HEALTH IMPACTS OF TRANSPORTATION AND THE BUILT ENVIRONMENT: A QUANTITATIVE RISK ASSESSMENT

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ABSTRACT

Theodore J. Mansfield: Health Impacts of Transportation and the Built Environment:
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The design of urban transportation networks can affect three kinds of human health risks: (1) motor vehicle crashes, (2) air pollution from automobiles, and (3) physical inactivity occurring when motor vehicles replace walking and cycling as the main means of transportation. However, the relative magnitude of each of these risks in relation to the way cities are designed is poorly understood, and tools and methods that simultaneously assess all three risks are limited. Furthermore, available tools rely on static methods that fail to account for cumulative health impacts over time. This work developed the first dynamic micro-simulation model for quantifying all three risks and then applied the model to compare transportation health risks between neighborhood groups of varying designs within the Raleigh-Durham-Chapel Hill region. The model combines information on crash risk as a function of vehicle miles traveled, demographic and built environment variables routinely collected by the US Census Bureau, modeled estimates of fine particulate air pollution arising from traffic computed at the census block scale, and baseline public health data from the North Carolina State Center for Health Statistics in order to estimate premature mortality risks from each of the three transportation-risk sources at the census block group scale. The model estimates that the combined health impacts of transportation are lowest in block groups with designs that encourage walking for transportation (18.4 annual excess deaths per 100,000 persons on average over 10 years, compared to 22.9 in the least walkable block groups). While air pollution health impacts are higher in the most walkable block groups (2.14 annual excess deaths per 100,000 persons compared to 1.15), physical inactivity and crash risks are lower in these areas (2.70 annual excess deaths

per 100,000 compared to 6.66 and 13.5 compared to 15.1, respectively). Similarly, net individual risks of premature mortality are lower among those who walk, bike, or ride transit to work due to increased physical activity and decreased risk of fatal crashes. These results illustrate that designing neighborhoods to encourage walking has important net health benefits.

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PREFACE

This dissertation is organized in a nontraditional format, which includes three manuscripts. Chapter 1 provides context for this dissertation and describes the significance of this research. Chapters 2, 3, and 4 must stand alone as manuscripts to be submitted for publication. As a result, these chapters have some redundancies with earlier chapters. Chapter 5 summarizes findings of this dissertation, discusses policy implications, addresses limitations of this research, and provides directions for future research.

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LIST OF ABBREVIATIONS

ACS	American Community Survey
BRFSS	Behavioral Risk Factor Surveillance System
BRRC	Blue Ridge Road Corridor
CDC	Centers for Disease Control and Prevention
CHD	Coronary heart disease
CI	Confidence interval
CVD	Cardiovascular disease
DOT	Department of Transportation
DYNAMO-HIA	Dynamic Model for Health Impact Assessment
DOT	Department of Transportation
EPA	Environmental Protection Agency
GEE	General estimating equations
GLM	Generalized linear models
HEAT	Health Economic Assessment Tool
HIA	Health impact assessment
HW	High walkability
LW	Low walkability
MET	Metabolic equivalent
MHW	Medium-high walkability
MLW	Medium-low walkability
MW	Medium walkability
N	Sample size
NEPA	National Environmental Policy Act
NCDOT	North Carolina Department of Transportation
NHTS	National Household Travel Survey

OR	Odds ratio
P	Probability
PA	Physical activity
PEF	Pedestrian environment factor
$PM_{2.5}$	Fine particulate matter
RR	Relative risk
SES	Socio-economic status
TPA	Transportation physical activity
US	United States
USDOT	United States Department of Transportation
VMT	Vehicle-miles travelled
WHO	World Health Organization

LIST OF SYMBOLS

AF_{TPA}	Fraction of mortality avoidable by additional active transportation (unitless)
AM_{TPA}	Avoided mortality due to active transportation (avoided premature deaths)
DR_b	Baseline death rate (deaths per year per 100,000 persons)
$E(t_{m,i})$	Expected daily number of trips take using mode *m* for individual *i* (trips)
μg/m^3	Micrograms per cubic meter
β	Regression coefficient (unitless)
$d_{p,m}$	Trip duration for a trip taken by individual *i* for purpose *p* using mode *m* (minutes)
$D_{s,before}$	Density of sidewalks before construction (km/km^2)
$D_{s,after}$	Density of sidