depicts trip length frequency by trip purpose as reported in the survey results. As seen, HBWork trips have similar median trip lengths while most HBWork trips are longer than 3 miles. For trip purposes HBWork and HBSchool, the first quartile is not shorter than 3miles while it is about 2 miles for other purposes, which is reasonable. Figure 12 shows that even for trips of length 5 miles or shorter, the private car has the highest mode share (over 65% as driver and over 20% as passenger). Walking is the next choice for short distance trips while bus transit and ridesharing and taxi has similar low shares.

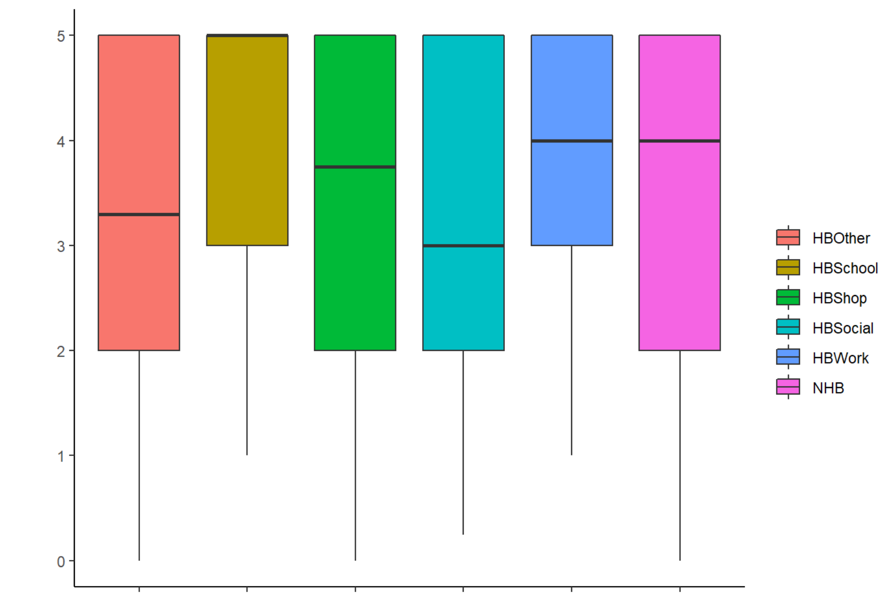


Figure 11. Trip length distribution by purpose

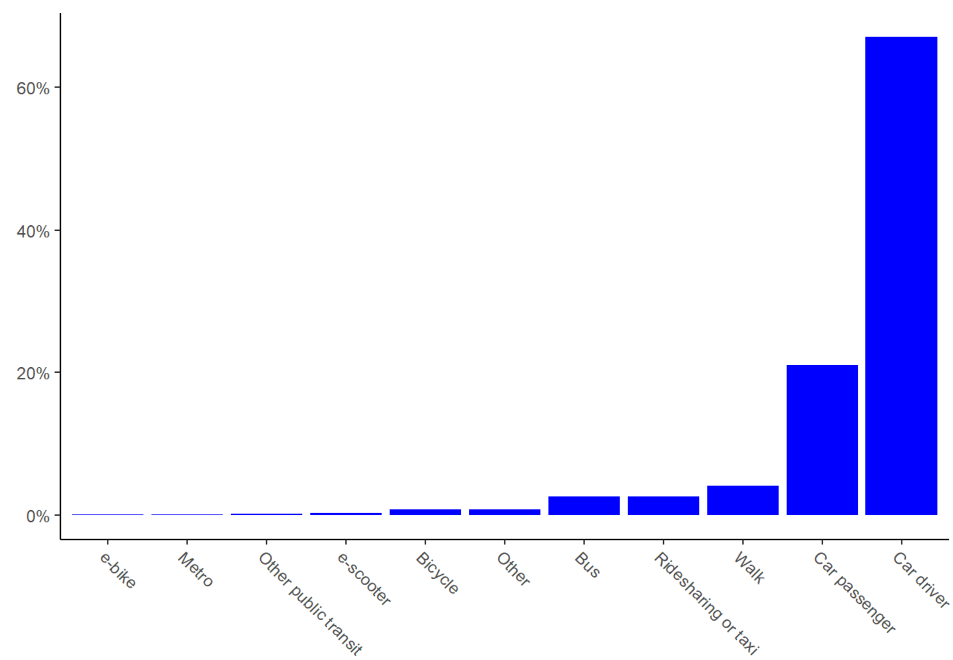


Figure 12. Share of modes used in last trip

A closer look to the data collected in the SCE, Figure13 shows the choices made in the scenarios. Most of them correspond to the Car alternative (1), although, satisfyingly enough for the purpose of this project, the bike and walk (2, and 3, respectively) alternatives show a good frequency of choice as well. This means that the statistical design did a good job in presenting trade-offs.

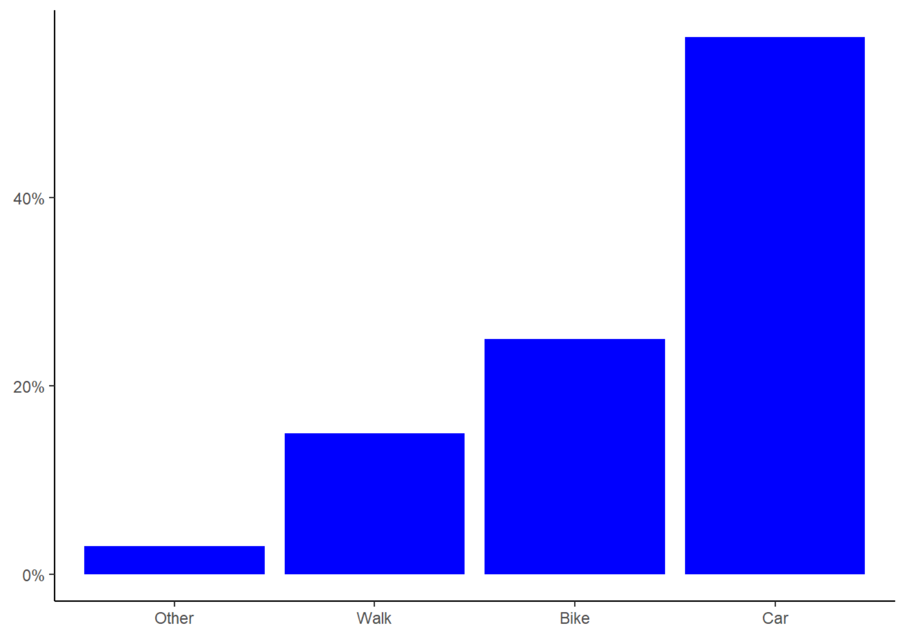


Figure 13. Frequency of mode choice in Stated Choice Experiment.

In more detail, Figures 14 and 15 depict the natural expected behavior. In general, when the LTS increases, the car alternative is chosen more frequently. When the conditions are more favorable for biking and walking (low LTS), these alternatives are selected more frequently.

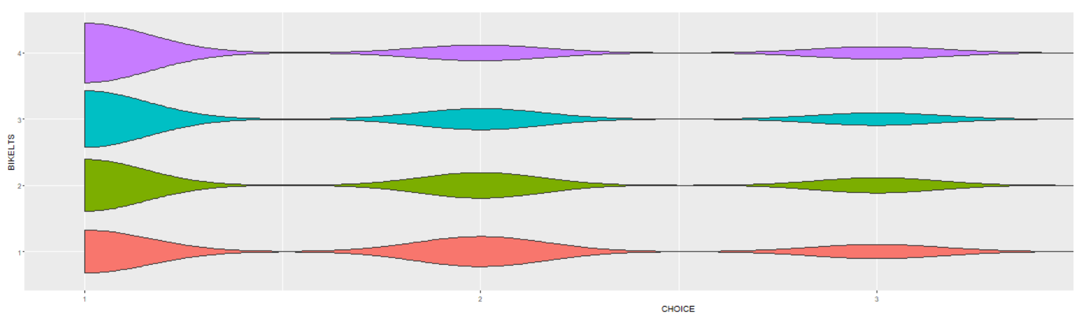


Figure 14. Frequency of mode choice by Bike LTS

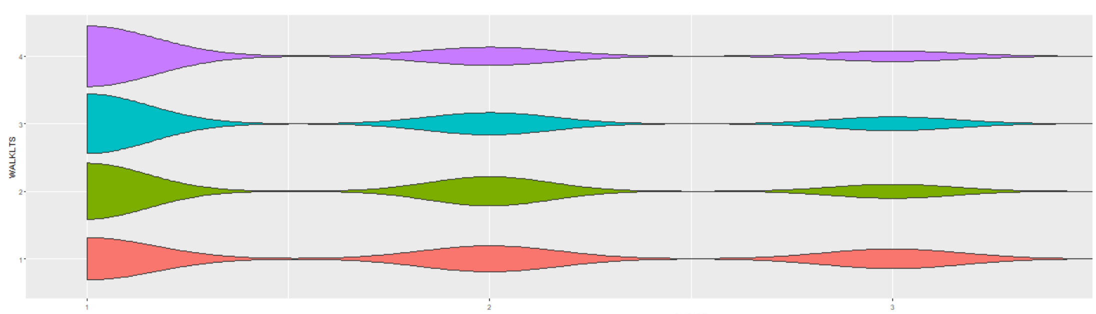
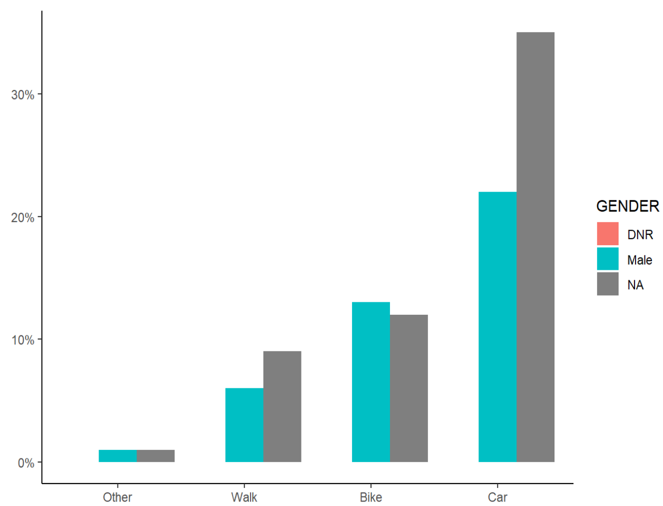
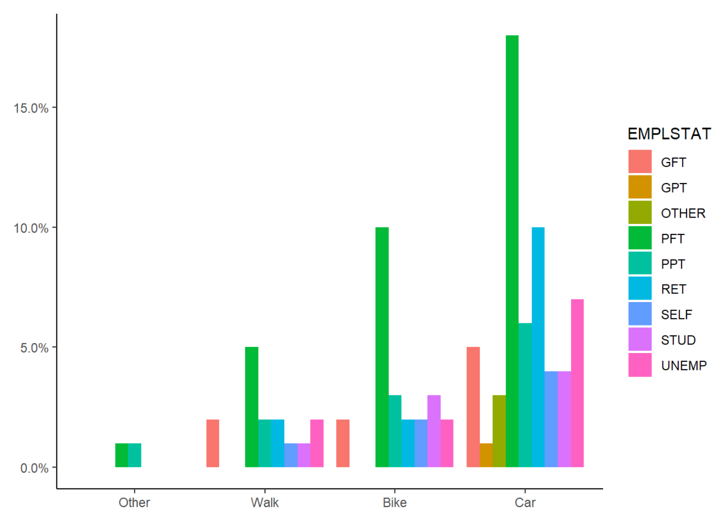


Figure 15. Frequency of mode choice by Walk LTS

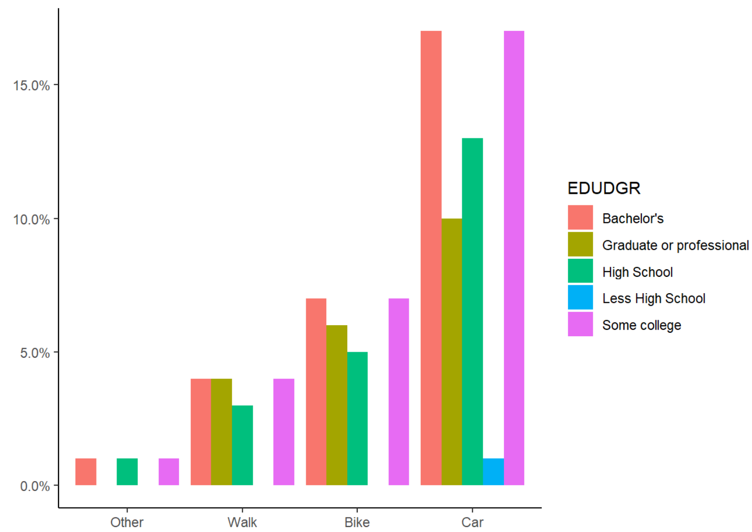
In conjunction with socioeconomics, the following figures (Figure 16. a-c) show that females frequently chose more car and walk alternatives. Also, that walk and bike options were not specifically used by people with a specific employment status (such as retired individuals or students) or with a particular education and/or degree.



a) Modes chosen by gender



b) Modes chosen by employment status



c) Modes chosen by educational degree

Figure 16. Mode choice by (a) gender, (b)employment status, (c) educational degree.

The structure of choices by purpose of the trip shown in the choice task is of particular interest. As Figure 17 depicts, Bike and Walk are used mainly for social or Other purposes.

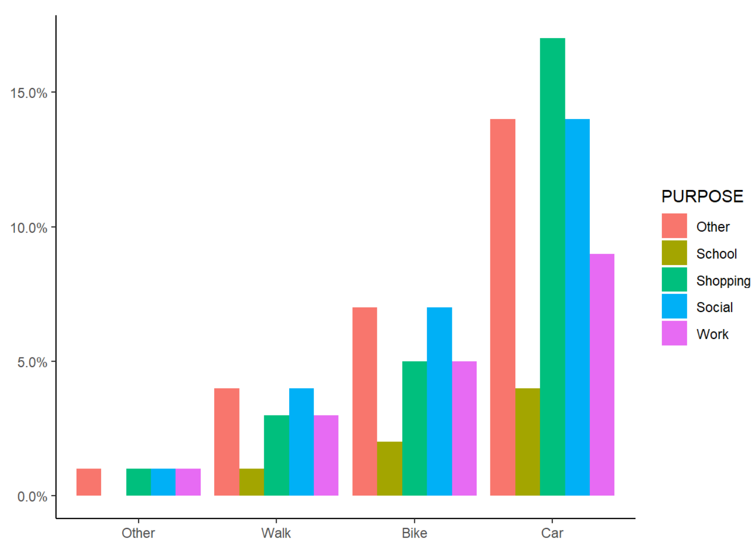


Figure 17. Chosen mode shares by purpose of the choice task

2.4. Models for travel behavior assessment

In the context of the Complete Streets project, the Discrete Choice theory is applied to calculate the probability of choosing non-motorized modes. In this case the choice set is composed of three modes: car, walk, and bike; a utility function is specified for each of the three modes considered. The utility function is linear in parameters and attributes reflect level of service variables as specified in the Stated Preference experiment (i.e., travel time, travel cost, parking cost and LTS), and household and individual socio-demographics. The model parameters are estimated on the assumptions that individuals maximize their utility when making their choices and calculating using maximum likelihood method.

Background

As for the analysis of the preference of individuals towards non-motorized means of transportation, we estimated a Multinomial Logit (MNL) model. MNL are based on the Random Utility Models paradigm. Following (Marschak, 1974) and (Train, 2009), the utility obtained by an individual n when choosing the alternative j pertaining to a set J is:

$$\boldsymbol{U_{nj} = \beta'_n x_{nj} + \mu'_n z_{nj} + \varepsilon_{nj}} \tag{1}$$

where x_{nj} and z_{nj} are observed attributes of alternative j, β'_{n} is a vector of coefficients representing individuals' tastes, μ'_n is vector of random terms with zero mean, and ε_{nj} is independent and identically Gumbel distributed. If ε's are independent and are not given, their cumulative distribution is the integral of all probabilities conditional on ε_{nj} weighted by its density. Fortunately, its mathematical expression can be ultimately expressed as:

$$P_{ni} = \frac{e^{\beta_n' x_{nj}}}{\sum_j e^{\beta_n' x_{nj}}} \tag{2}$$

The logit probabilities exhibit desirable properties. First, the resulting probability is between zero and one. When the attribute of an alternative makes the utility increase, the probability of that alternative being chosen increases as well, while the probabilities of the others decrease. Second, all probabilities sum up to one and its relation to utility is sigmoid. This means that if the utility of an alternative is very low compared with other alternatives, a small increase in its utility has little effect on the probability of being chosen. Analogously, if one alternative is far superior to the others in observed attributes, a further increase in its representative utility has little effect on the choice probability.

On the other hand, a key element in this project is the calculation of elasticities. Elasticities represent the change in the probabilities of choosing an alternative in response to a change in some observed factor. For instance, to what extent would a car be in demand less if car travel times would increase. This are the so-called *direct elasticities*. On the contrary, to what extent the probabilities of choosing an alternative are affected by a change in the attribute of another alternative (e.g., to what extent bike would be more demanded if car travel times would increase) are called *cross elasticities.*

The calculation of elasticities involves the derivatives of the choice probabilities. Ultimately, they can be expressed (direct and cross, respectively) as shown in equations (3) and (4):

$$\xi_{iz_{ni}} = \frac{\partial V_{ni}}{\partial z_{ni}} z_{ni}(1 - P_{ni}) \tag{3}$$

$$\xi_{iz_{ni}} = -\frac{\partial V_{ni}}{\partial z_{nj}} z_{ni} P_{nj} \tag{4}$$

However, when the utility is linear in z_{ni} with coefficient β_z, the derivates become $\beta_z z_{ni}(1 - P_{ni})$, and $\beta_z z_{ni} P_{nj}$, respectively.

It is worth mentioning that other models were considered and tested. Concretely, the Multinomial Nested Logit (NL). NL is a specification similar in nature to MNL, but that groups alternatives (according to the researcher's interest) in nests, aiming to consider correlations among them. This seemed a natural option since the non-motorized alternatives might pertain to the same *family*. However, although this may be the case, the tests performed with both pilot and released data showed that there was no significant improvement in the use of NL. Therefore, we utilized the MNL.

Model estimation and results

Following the specification defined in the previous section, several models were explored with a two-fold aim. First, identifying the key variables of influence on the decision of users to choose among motorized and non-motorized alternatives. Namely, Car, Bicycle, Walk, and Other (as an opt-out alternative). These variables included the *Level of Service* (the attributes defined in Chapter 2, Section 2.1) and socioeconomic variables. Also, recalling the importance that trip purpose could have on user behavior, we also estimated a series of models only on the data corresponding to each purpose. Moreover, since we presumed that income could play a capital role as well in the preference for non-motorized means, and in accordance with the structure of MSTM, we estimated one independent model on the subsample of each combination of purpose and income bracket (5 purposes, 5 income brackets; 25, in total). This led to 40 different models, which materialized in around 500 estimations. They all were evaluated attending to coefficients' sign, coefficients' significance, and adjusted R-squared (a usual measure of goodness of fit in these type of models).

The second aim of these estimations was to calculate elasticities from the coefficients obtained. Namely, the direct and cross elasticities for each attribute, for each alternative, for each of the 25 models (please see Appendix A4 for elasticity computation source files). This led to the 525 elasticity values shown below. However, it is important to highlight that, due to data sparsity, some of these submodels were not completely identified, or provided results contrary to expectations. In those cases, as will be explained below, we opted for taking the elasticity from the general model, which is highly reliable given the larger amount of data used for their estimation, and its coherence.

Thus, Tables 11 and 12 below present the results of the general model, and the results of the specific models estimated on each subsample of purpose/income models.

Table 11. General model results

	Estimate	Robust t-ratio
ASC car	0	
ASC bike	0.1113	0.5281
ASC walk	0.3081	1.2605
ASC other	-3.5582	-14.1855
Travel time (car)	-0.0084	-0.7340
Travel time (bike)	-0.0318	-3.9860
Travel Time (walk)	-0.0468	-7.1441
Travel cost car	-0.1236	-1.4633
Parking cost (car)	-0.0703	-3.8053
LTS bike	-0.3097	-8.8865
LTS walk	-0.2751	-6.5374
Male	0.2602	2.9508
Age	-0.0131	-4.3625
Income 2	0.3240	2.9076
Income_3	0.3450	2.4408
Income 4	0.0849	0.4710
Income 5	0.0437	0.1363
Bike ownership	1.2131	5.9979
Frequency use bike (other)	-0.2068	-3.7172
Purpose work	0.0618	0.8111
Purpose school	0.1771	1.5044
Purpose shop	0.3478	4.2433

Purpose social	0.0048	0.0758
Adj. Rho-square	0.2908	
AIC	10182.22	
BIC	10326.37	

The attributes referring to the alternatives have the expected negative effect (time, cost, level of stress) and are also highly significant, except some cases. This is not a deficiency of the model; on the contrary, it makes sense. Travel time by bike or walk are highly significant variables, while travel time by car is not. This is a natural result in this specific experiment since driving time in short trips is reduced and, therefore, increments on it do not make users change their minds. In other words, once driving, even a 100% increase in driving time from 2 to 4 minutes, is not perceived as a big loss. Something similar occurs with the travel cost by car, which is not perceived as harmful as the parking cost (which can go up to $3). It is especially significant the effect of LTS for both non-motorized modes. Finally, not all trip purposes played a relevant role in the users' choices. The only purpose that had a significant effect was shopping. In other words, the purpose of the trips is not that relevant when users are deciding among Car, Bike, or Walk. Nevertheless, it is worth a mention that the utility function specified in Equation (1) above, takes the following form:

$$U_{nj} = \sum \alpha_n' x_{nj} * \ (1 + \ \sum \beta_n' P_{nj}) + \sum \gamma_n' SE_{nj} + \varepsilon_{nj} \qquad (5)$$

where α are the LOS coefficients, β the purpose coefficients, and γ the socioeconomic coefficients. Therefore, a positive sign in β implies a smoothing of the negative effect of the attributes of the LOS. Finally, a Rho-square of 0.29 is evidence of a sound goodness of fit.

For the sake of brevity, the results of the 25 models estimated for each combination of LTS and income has been placed in Appendix B (named with two digits, the first referring to the LTS level, the second to the income bracket). It can be noted that the results are coherent with respect to those of the general one, except for those cases mentioned above in which the sparsity of data impeded the identification of the model.

Analogously, the elasticities resulting from these estimations are displayed below in Table12 for the general model, and in Table B2 in the Appendix B for the models estimated for each combination of LTS. It is worth to recall that, since LOS have an inverse relation with the probabilities of choice (the higher the travel time, cost, LTS; the less demanded the alternative), the direct elasticities should have negative sign. Correspondingly, the cross elasticities should be positive (the higher the travel time, cost or LTS of an alternative; the more demanded are the other alternatives). Additionally, larger values of the elasticity mean that a 1% change in the LOS provoke a more intense impact in the probabilities of the alternative.

Table 12. Direct and cross elasticities resulting from the general model

	Car	Bike	Walk
Travel time Car	-0.0420	0.0597	0.0472
Travel time Bike	0.1309	-0.3852	0.1234
Travel time Walk	0.1630	0.1932	-0.9905
Travel Cost Car	-0.0709	0.1003	0.0810
Parking Cost Car	-0.0404	0.0542	0.0528
LTS Bike	0.1871	-0.5653	0.2021
LTS Walk	0.0958	0.1068	-0.5679

As expected, travel times and costs impact the demand of the alternatives, although the effect is stronger for bike and walk, especially for the latter. Interestingly, the walking travel time is close to what is called *elastic* demand (elasticity above one in absolute value). This means that increments in walking travel time would impact, more than proportionally, the probability of that alternative being demanded. On the other hand, the magnitude of the elasticity of the travel and parking costs are also in line with that of travel time.

However, more importantly for our analysis, the second factor with the strongest impact on demand is the LTS, as can be seen in their corresponding Bike and Walk column. A deterioration in the driving conditions for cyclists and/or pedestrians significantly reduce the willingness to use this means of transportation. Of course, the opposite is also true: implementing roadway improvement policies that reduce the level of stress to which cyclists and pedestrians are subjected to when completing their trips (such as the construction or design of more Complete Streets elements) would significantly increase the demand for these modes of transportation.

CHAPTER 3 MODIFIED NON-MOTORIZED SHARE COMPUTATIONS

The MSTM (current official version v1.0.8.5 and later versions) still utilizes household characteristics and trip rates obtained from 2007-2008 HTS data and 2010 US Census data. The trip generation model uses trip production and attraction rates by household size, income and number of workers in a household (for details, please see MSTM Users' Guide, 2013). The model (MSTM) works only with motorized trips. Walk and bike trips, together forming the non-motorized trips, are generated but they are not included as separate modes in the trip tables in subsequent steps. Instead, the share of walk and bike trips, i.e., non-motorized trips are dropped before trip productions and attractions are fed into the destination choice model.

In all MSTM model versions, the non-motorized mode share input has been fixed, which was estimated using the 2007 Household Travel Survey data by zone. A stepwise multiple regression model approach was followed for estimation using various measures of densities (namely household, employment and activity densities) and accessibilities (i.e., a relative measure that describes for a given zone how easily all other zones can be reached). Twelve different accessibility values by transit and auto to six locations such as households and various employment were used in regression (for details, see MSTM Users' Guide, 2013). However, this regression model does not include level of traffic stress (LTS) as one of the independent variables and does not reflect the impact of this important variable on the non-motorized share calculation.

To represent the impacts of CS project implementations on non-motorized mode share and consequently on the mode choice in MSTM, we developed a robust approach that can readily be implemented in all model versions. Our approach incorporates LTS as an additional variable in the regression model and generates a new non-motorized share input to MSTM. Since the LTS information was not available at the time of this project (i.e., LTS was not among the link level network attribute in MSTM) we followed an approximate approach to come up with LTS values at zone level. Without loss of generality, our approach can still be applicable when the LTS values become available. The LTS was approximately estimated and added as a new independent variable to the currently used regression model. Moreover, the approximated LTS values were used as a reference in modifying the current non-motorized shares using the elasticities computed in chapter 2. The following sections describe the method and the process in detail.

3.1. The non-motorized share estimation in the MSTM

The MSTM is a multi-layer model that covers urban, regional, and statewide levels. It is an analytic tool designed to address Maryland statewide transportation issues such as traffic in rural areas outside the Baltimore and Washington MPOs, Baltimore and Washington, freight traffic, and activity in the interface between Baltimore and Washington metropolitan regions. The model allows consistent and defensible estimates of how different patterns of future development change key measures of transportation performance. MSTM coverage includes the entire states of Maryland and Delaware, the District of Columbia and portions of southern Pennsylvania, northern Virginia and West Virginia. The MSTM also covers the remainder of the United States (primarily for freight) but in less detail. MSTM uses statewide modeling zones (same as Traffic Analysis zones in urban areas, larger in exurban and rural areas). All socioeconomic data (for 2015 and 2040) are divided into zones. Statewide Modeling Zones (SMZs) cover the inner area of Maryland, Delaware, and portions of immediately surrounding areas and regional modeling zones (RMZ) cover the rest of the country. There are 1588 SMZs in MSTM. The following Table 13 from the MSTM provides detailed information about the covered zones (SMZs) and their numbering (MSTM User's Guide, 2013).

Table 13. Zones covered in the MSTM and their numbering

Model Area	Coverage	Count	CUBE Zone Number	
			Start	End
Maryland				
MD-BMC	6 counties/cities	599	1	599
MD-MWCOG	6 counties/cities	401	609	1009
MD West	3 counties	65	1019	1083
MD Eastern Shore	9 counties	86	1093	1178
District of Columbia				
District of Columbia	All	84	1188	1271
Virginia				
VA-MWCOG	15 counties/cities	148	1281	1428
VA-Frederick County	2 county/city	5	1438	1442
VA-Mid Pen	2 counties	7	1443	1449
VA-Eastern Shore	2 counties	11	1450	1460
West Virginia				
WV-MWCOG	1 county	4	1470	1473
WV	7 counties	26	1474	1499
Delaware				
DelDOT	3 counties	97	1509	1605
Pennsylvania				
PennDOT	5 counties	31	1615	1645
PennDOT	4 counties	24	1651	1674
SMZ Total		1588	1	1674

The current model uses data from the 2007 Household Travel Survey to calculate the observed non-motorized shares for each SMZ by finding the ratio of the non-motorized trips to total trips generated in each zone. The MSTM provides non-motorized shares for six different trip purposes and five different income levels. The income level varies from level 1 (low-income level, $30,000 or less) to level 5 (high income level, $150,000 or more). The other income groups are defined as Level 2 ($30,000-$60,000), Level 3 ($60,000-$90,000), and Level 4 ($90,000-$150,000). Table 14 summarizes all six purposes as identified in the MSTM.

Table 14. Trip purposes identified in the MSTM

Purpose	Definition	Per level of income
HBWORK	Home Based Work	HBWORK1, HBWORK2, HBWORK3, HBWORK4, HBWORK5
HBSHOP	Home Based Shop	HBSHOP1, HBSHOP2, HBSHOP3, HBSHOP4, HBSHOP5
HBOTHER	Home Based Other	HBOTHER1, HBOTHER2, HBOTHER3, HBOTHER4, HBOTHER5
HBSCHOOL	Home Based School	HBSCHOOL
NHBWORK	Non-Home-Based Work	NHBWORK
NHBOTHER	Non-Home Based Other	NHBOTHER

The initial trial of re-calculating the observed non-motorized shares in the MSTM showed intermittent patterns in the results. Most of the non-motorized shares were either 0 percent or 100 percent. The reason was because of the small number of observations in the specific zones. The survey was not able to capture all traffic modes. However, the non-motorized shares were smoothed in the MSTM by spatially interpolating them across zones. For every zone, the records from the nearest surrounding zones were taken into account in smoothing the non-motorized shares to get reasonable values. The interpolated observed non-motorized shares were used in a stepwise multiple regression analysis as the dependent variables and densities and accessibilities as the independent variables to predict the non-motorized shares in each zone of the specific SMZs. Equations 3.1 (MSTM Users' Guide, 2013) shows the current model and the independent variables used in the MSTM to estimate the non-motorized shares. Table 15 summarizes the final coefficients of the current model as provided in the MSTM.

$$\boxed{\begin{aligned}&Estimated\ Shares = hhDC * hhD + empDC * empD + actDC * actD + hhCAC * hhCA + \\ &retCAC * retCA + othCAC * othCA + hhTAC * hhTA + offTAC * offTA + othTAC * \\ &othTA\end{aligned}} \tag{3.1}$$

hhDC	= Household density coefficient
hhD	= Household density
empDC	= Employment density coefficient
empD	= Employment density
actDC	= Activity density coefficient
actD	= Activity density
hhCAC	= Household car accessibility coefficient
hhCA	= Household car accessibility
retCAC	= Retail employment car accessibility coefficient
retCA	= Retail employment car accessibility
othCAC	= Other employment car accessibility coefficient
othCA	= Other employment car accessibility
hhTAC	= Household transit accessibility coefficient
hhTA	= Household transit accessibility
offTAC	= Office employment transit accessibility coefficient
offTA	= Office employment transit accessibility
othTAC	= Other employment transit accessibility coefficient
othTA	= Other employment transit accessibility

Table 15. The final independent variable coefficients as listed in the MSTM

Purpose	hhDensity	actDensity	CarAccHH	carAccRetailEmp	carAccOtherEmp	trnAccOtherEmp
HBW1	0	0	0.002127	0	0	0
HBW2	0	0	0.001456	0.000631	0	0
HBW3	0	0.00035	0.00103	0.000267	0	0
HBW4	0	0	0.001615	0	0	0
HBW5	0	0	0.001254	0	0	0
HBS1	0	0	0.006644	0	0	0
HBS2	0	0	0.002246	0.00405	0	0
HBS3	0	0	0.000928	0.005008	0	0
HBS4	0.001081	0	0.00204	0.002734	0	0
HBS5	0	0	0.003353	0	0.000914	0.002194
HBO1	0	0	0.004424	0	0	0
HBO2	0	0	0.002794	0.000645	0	0
HBO3	0	0	0.002721	0.000854	0	0
HBO4	0	0	0.00225	0.001837	0	0
HBO5	0	0	0.003816	0	0	0.002461
HBSCH	0	0	0.004713	0	0	0
NHBW	0.001161	0	0.00314	0.002622	0.001532	0
NHBO	0	0	0.002191	0.002258	0.001904	0

A sample of the current estimated motorized shares per purpose as they were provided by the MSTM is shown in Figure 18 below. The complementary percentages represent the non-motorized shares.

SMZ	HBW1	HBW2	HBW3	HBW4	HBW5	HBS1	HBS2	HBS3	HBS4	HBS5	HBO1	HBO2	HBO3	HBO4	HBO5	HBSCH	NHBW	NHBO
1	0.887	0.924	0.939	0.916	0.931	0.643	0.871	0.910	0.889	0.865	0.755	0.834	0.838	0.837	0.848	0.762	0.826	0.867
2	0.905	0.935	0.949	0.929	0.942	0.700	0.886	0.917	0.908	0.884	0.794	0.859	0.862	0.859	0.872	0.799	0.850	0.879
3	0.768	0.840	0.879	0.827	0.858	0.267	0.714	0.787	0.775	0.710	0.496	0.655	0.661	0.652	0.688	0.510	0.623	0.687
4	0.866	0.907	0.925	0.900	0.918	0.578	0.834	0.875	0.866	0.834	0.710	0.801	0.804	0.799	0.821	0.718	0.778	0.819
5	0.814	0.874	0.898	0.861	0.887	0.413	0.781	0.843	0.821	0.771	0.597	0.726	0.731	0.728	0.751	0.608	0.704	0.762

Figure 18. The current motorized shares for zones 1 to 5

3.2. Back-calculations of the current independent variables

Since both of the independent variable coefficients and the estimated non-motorized shares are known for each SMZ as shown in Table 15 and Figure 18, respectively, the independent variables of densities and accessibilities for each zone can be calculated back from equation 3.1. This was done using an Excel solver and Excel macro through Visual Basic programming. A sample of the final back-calculated independent variables are listed in Figure 19.

SMZ	hhDensity	actDensity	carAccHH	carAccRetailEmp	carAccOtherEmp	trnAccOtherEmp
1	0.00	23.37	49.50	8.10	0.00	0.00
2	0.00	17.60	41.84	8.02	0.00	0.00
3	0.00	28.17	102.30	21.13	3.70	0.00
4	0.00	29.67	59.00	12.94	1.78	0.00
5	0.00	38.56	81.94	14.75	0.40	0.00

Figure 19. Back-calculated independent variables for zones 1 to 5

3.3. Approximate estimation of the LTS

The current MSTM does not include the level of traffic stress (LTS) as a variable in the non-motorized share model, and it is not possible to estimate it accurately from the available data. Therefore, the current LTS was approximated from the LTS definition using the motorized shares. The LTS ranges from one (highest walkability and bikeability level as people are more likely to bike or walk with separated bike lanes or pedestrian walkways) to four (lowest walkability and bikeability as traffic volume or speeds get higher which make people uncomfortable to bike or walk). Based on this definition, the LTS for each zone was linearly interpolated between the two values (1 and 4) based on the average motorized share in each zone. A 0% of motorized share means LTS of 1, and 100% percent of motorized share means LTS of 4. For example, in zone 1, the average motorized share of 0.852 means an interpolated value of LTS of 3.56 on a scale of 1 to 4. Figure 20 shows the estimated LTS as a new independent variable added to the current regression model in the following chart.

SMZ	hhDensity	actDensity	carAccHH	carAccRetailEmp	carAccOtherEmp	trnAccOtherEmp	Current LTS
1	0.00	23.37	49.50	8.10	0.00	0.00	3.56
2	0.00	17.60	41.84	8.02	0.00	0.00	3.62
3	0.00	28.17	102.30	21.13	3.70	0.00	3.07
4	0.00	29.67	59.00	12.94	1.78	0.00	3.46
5	0.00	38.56	81.94	14.75	0.40	0.00	3.26

Figure 20. The estimated LTS for zones 1 to 5

3.4. Modified non-motorized model estimation

The interpolated observed non-motorized shares are needed in this step for model estimation. However, the interpolated non-motorized shares are not provided by the MSTM documentation and are difficult to estimate. Therefore, the current estimated non-motorized shares were used in a linear regression analysis as the dependent variables and the back-calculated densities and accessibilities with the estimated LTS as the independent variables to predict the non-motorized shares in each zone of the specific SMZs. Equation 3.2 shows the modified proposed model to estimate the non-motorized shares.

$$\begin{aligned}\text{Modified Estimated Shares}\\ &= \text{hhDenisty} + \text{actDensity} + \text{CarAccHH} + \text{carAccRetailEmp}\\ &+ \text{carAccOtherEmp} + \text{trnAccOtherEmp} + \text{LTS}\end{aligned} \tag{3.2}$$

The following Table 16 summarizes the final re-estimated coefficients and the LTS coefficients after adding the LTS as a new independent variable.

Table 16. The final estimates of the independent variable coefficients of the modified non-motorized share model

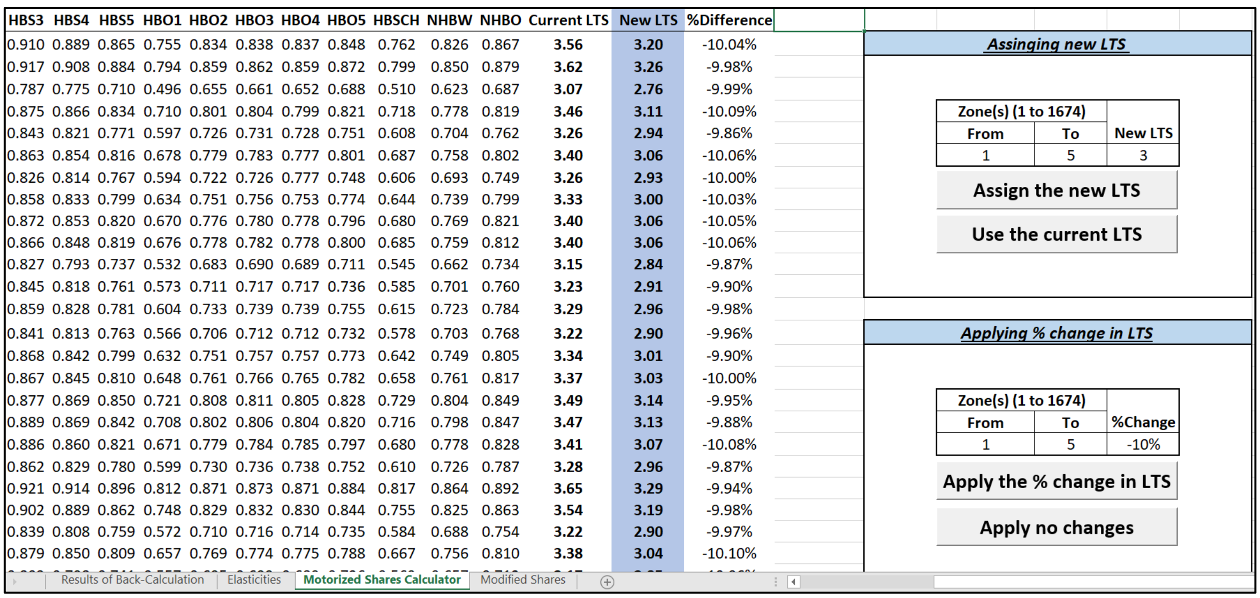
Purpose	hhDensity	actDensity	CarAccHH	carAccRetailEmp	carAccOtherEmp	trnAccOtherEmp	LTS
HBW1	0	0	0.002248	0	0	0	0.0000616
HBW2	0	0	0.001430	0.000623	0	0	0.0000205
HBW3	0	0.00035	0.00103	0.000264	0	0	-0.0000385
HBW4	0	0	0.001678	0	0	0	0.0000459
HBW5	0	0	0.001372	0	0	0	0.00003737
HBS1	0	0	0.006994	0	0	0	0.0007
HBS2	0	0	0.002022	0.00369	0	0	-0.0000068
HBS3	0	0	0.001005	0.005172	0	0	-0.0000465
HBS4	0.001818	0.000008	0.0018	0.002302	0	0	-0.0000404
HBS5	0	0	0.001373	0	0	0	0.0000374
HBO1	0	0	0.004879	0	0	0	0.0001345
HBO2	0	0	0.003211	0.0007190	0	0	0.0000555
HBO3	0	0	0.003105	0.000966	0	0	0.0000502
HBO4	0	0	0.002889	0.002403	0	0	0.0000273
HBO5	0	0	0.003103	0	0	0.004244	-0.0002689
HBSCH	0	0	0.004745	0	0	0	0.0001307
NHBW	0.00322	0	0.003127	0.002611	0.001558	0	-0.0004293
NHBO	0	0	0.002405	0.002442	0.002083	0	-0.0004520

The new re-estimated coefficients showed unreasonable results. There were no significant changes in the re-estimated coefficients. Moreover, the coefficients of the LTS variable were too small. This is possibly due to either an incorrect estimation of the current LTS (Section 3.3) or overfitting to the model by using the estimated non-motorized shares as the independent variables instead of the interpolated observed non-motorized shares, or due to both reasons.

3.5. Motorized shares calculator

As explained in section 3.4, the simple approach we tested by including the LTS as a new variable to the current non-motorized shares model in the MSTM gave unreasonable results, as expected. The next approach is to incorporate the computed elasticities of the LTS variable (see Chapter 2 for details) to directly modify the current estimated non-motorized shares associated with the new LTS in each zone after the complete street concept is applied. An Excel calculator (see Appendix C) was prepared by the research team to put all needed information together and to quickly calculate the modified shares based on the expected new LTS value or the percent change in the LTS value. Figure 21 shows the main tab of the calculator.

The calculator includes the following tabs (for details, see the Excel file):



HBS3	HBS4	HBS5	HBO1	HBO2	HBO3	HBO4	HBO5	HBSCH	NHBW	NHBO	Current LTS	New LTS	%Difference
0.910	0.889	0.865	0.755	0.834	0.838	0.837	0.848	0.762	0.826	0.867	3.56	3.20	-10.04%
0.917	0.908	0.884	0.794	0.859	0.862	0.859	0.872	0.799	0.850	0.879	3.62	3.26	-9.98%
0.787	0.775	0.710	0.496	0.655	0.661	0.652	0.688	0.510	0.623	0.687	3.07	2.76	-9.99%
0.875	0.866	0.834	0.710	0.801	0.804	0.799	0.821	0.718	0.778	0.819	3.46	3.11	-10.09%
0.843	0.821	0.771	0.597	0.726	0.731	0.728	0.751	0.608	0.704	0.762	3.26	2.94	-9.86%
0.863	0.854	0.816	0.678	0.779	0.783	0.777	0.801	0.687	0.758	0.802	3.40	3.06	-10.06%
0.826	0.814	0.767	0.594	0.722	0.726	0.777	0.748	0.606	0.693	0.749	3.26	2.93	-10.00%
0.858	0.833	0.799	0.634	0.751	0.756	0.753	0.774	0.644	0.739	0.799	3.33	3.00	-10.03%
0.872	0.853	0.820	0.670	0.776	0.780	0.778	0.796	0.680	0.769	0.821	3.40	3.06	-10.05%
0.866	0.848	0.819	0.676	0.778	0.782	0.778	0.800	0.685	0.759	0.812	3.40	3.06	-10.06%
0.827	0.793	0.737	0.532	0.683	0.690	0.689	0.711	0.545	0.662	0.734	3.15	2.84	-9.87%
0.845	0.818	0.761	0.573	0.711	0.717	0.717	0.736	0.585	0.701	0.760	3.23	2.91	-9.90%
0.859	0.828	0.781	0.604	0.733	0.739	0.739	0.755	0.615	0.723	0.784	3.29	2.96	-9.98%
0.841	0.813	0.763	0.566	0.706	0.712	0.712	0.732	0.578	0.703	0.768	3.22	2.90	-9.96%
0.868	0.842	0.799	0.632	0.751	0.757	0.757	0.773	0.642	0.749	0.805	3.34	3.01	-9.90%
0.867	0.845	0.810	0.648	0.761	0.766	0.765	0.782	0.658	0.761	0.817	3.37	3.03	-10.00%
0.877	0.869	0.850	0.721	0.808	0.811	0.805	0.828	0.729	0.804	0.849	3.49	3.14	-9.95%
0.889	0.869	0.842	0.708	0.802	0.806	0.804	0.820	0.716	0.798	0.847	3.47	3.13	-9.88%
0.886	0.860	0.821	0.671	0.779	0.784	0.785	0.797	0.680	0.778	0.828	3.41	3.07	-10.08%
0.862	0.829	0.780	0.599	0.730	0.736	0.738	0.752	0.610	0.726	0.787	3.28	2.96	-9.87%
0.921	0.914	0.896	0.812	0.871	0.873	0.871	0.884	0.817	0.864	0.892	3.65	3.29	-9.94%
0.902	0.889	0.862	0.748	0.829	0.832	0.830	0.844	0.755	0.825	0.863	3.54	3.19	-9.98%
0.839	0.808	0.759	0.572	0.710	0.716	0.714	0.735	0.584	0.688	0.754	3.22	2.90	-9.97%
0.879	0.850	0.809	0.657	0.769	0.774	0.775	0.788	0.667	0.756	0.810	3.38	3.04	-10.10%

Figure 21. The motorized shares calculator

1. ***Results of Back-Calculation:*** This tab includes all the back-calculated results of the current dependent variables (densities and accessibilities) used in the non-motorized shares model. These results are just presented here and not used in the calculator to modify the mode shares. They can be used later to produce more reasonable estimates when the LTS values are available.

2. ***Elasticities:*** This tab has the summary of all results of the LTS elasticities that were calculated in chapter 2. The results are used in the calculator to modify the current motorized mode shares.

3. ***Motorized Shares Calculator:*** This is the main tab of the calculator and can be used to assign the potential new LTS to the specific zone(s) using the "assigning new LTS" button or apply the expected percent change in the LTS value using the "Applying % change in LTS" button. Figure 21 shows examples of changing the current LTS for zones 1 to 5 to LTS of 3 or applying a reduction of 10% of the current LTS for the same zones. These tools can be used multiple times to assign new LTS or apply percent change in the LTS for other zones. Since the estimated current LTS is approximated value and not accurately known, it is highly recommended to use the applying % change tool instead of the assigning new LTS tool.

4. ***Modified shares:*** This tab shows the final results of the modified mode shares calculated based on the new LTS or percent change in the current LTS entered in the "Motorized Shares Calculator" tab. Figure 22 illustrates the final modified motorized shares for all purposes when the LTS is improved by 10% for zones 1 to 5. See the shares before the improvement in Figure 18 to compare results.

SMZ	HBW1	HBW2	HBW3	HBW4	HBW5	HBS1	HBS2	HBS3	HBS4	HBS5	HBO1	HBO2	HBO3	HBO4	HBO5	HBSCH	NHBW	NHBO
1	0.879	0.904	0.913	0.891	0.929	0.640	0.859	0.895	0.877	0.853	0.743	0.813	0.819	0.817	0.836	0.747	0.814	0.855
2	0.897	0.915	0.923	0.904	0.939	0.696	0.874	0.901	0.895	0.871	0.781	0.838	0.843	0.838	0.860	0.784	0.838	0.867
3	0.761	0.822	0.855	0.805	0.856	0.266	0.704	0.774	0.765	0.700	0.489	0.639	0.646	0.636	0.679	0.500	0.614	0.677
4	0.859	0.888	0.900	0.876	0.916	0.575	0.822	0.860	0.853	0.822	0.699	0.781	0.786	0.779	0.809	0.704	0.767	0.808
5	0.807	0.855	0.874	0.839	0.884	0.411	0.770	0.829	0.809	0.760	0.588	0.708	0.715	0.711	0.740	0.596	0.694	0.751

Figure 22. The modified motorized shares for zones 1 to 5 when the LTS is improved by

3.6. Interactive Visualization Tool

Considering the future use of the motorized share calculator described in the previous section by the MDOT SHA staff members, we developed a more user-friendly visualization tool that can be developed into a Scenario Generation Tool in the future using the Tableau application. With this tool, users will be able to select zones that complete streets project are implemented in and adjust other input such as income, trip purposes to calculate non-motorized shares.

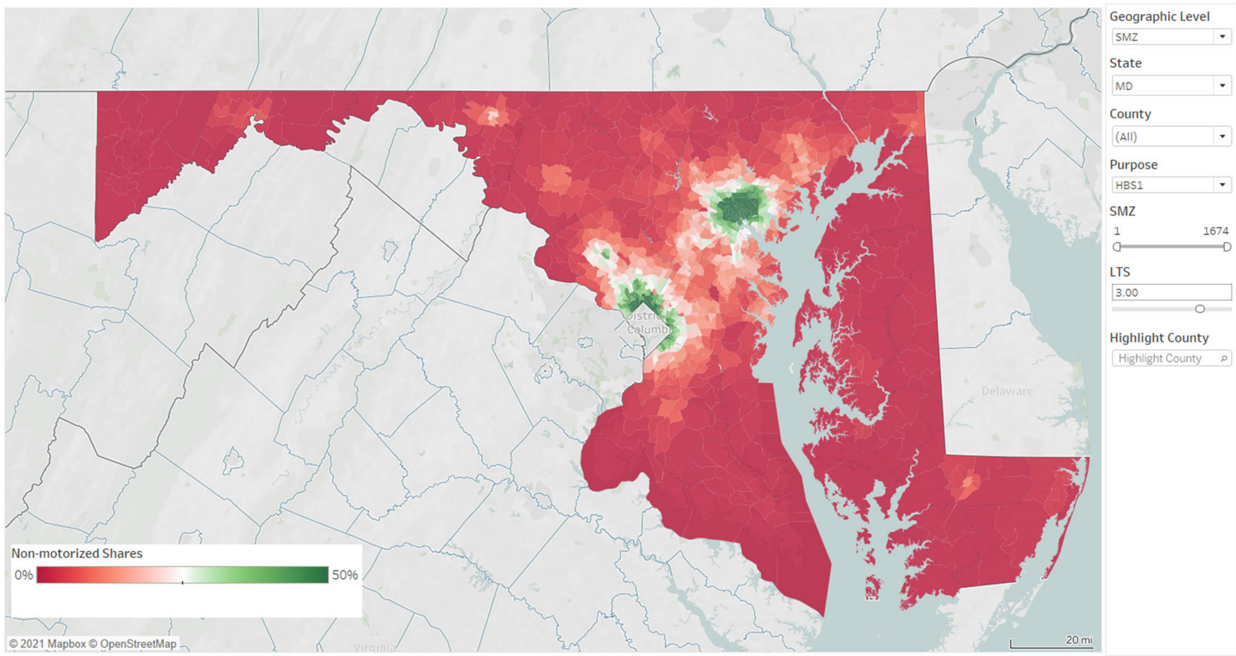


Figure 23 . Interactive non-motorized shares map

CHAPTER 4 MODEL DEMONSTRATION ON SCENARIOS

In this chapter, we test the model developed in the previous chapter on two scenarios to demonstrate its capability in estimating the change in mode share in MSTM model given a CS scenario. The elasticities calculated from the implemented logit models have been used to recalculate the LTS values for each MSTM zone. We developed two scenarios to examine the effect of modifying the LTS values in a county level and statewide.

4.1. Scenario 1: Application on Prince George's County

For county level, we assumed an LTS value of 1.0 for all the zones within Prince George County and recalculated the motorized shares model attributes for different income groups and travel purposes. Although this scenario is rather aspirational, it can provide a benchmark (upper level) as to maximum mode shift that can be achieved if all the roads in the county were designed as CS. This data has been fed to the MSTM model. Figure 24 shows the MSTM zones that are located within PG County.

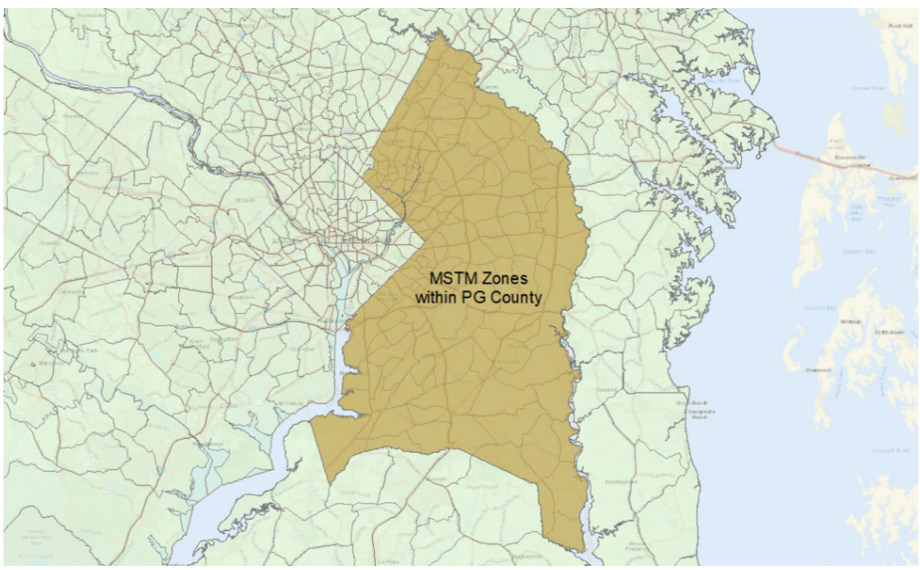


Figure 24 County level CS project boundary- Prince George's County Scenario

The first available baseline output results were for 2012 base model runs. These results have been obtained using the MSTM v.1.0.8.5. Therefore, we used these results as a baseline for comparison purposes. Table 17 shows the results of motorized modes travel shares from the baseline 2012 model.

Table 17 Motorized mode share results from MSTM by county – Baseline (before CS)

Baseline							
County	Drive Alone	HOV	Bus	EXP Bus	Rail	Commuter Rail	TOTAL
Alleghany	196,203	156,237	0	0	0	0	352,440
Anne Arundel	1,438,199	1,093,317	25,332	74	48,680	11,975	2,617,577
Baltimore	2,025,431	1,531,330	109,134	639	99,471	4,468	3,770,472
Calvert	183,464	167,036	1,388	0	1,962	7	353,857
Caroline	67,880	64,169	0	0	0	0	132,049
Carroll	419,616	353,321	377	0	2,895	30	776,239
Cecil	229,936	191,078	11	114	31	25	421,195
Charles	335,091	283,037	2,278	0	4,647	9	625,061
Dorchester	77,336	67,359	0	0	0	0	144,696
Frederick	535,433	461,232	558	1	2,207	5,874	1,005,306
Garrett	76,826	73,520	0	0	0	0	150,346
Harford	641,727	488,878	4,815	577	1,144	456	1,137,597
Howard	843,059	603,464	15,625	248	7,812	5,200	1,475,409
Kent	49,735	43,291	0	0	0	0	93,026
Montgomery	2,099,941	1,678,425	109,147	102	393,036	25,652	4,306,303
Prince Georges	1,790,848	1,533,139	59,693	55	161,858	13,457	3,559,050
Queen Annes	102,047	95,808	0	0	0	0	197,855
St. Mary's	276,491	224,125	240	0	210	0	501,066
Somerset	44,734	41,284	0	0	0	0	86,018
Talbot	117,347	92,206	0	0	0	0	209,554
Washington	386,491	312,075	5	0	574	70	699,216
Wicomico	295,939	228,254	0	0	0	0	524,193
Worcester	158,710	125,736	0	0	0	0	284,446
Baltimore City	1,354,019	996,145	202,112	866	99,564	7,892	2,660,597
External	747,306	647,416	31,517	118	342,348	21,511	1,790,216

The travel counts for PG county has been highlighted for comparison purposes. Changing the motorized share input with new the LTS value of 1.0 for PG county, the new count values that are obtained from the mode share scripts of the MSTM, are summarized in Table 18.

Table 18 Motorized mode share results – Scenario (after the CS)

Complete Street							
County	Drive Alone	HOV	Bus	EXP Bus	Rail	Commuter Rail	TOTAL
Alleghany	196,090	156,201	0	0	0	0	352,291
Anne Arundel	1,439,397	1,091,793	25,520	72	47,617	11,726	2,616,125
Baltimore	2,023,138	1,530,337	109,210	640	99,284	4,307	3,766,915
Calvert	182,807	166,927	1,308	0	1,984	8	353,034
Caroline	67,810	64,141	0	0	0	0	131,951
Carroll	418,711	353,171	384	0	2,913	28	775,206
Cecil	229,979	191,009	11	113	31	25	421,169
Charles	330,976	281,709	2,388	0	5,069	12	620,154
Dorchester	77,219	67,325	0	0	0	0	144,544
Frederick	535,115	461,115	558	1	2,199	5,850	1,004,839
Garrett	76,784	73,503	0	0	0	0	150,286
Harford	641,454	488,753	4,818	573	1,134	472	1,137,203
Howard	840,141	602,227	15,601	250	7,766	5,041	1,471,027
Kent	49,714	43,280	0	0	0	0	92,994
Montgomery	2,093,092	1,673,655	108,622	113	388,925	25,408	4,289,814
Prince Georges	1,599,905	1,360,757	52,572	50	142,482	12,095	3,167,861
Queen Annes	101,994	95,750	0	0	0	0	197,744
St. Mary’s	275,958	224,037	194	0	252	0	500,440
Somerset	44,709	41,275	0	0	0	0	85,984
Talbot	117,634	92,142	0	0	0	0	209,776
Washington	385,961	311,903	5	0	491	68	698,426
Wicomico	296,097	228,252	0	0	0	0	524,349
Worcester	158,530	125,687	0	0	0	0	284,217
Baltimore City	1,350,572	995,058	201,954	862	98,689	7,286	2,654,421
External	730,803	632,984	29,794	128	326,675	21,116	1,741,498

The percentage difference in travel counts is shown in Table 19. In the ideal case of modifying the complete streets to represent a LTS equal to 1.0, the motorized shares will be reduced by 10% which is significant. Since the non-motorized share of the travels are very tiny compared to motorized shares, a 10 percent change in travel mode to non-motorized modes would make a big difference in overall non-motorized travel counts. Also, the results show a very marginal change in travel mode patterns in counties other than the PG County, which indicates the goodness of convergence for the run.

Table 19 Change in motorized mode share for Prince George's County after CS implementation

	Drive Alone	HOV	Bus	EXP Bus	Rail	Commuter Rail	TOTAL
Percentage difference in mode shares	-10.66%	-11.24%	-11.93%	-9.09%	-11.97%	-10.12%	-10.99%

4.2. Scenario 2: Statewide Application

The second scenario which is still ongoing, is the statewide change in urban areas within the Maryland. Figure 25 shows the urban areas and its overlap with the MSTM zones.

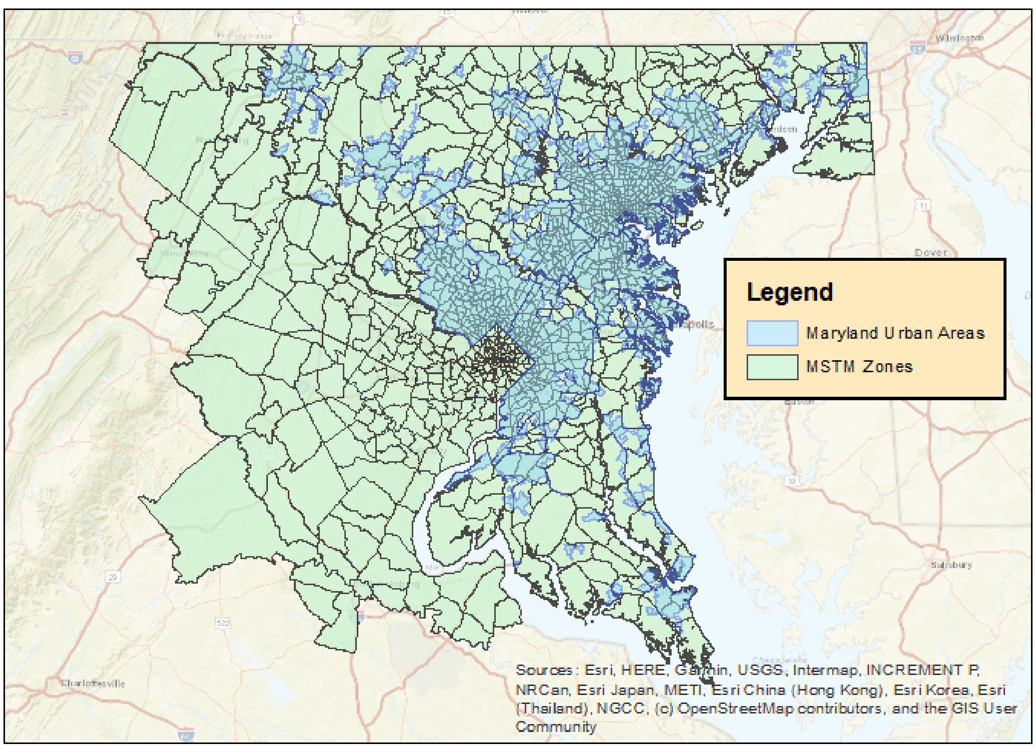


Figure 25 Urban areas in Maryland that are used as CS implementation areas for statewide scenario

A LTS of 2.0 has been assigned to each zone that intersects with the urban areas. Although the LTS can be adjusted based on the area that each zone shares from the urban polygons, our model indicates that the network links are very dense in the urban areas, and it is not appropriate to use weighted adjustments according to the area shares. Therefore, we simply used LTS equal to 2.0 for the entire zone if it shares a remarkable area with urban areas. The motorized shares' model attributes have been recalculated for these zones and the MSTM is run.

Table 20. Motorized mode share results from MSTM by County –Statewide Scenario Baseline (before CS)

Baseline							
County	Drive Alone	HOV	Bus	EXP Bus	Rail	Commuter Rail	TOTAL
Alleghany	196,203	156,237	0	0	0	0	352,440
Anne Arundel	1,438,199	1,093,317	25,332	74	48,680	11,975	2,617,577
Baltimore	2,025,431	1,531,330	109,134	639	99,471	4,468	3,770,472
Calvert	183,464	167,036	1,388	0	1,962	7	353,857
Caroline	67,880	64,169	0	0	0	0	132,049
Carroll	419,616	353,321	377	0	2,895	30	776,239
Cecil	229,936	191,078	11	114	31	25	421,195
Charles	335,091	283,037	2,278	0	4,647	9	625,061
Dorchester	77,336	67,359	0	0	0	0	144,696
Frederick	535,433	461,232	558	1	2,207	5,874	1,005,306
Garrett	76,826	73,520	0	0	0	0	150,346
Harford	641,727	488,878	4,815	577	1,144	456	1,137,597
Howard	843,059	603,464	15,625	248	7,812	5,200	1,475,409
Kent	49,735	43,291	0	0	0	0	93,026
Montgomery	2,099,941	1,678,425	109,147	102	393,036	25,652	4,306,303
Prince Georges	1,790,848	1,533,139	59,693	55	161,858	13,457	3,559,050
Queen Annes	102,047	95,808	0	0	0	0	197,855
St. Marys	276,491	224,125	240	0	210	0	501,066
Somerset	44,734	41,284	0	0	0	0	86,018
Talbot	117,347	92,206	0	0	0	0	209,554
Washington	386,491	312,075	5	0	574	70	699,216
Wicomico	295,939	228,254	0	0	0	0	524,193
Worcester	158,710	125,736	0	0	0	0	284,446
Baltimore City	1,354,019	996,145	202,112	866	99,564	7,892	2,660,597
External	747,306	647,416	31,517	118	342,348	21,511	1,790,216

The travel counts for PG county have been highlighted for comparison purposes. Changing the motorized share input with the new LTS value of 1.0 for PG county, the new count values that are obtained from the mode share scripts of MSTM, are summarized in Table 18.

Table 21. Motorized mode share results – MSTM by County – Statewide Scenario (after the CS)

Complete Street							
County	Drive Alone	HOV	Bus	EXP Bus	Rail	Commuter Rail	TOTAL
Alleghany	196,192	156,189	0	0	0	0	352,381
Anne Arundel	1,343,051	1,014,771	23,270	70	43,334	10,503	2,434,999
Baltimore	1,888,471	1,423,646	100,733	579	90,900	3,778	3,508,106
Calvert	173,025	157,967	1,160	0	1,789	7	333,948
Caroline	67,868	64,138	0	0	0	0	132,007
Carroll	398,196	336,689	345	0	2,634	24	737,889
Cecil	219,668	182,281	10	92	28	12	402,091
Charles	316,265	266,816	1,829	0	3,733	9	588,652
Dorchester	77,327	67,332	0	0	0	0	144,659
Frederick	507,806	439,343	527	1	2,252	5,282	955,210
Garrett	76,820	73,495	0	0	0	0	150,315
Harford	602,340	458,207	4,432	534	1,067	310	1,066,891
Howard	785,215	560,244	14,356	226	7,213	4,327	1,371,582
Kent	49,742	43,271	0	0	0	0	93,013
Montgomery	1,963,039	1,560,328	99,905	101	365,494	22,895	4,011,761
Prince Georges	1,671,731	1,423,136	54,453	51	148,018	11,955	3,309,343
Queen Annes	101,878	95,736	0	0	0	0	197,614
St. Marys	263,738	213,774	57	0	82	0	477,652
Somerset	44,725	41,269	0	0	0	0	85,994
Talbot	117,273	92,187	0	0	0	0	209,460
Washington	365,288	297,008	5	0	523	68	662,891
Wicomico	296,388	228,235	0	0	0	0	524,623
Worcester	158,630	125,677	0	0	0	0	284,306
Baltimore City	1,269,662	931,135	188,697	790	89,836	6,628	2,486,748
External	726,526	629,418	28,211	115	317,928	19,202	1,721,400

The percentage difference in travel counts is shown in Table 22. In the ideal case of modifying the streets to represent a LTS equal to 1.0, the motorized shares will be reduced by 10% which is significant. Since the non-motorized share of the travels are very tiny compared to motorized shares, a 10 percent change in travel mode to non-motorized modes would make a big difference in overall non-motorized travel counts. Also, the results show a very marginal change in travel mode patterns in counties other than the PG County, which indicates the goodness of convergence for the run.

Table 22. Change in motorized mode share for Maryland after statewide CS implementation

Percentage difference in mode shares	% difference						
	Drive Alone	HOV	Bus	EXP Bus	Rail	Commuter Rail	TOTAL
Alleghany	-0.01%	-0.03%	-	-	-	-	-0.02%
Anne Arundel	-6.62%	-7.18%	-8.14%	-5.41%	-10.98%	-12.29%	-6.98%
Baltimore	-6.76%	-7.03%	-7.70%	-9.39%	-8.62%	-15.44%	-6.96%
Calvert	-5.69%	-5.43%	-16.43%	-	-8.82%	0.00%	-5.63%
Caroline	-0.02%	-0.05%	-	-	-	-	-0.03%
Carroll	-5.10%	-4.71%	-8.49%	-	-9.02%	-20.00%	-4.94%
Cecil	-4.47%	-4.60%	-9.09%	-19.30%	-9.68%	-52.00%	-4.54%
Charles	-5.62%	-5.73%	-19.71%	-	-19.67%	0.00%	-5.82%
Dorchester	-0.01%	-0.04%	-	-	-	-	-0.03%
Frederick	-5.16%	-4.75%	-5.56%	0.00%	2.04%	-10.08%	-4.98%
Garrett	-0.01%	-0.03%	-	-	-	-	-0.02%
Harford	-6.14%	-6.27%	-7.95%	-7.45%	-6.73%	-32.02%	-6.22%
Howard	-6.86%	-7.16%	-8.12%	-8.87%	-7.67%	-16.79%	-7.04%
Kent	0.01%	-0.05%	-	-	-	-	-0.01%
Montgomery	-6.52%	-7.04%	-8.47%	-0.98%	-7.01%	-10.75%	-6.84%
Prince Georges	-6.65%	-7.18%	-8.78%	-7.27%	-8.55%	-11.16%	-7.02%
Queen Annes	-0.17%	-0.08%	-	-	-	-	-0.12%
St. Marys	-4.61%	-4.62%	-76.25%	-	-60.95%	-	-4.67%
Somerset	-0.02%	-0.04%	-	-	-	-	-0.03%
Talbot	-0.06%	-0.02%	-	-	-	-	-0.04%
Washington	-5.49%	-4.83%	0.00%	-	-8.89%	-2.86%	-5.20%
Wicomico	0.15%	-0.01%	-	-	-	-	0.08%
Worcester	-0.05%	-0.05%	-	-	-	-	-0.05%
Baltimore City	-6.23%	-6.53%	-6.64%	-8.78%	-9.77%	-16.02%	-6.53%
External	-2.78%	-2.78%	-10.49%	-2.54%	-7.13%	-10.73%	-3.84%

CHAPTER 5 CONCLUSIONS

The goal of this project was to enhance regional travel demand modeling capability of MDOT SHA by developing data-driven mode choice models that incorporate bicycling, walking, transit and multi-modal connections among these modes so that impacts of Complete Street projects and plans can be forecasted in the future. Throughout the progress of the project, some modifications have been made in the goals and objectives of the project with the consensus of the MDOT SHA project team. These changes are typically due to data availability or to reduce the model complexity in the context of complete streets. Namely, we only considered car, walking, biking and other as the mode alternatives and we did not consider transit or multi-modal connections in the study. This was decided because including transit trips would require considering longer trips (longer than 5 miles) and a complex survey design. The second modification we did, with input from the MDOT SHA team, is to not re-estimate a mode choice model but to update the existing motorized share input using estimated elasticities to e.g., travel time, cost and LTS. This was due to lack of individual level data as well as the level of effort required to complete such a complex task with this project's resources.

We completed the seven tasks of this project with the above-mentioned modifications in the process. A Stated Choice Experiment (SCE) in which respondents are asked to evaluate different alternatives (including walking, biking and other) characterized by attributes related to trips made in a CS context was completed. The complete data set collected through Qualtrics, 862 complete sets, used to estimate discrete choice models to assess travel behavior and discrete choice models were estimated to explain the preferences for bike and walking modes in a Complete Street context. We explored several models with the aim of identifying the key variables of influence on the decision of users to choose among Car, Bicycle, Walk, and Other (as an opt-out alternative). These variables included the Level of Service and socioeconomic variables. Considering the implementation of the model in MSTM, we also estimated a series of models only on the data corresponding to each trip purpose. In addition, since we presumed that income could play a significant role in the preference for non-motorized modes, we estimated one independent model on the subsample of each combination of purpose and income bracket (5 purposes, 5 income brackets; 25 in total). This led to 40 different models and around 500 estimations. We calculated both direct and cross elasticities from the coefficients obtained. Namely, the direct and cross elasticities for each attribute, for each alternative, for each of the 25 models. This led to the 525 elasticity values.

We then utilized calculated elasticities to update non-motorized share table input used in MSTM. The MSTM does not have direct information about the LTS for the specific regions. Therefore, the LTS was approximately estimated and added as a new independent variable to the currently used model. The approximated LTS was used as a reference in modifying the current non-motorized shares using the elasticities computed. We developed an Excel spreadsheet tool to update the non-motorized share table by incorporating the computed elasticities of the LTS variable (see chapter 2 for details). We then tested our elasticity estimate results and the Excel spreadsheet tool on two hypothetical scenarios: one assumes all Prince George's County roads have LTS=1 (can be considered as a best-case scenario) and one at statewide level where we assumed all urban areas in Maryland have LTS=2. The scenario results demonstrated that the methods and tools we developed in this project are successfully reflecting the potential impacts of CS within a statewide transportation model, i.e., MSTM, albeit requiring further refinement and validation.

In previous discussions with the MDOT SHA TFAD team, we proposed two methodological approaches: (1) the integration of LTS related variables into MSTM, to update the input table that contains the percentage of non-motorized trips in the Maryland Statewide Transportation Model (MSTM) as an external module, for analysis at the regional level (statewide evaluation tool), and (2) a microsimulation of non-motorized trips for analysis at the project/local level. We completed the first approach, which addresses the project requirement and is ready for use subject to validation results. Thus, the first step in future work should include the validation of the models and tools we developed. This will include coding the proper LTS values as link attributes to the multi-resolution MSTM (version 1.5). Coding/incorporating LTS into MSTM network, at least to a selected project evaluation area, is needed. Since LTS information was not coded in the MSTM network, we used an approximate approach to input LTS values. This however does not affect our approach as LTS values, when available, can be replaced with updated values. Similarly, we used hypothetical scenarios to test our model results. Conducting further scenario analysis or project evaluation studies is another future direction.

The second method was to explore the use of a novel approach that the UMD project team has developed and was not part of the original scope. We have the framework ready and preliminary analysis has been done. However, the project team needs subarea input and further development and analysis to complete it. Thus, the completion of this method can be a significant future research direction for this project, where the method can be incorporated in MDOT SHA's new multi-resolution MSTM 1.5 model's Level 3 framework.

Based on our analysis of MSTM, and discussions with MDOT SHA TFAD team, the first method (reported herein) can be used to update non-motorized share input to MSTM 1.5 Level 1 (or the older version) and make the model sensitive to non-motorized modes. The second method was to explore the use of a novel approach that the UMD project team has developed and was not part of the original scope. We have the framework ready and preliminary analysis has been done. However, the project team needs subarea input and further development and analysis to complete it. The second method can be applied to a selected local area, using an extracted subarea network (from the MSTM v1.5 L3 or L2). Implementation of the second method in MSTM 1.5 can be considered for a second phase of the project and can eventually be used for evaluating complete street projects in Maryland.

Limitations and Future work

The project successfully estimated modal shares on Complete Streets based on different Levels of Traffic Stress for Bike and Walk alternatives based on behavioral data exclusively collected for this project. A strategy for implementation into MSTM was proposed and applied to two scenarios. This is a fundamental step in understanding travel behavior on Complete Streets and in the definition of a methodology to assess the effects of CS projects on the tendency to walk and bike. In this section, we highlight limitations of the study proposed and possible ways to improve data collection, model estimation, validation and application to real case studies.

Data collection. Although a consistent number of responses were collected in our Stated Preference experiment, more observations would help better estimate elasticities to LTS for different income segments and trip purpose. Future data collection efforts might include the alternative walk and bike as access mode to transit.

Model estimation. The current mode choice model just include car, walk and bike as alternatives. Future work should be directed towards the estimation of the MSTM mode choice with inclusion of the walk and bike alternatives. In that case the adjustment of the motorized-share input will no longer be necessary.

Induced Demand. More attractive bike and walk path will induce people to take more trips on non-motorized modes, this is known in transportation as induced demand. The study of induced demand was outside the scope of this project. Future studies may approach this aspect of the problem by re-estimating trip generation, taking into account improved accessibility due to the introduction of Complete Streets in certain neighborhoods, corridors, or downtown areas.

LTS definition. In this project, we calculated an approximate aggregate LTS value at SMZ level. In the future, a more accurate network-based measure can be used to evaluate LTS especially for small area project analysis. Currently, MDOT SHA is working on the definition of LTS for the Maryland network; the outcomes of our project can be used for the network based LTS definition and to evaluate local CS projects.

Validation. The elasticities and non-motorized modal shares obtained from Stated Preference data should be validated using data that reflect current behavior. To that scope, the National Household Travel Survey (2017 NHTS) and Regional Travel Surveys (2018 MWCOG and BMC data) could be used to validate the project results. However, locations of trip origins and destinations should be available for the validation exercise.

Integration into MSTM. The team integrated the elasticities to LTS into the MSTM available at the NCSG. The integration to more advanced versions of MSTM that allow analysis at different geographical levels (Level 2 and Level 3) will enable MDOT - SHA to evaluate the effectiveness of local infrastructure projects aiming at improving local accessibility to walkers and bikers.

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APPENDIX A

A1. The survey SCE questionnaire is provided in the following file.

SHA CS- SCE
Qualtrics Survey - 10

A2. Complete data set used for analysis and model estimation. It is presented in long format, meaning that the same user ID is repeated for each of the choice tasks. This way, the 862 completes become 5,178 pseudo-observations.

data.csv

A3. Codebook containing the variables names, description and content.

codebook.xlsx

A4. Elasticity Estimates.

Elasticities_income_LT
S.xlsx

APPENDIX B

Table B1: Submodels estimation results

	LTS_INC11		LTS_INC12		LTS_INC13		LTS_INC14		LTS_INC15	
	estimate	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**
asc_car	0	NA	0	NA	0	NA	0	NA	0	NA
asc_bike	0.3932	0.6	1.2208	0.91	-1.1063	-1.97	-0.3965	-0.76	0.1326	0.25
asc_walk	0.8875	1.08	0.4693	0.35	-0.3768	-0.5	-0.8038	-1.47	-0.2959	-0.43
asc_other	-2.6953	-4.52	-2.9224	-3.06	-3.8495	-7.79	-2.6726	-4.05	-3.648	-6.99
b_travel_time_car	-0.0156	-0.38	0.0276	0.43	-0.067	-1.99	0.0164	0.4	-0.0063	-0.15
b_travel_time_bike	-0.054	-2.15	-0.0681	-1.45	-0.0587	-2.47	-0.0396	-1.41	-0.0536	-2.06
b_travel_time_walk	-0.0643	-2.74	-0.0153	-0.46	-0.0927	-4.6	-0.0348	-1.76	-0.0416	-2.12
b_male	0.1481	0.54	0.3892	0.63	0.3245	1.84	0.0314	0.15	0.5999	2.98
b_age	-0.0164	-1.8	-0.0221	-1.12	-0.0059	-0.85	-0.0111	-1.69	-0.0102	-1.44
b_ownbike	2.0067	3.22	-0.0801	-0.07	2.0746	3.85	0.8738	1.71	1.3307	2.74
b_frequsebikeother	-0.5645	-3.18	-0.0061	-0.02	-0.34	-2.37	-0.0327	-0.25	-0.1909	-1.34
b_travel_cost_car	-0.1039	-0.25	-0.6694	-1.07	0.0465	0.17	-0.0863	-0.29	-0.2967	-1.1
b_parking_cost_car	-0.1062	-1.07	-0.2041	-0.89	-0.1437	-2.11	-0.0616	-0.82	-0.1397	-1.81
b_LTS_bike	-0.1559	-1.29	-0.4609	-1.49	-0.1667	-1.53	0.0109	0.11	-0.435	-3.94
b_LTS_walk	-0.3486	-1.84	-0.7255	-1.65	-0.1516	-1	0.1793	1.37	-0.3699	-2.49
Adj.Rho-square	0.2178		0.1471		0.3293		0.2525		0.2929	
AIC	626.73		212.83		1019.05		1075.61		964.52	
BIC	678.06		247.83		1079.34		1135.14		1023.3	

Table B1 (continues)

	LTS_INC21		LTS_INC22		LTS_INC23		LTS_INC24		LTS_INC25	
	estimate	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**
asc_car	0	NA	0	NA	0	NA	0	NA	0	NA
asc_bike	1.1654	1.76	0.164	0.14	0.9706	1.72	0.1866	0.36	-0.186	-0.34
asc_walk	1.0572	1.4	-0.729	-0.56	0.845	1.36	0.534	0.94	1.5253	2.55
asc_other	-2.6982	-3.28	-4.2365	-3.74	-4.8633	-6.28	-4.8264	-7.05	-4.893	-5.13
b_travel_time_car	0.0484	0.93	-0.0668	-0.78	-0.0383	-0.92	-0.0387	-0.93	-0.025	-0.52
b_travel_time_bike	-0.0062	-0.2	-0.0512	-0.97	-0.085	-3.13	-0.0241	-0.92	-0.0329	-1
b_travel_time_walk	-0.0176	-0.79	-0.041	-1.14	-0.0608	-3.18	-0.0686	-3.71	-0.0884	-3.84
b_male	0.4793	1.96	-0.1516	-0.38	0.2521	1.14	0.1597	0.77	0.335	1.58
b_age	-0.0099	-0.95	-0.0023	-0.12	-0.0213	-3	-0.0107	-1.67	-0.0148	-2.09
b_ownbike	-0.4672	-0.81	-0.203	-0.25	1.2123	2.38	0.9912	1.98	0.5255	1.05
b_frequsebikeother	0.2077	1.33	0.1393	0.62	-0.2539	-1.89	-0.1591	-1.19	-0.0685	-0.49
b_travel_cost_car	-0.0428	-0.12	-0.135	-0.22	-0.285	-1	-0.1431	-0.51	-0.5316	-1.95
b_parking_cost_car	-0.017	-0.22	-0.2947	-1.69	0.0535	0.74	-0.0857	-1.14	-0.1123	-1.61
b_LTS_bike	-0.4403	-3.25	-0.507	-2.36	-0.3894	-3.28	-0.468	-4.43	-0.3259	-3.18
b_LTS_walk	-0.3897	-2.94	-0.3496	-1.16	-0.3297	-2.4	-0.2609	-2.27	-0.4449	-3.5
Adj.Rho-square	0.222		0.1771		0.3412		0.2896		0.2699	
AIC	748.52		264.65		900.56		972.99		1012.12	
BIC	802.41		303.2		959.36		1031.83		1071.12	

Table B1 (continues)

	LTS_INC31		LTS_INC32		LTS_INC33		LTS_INC34		LTS_INC35	
	estimate	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**
asc_car	0	NA	0	NA	0	NA	0	NA	0	NA
asc_bike	2.2394	2.19	-0.3966	-0.23	1.3294	1.17	1.3263	1.18	2.1412	2.53
asc_walk	2.1586	1.81	0.5297	0.26	2.1587	1.65	2.5085	2.38	2.15	2.07
asc_other	-2.099	-2.03	-5.7995	-3.14	-3.648	-2.65	-4.6643	-3.48	-4.042	-3.76
b_travel_time_car	0.0765	0.8	-0.0113	-0.11	0.046	0.46	-0.037	-0.49	-0.1415	-2.64
b_travel_time_bike	0.0626	1.12	-0.0726	-1.16	-0.0433	-0.69	-0.098	-2.02	-0.0987	-2.68
b_travel_time_walk	-0.0065	-0.17	-0.0943	-1.77	-0.0859	-1.73	-0.095	-2.66	-0.083	-3.4
b_male	0.3175	0.8	1.0064	1.36	0.5826	1.26	0.1644	0.4	0.2202	0.61
b_age	-0.0225	-1.67	-0.0364	-1.23	-0.0281	-1.91	-0.0176	-1.43	-0.0232	-1.87
b_ownbike	2.4861	2.9	0.4539	0.39	1.7428	1.72	2.6061	2.7	1.2845	1.35
b_frequsebikeother	-0.5845	-2.55	-0.2017	-0.75	-0.2195	-0.9	-0.4202	-1.48	-0.1545	-0.58
b_travel_cost_car	0.4916	0.86	-0.6214	-0.84	-0.366	-0.62	-0.1116	-0.23	0.8498	2.05
b_parking_cost_car	0.0833	0.55	-0.6131	-2.87	0.0183	0.12	-0.0219	-0.17	-0.0222	-0.2
b_LTS_bike	-0.5314	-2.94	-0.1515	-0.54	-0.7352	-3.22	-0.2845	-1.72	-0.5057	-2.94
b_LTS_walk	-0.4653	-1.84	-0.052	-0.15	-0.8302	-3.16	-0.7026	-2.91	-0.3749	-1.56
Adj.Rho-square	0.2526		0.2123		0.4469		0.3064		0.233	
AIC	314.98		146.32		271.45		361.53		442.32	
BIC	357.31		177.19		315.91		406.84		489.04	

Table B1 (continues)

	LTS_INC41		LTS_INC42		LTS_INC43		LTS_INC44		LTS_INC45	
	estimate	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**	**estimate**	**Rob.t-ratio**
asc_car	0	NA	0	NA	0	NA	0	NA	0	NA
asc_bike	-1.1073	-0.67	-0.2444	-0.12	0.8984	0.54	0.7826	0.43	1.0321	0.8
asc_walk	0.1813	0.08	-1.5621	-0.71	1.6149	0.8	1.7104	0.94	-0.4492	-0.29
asc_other	-5.8422	-3.57	-11.6876	-4.26	-3.4177	-2.16	-4.4002	-2.86	-1.1251	-0.98
b_travel_time_car	-0.0607	-0.72	-0.1414	-0.88	0.3086	2.51	0.0617	0.64	0.3047	2.82
b_travel_time_bike	-0.072	-1.42	-0.1016	-0.8	0.1235	1.16	0.0183	0.38	0.1892	3.04
b_travel_time_walk	-0.1287	-3.23	-0.0367	-0.49	-0.1063	-1.65	-0.0278	-0.69	0.1071	2.57
b_male	0.9939	1.6	-0.7707	-0.9	0.1248	0.2	-0.9064	-1.22	0.5807	0.89
b_age	-0.0137	-0.53	0.054	1.49	-0.0323	-1.4	-0.0088	-0.31	-0.0128	-0.67
b_ownbike	3.9397	3.64	0.9634	0.73	0.8288	0.58	2.3589	2.2	1.656	1.49
b_frequsebikeother	-0.7358	-2.91	-0.2695	-0.62	-0.3096	-0.83	-0.594	-1.88	-0.3388	-0.98
b_travel_cost_car	-0.9942	-1.13	1.2476	1.15	-2.4468	-2.54	-0.914	-1.11	-0.192	-0.28
b_parking_cost_car	-0.1186	-0.49	0.1574	0.62	0.3071	1.21	-0.2128	-1.03	-0.2556	-1.3
b_LTS_bike	-0.988	-2.78	-0.1011	-0.33	-0.9957	-2.59	-0.6689	-2.09	-0.7815	-3.21
b_LTS_walk	-0.7371	-1.83	0.0471	0.12	0.1873	0.34	-0.8804	-1.88	-0.3183	-1
Adj.Rho-square	0.3051		0.1174		0.4513		0.2032		0.2224	
AIC	146.42		119.91		126.26		167.89		202.66	
BIC	179.05		146.4		160.12		200.52		238.26	

Table B1 (continues)

	LTS_INC51		LTS_INC52		LTS_INC53		LTS_INC54		LTS_INC55	
	estimate	Rob.t-ratio	estimate	Rob.t-ratio	estimate	Rob.t-ratio	estimate	Rob.t-ratio	estimate	Rob.t-ratio
asc_car	0	NA	0	NA	0	NA	0	NA	0	NA
asc_bike	16.2258	1.58	-24.1226	NA	62.207	NA	-3.024	-1.09	-3.037	-1.53
asc_walk	18.3919	1.72	-14.7224	NA	235.6979	NA	-1.348	-0.42	-0.4904	-0.16
asc_other	-7.0767	-2.41	-100.2515	NA	-19.9179	NA	-22.2149	-4.85	-17.258	-4.79
b_travel_time_car	-1.9104	-2.44	17.4967	NA	3.0599	NA	-0.2638	-1.21	0.0334	0.12
b_travel_time_bike	0.0838	0.74	-14.3726	NA	2.3096	NA	-0.2714	-1.74	-0.0948	-0.56
b_travel_time_walk	-0.013	-0.25	-2.1407	NA	-2.9004	NA	-0.1754	-1.55	-0.1044	-0.97
b_male	12.3832	2.54	-63.5305	NA	-1.3434	NA	-0.6459	-0.94	-1.2107	-1.35
b_age	-0.6187	-2.29	3.7624	NA	-0.8524	NA	0.0592	1.14	0.0203	1.13
b_ownbike	16.3296	2.87	235.2734	NA	16.5001	NA	4.5756	2.21	-0.1128	-0.05
b_frequsebikeother	-5.7284	-2.5	-10.5559	NA	-5.8482	NA	-0.8943	-1.79	0.2486	0.33
b_travel_cost_car	21.231	2.29	-156.2264	NA	23.7324	NA	-0.5113	-0.52	-1.0954	-0.97
b_parking_cost_car	-1.2608	-2.84	108.861	NA	-13.0451	NA	-0.4378	-1.31	-0.194	-0.61
b_LTS_bike	-0.0495	-0.06	42.6375	NA	-7.8272	NA	-0.2134	-0.55	0.8468	1.92
b_LTS_walk	-0.2471	-0.3	-25.0212	NA	-51.9824	NA	-1.4651	-1.97	0.2344	0.47
Adj.Rho-square	0.1111		-0.1221		0.5307		0.1867		0.0711	
AIC	56.68		28		32.53		76.67		74.69	
BIC	72.58		30.76		49.59		98.03		93.83	

Table B2: Direct and cross elasticities resulting from the submodels

	LTS_INC11			LTS_INC12			LTS_INC13			LTS_INC14			LTS_INC15		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	-0.079	0.103	0.078	0.126	-0.152	-0.163	-0.284	0.532	0.367	0.073	-0.109	-0.099	-0.026	0.039	0.037
Travel time Bike	0.201	-0.572	0.186	0.200	-0.651	0.247	0.196	-0.709	0.180	0.117	-0.445	0.116	-0.549	0.160	0.195
Travel time Walk	0.151	0.182	-1.208	0.044	0.051	-0.333	0.179	0.234	-1.702	0.123	0.136	-0.686	-0.841	0.120	0.153
Travel Cost Car	-0.055	0.072	0.055	-0.331	0.402	0.424	0.021	-0.039	-0.028	-0.042	0.062	0.057	-0.135	0.202	0.190
Parking Cost Car	-0.057	0.071	0.072	-0.099	0.127	0.129	0.116	-0.066	0.116	-0.029	0.043	0.041	-0.066	0.097	0.099
LTS Bike	0.093	-0.271	0.103	0.233	-0.731	0.247	0.079	-0.292	0.094	-0.005	0.021	-0.007	0.211	-0.723	0.259
LTS Walk	0.081	0.100	-0.647	0.160	0.177	-1.198	0.034	0.041	-0.309	-0.065	-0.082	0.374	0.105	0.125	-0.717

Table B2 (continues)

	LTS_INC21			LTS_INC22			LTS_INC23			LTS_INC24			LTS_INC25		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	0.266	-0.282	-0.257	-0.363	0.421	0.420	-0.157	0.270	0.251	-0.197	0.263	0.194	-0.135	0.172	0.111
Travel time Bike	0.025	-0.064	0.024	0.222	-0.560	0.254	0.244	-0.944	0.265	0.106	-0.260	0.088	0.147	-0.374	0.110
Travel time Walk	-0.341	0.081	0.086	0.139	0.156	-0.988	0.208	0.240	-1.253	0.217	0.241	-1.227	0.320	0.368	-1.426
Travel Cost Car	-0.025	0.026	0.024	-0.078	0.090	0.092	-0.124	0.212	0.200	-0.079	0.104	0.079	-0.307	0.387	0.257
Parking Cost Car	-0.011	0.011	0.011	-0.152	0.174	0.189	0.024	-0.040	-0.042	-0.046	0.056	0.056	-0.067	0.074	0.071
LTS Bike	0.262	-0.699	0.276	0.139	-0.988	0.156	0.168	-0.657	0.196	0.276	-0.696	0.265	0.320	-1.426	0.368
LTS Walk	0.163	0.173	-0.688	0.108	0.101	-0.712	0.105	0.121	-0.631	0.093	0.085	-0.489	0.179	0.170	-0.743

Table B2 (continues)

	LTS_INC31			LTS_INC32			LTS_INC33			LTS_INC34			LTS_INC35		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	0.390	-0.365	-0.288	-0.056	0.088	0.059	0.120	-0.325	-0.230	-0.200	0.219	0.151	-0.827	0.735	0.627
Travel time Bike	-0.299	0.510	-0.306	0.278	-0.910	0.294	0.096	-0.450	0.128	0.482	-0.946	0.492	0.421	-0.936	0.418
Travel time Walk	0.018	0.023	-0.115	0.307	0.454	-1.803	0.112	0.217	-1.447	0.246	0.358	-1.749	0.354	0.401	-1.486
Travel Cost Car	0.270	-0.251	-0.201	-0.337	0.517	0.377	-0.109	0.293	0.212	-0.065	0.071	0.051	0.523	-0.472	-0.405
Parking Cost Car	0.047	-0.041	-0.041	-0.272	0.402	0.319	0.005	-0.013	-0.013	-0.012	0.012	0.011	-0.014	0.012	0.012
LTS Bike	0.400	-0.724	0.485	0.078	-0.269	0.106	0.228	-1.093	0.343	0.201	-0.407	0.242	0.291	-0.682	0.350
LTS Walk	0.145	0.170	-0.881	0.017	0.023	-0.095	0.110	0.175	-1.341	0.160	0.254	-1.185	0.147	0.176	-0.626

Table B2 (continues)

	LTS_INC41			LTS_INC42			LTS_INC43			LTS_INC44			LTS_INC45		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	-0.240	0.379	0.272	-0.848	0.751	0.892	0.653	-2.453	-1.423	0.345	-0.373	-0.287	1.448	-1.537	-1.776
Travel time Bike	0.215	-0.733	0.259	0.411	-0.997	0.499	-0.246	1.435	-0.222	-0.089	0.203	-0.108	-0.706	1.824	-0.914
Travel time Walk	0.272	0.468	-2.178	0.213	0.217	-0.841	0.123	0.199	-1.495	0.099	0.147	-0.570	-0.706	-0.914	1.824
Travel Cost Car	-0.413	0.643	0.497	0.812	-0.740	-0.854	-0.623	2.216	1.407	-0.522	0.553	0.441	-0.100	0.103	0.121
Parking Cost Car	-0.049	0.068	0.073	0.087	-0.082	-0.087	0.069	-0.217	-0.215	-0.124	0.126	0.115	-0.139	0.138	0.160
LTS Bike	0.372	-1.302	0.508	0.213	-0.841	0.217	0.236	-1.470	0.312	0.429	-0.955	0.460	0.364	-0.974	0.475
LTS Walk	0.164	0.212	-1.168	-0.021	-0.026	0.089	-0.035	-0.043	0.400	0.258	0.295	-1.331	0.127	0.117	-0.606

Table B2 (continues)

	LTS_INC51			LTS_INC52			LTS_INC53			LTS_INC54			LTS_INC55		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	-4.754	6.044	2.818	NA	NA	NA	NA	NA	NA	-1.183	1.041	1.037	0.138	-0.205	-0.130
Travel time Bike	-0.143	0.844	-0.464	NA	NA	NA	NA	NA	NA	1.229	-1.936	1.749	0.285	-0.846	0.222
Travel time Walk	0.019	0.122	-0.175	NA	NA	NA	NA	NA	NA	0.361	0.525	-3.344	0.339	0.430	-1.418
Travel Cost Car	4.212	-5.970	-2.897	NA	NA	NA	NA	NA	NA	-0.252	0.227	0.211	-0.535	0.760	0.531
Parking Cost Car	-0.342	0.319	0.300	NA	NA	NA	NA	NA	NA	-0.185	0.162	0.174	-0.086	0.104	0.107
LTS Bike	0.009	-0.071	0.046	NA	NA	NA	NA	NA	NA	0.149	-0.223	0.185	-0.413	1.321	-0.454
LTS Walk	0.045	0.199	-0.329	NA	NA	NA	NA	NA	NA	0.203	0.343	-2.035	-0.075	-0.119	0.339

APPENDIX C.

The Excel Sheet Calculator

Motorized Shares
Calculator.xlsm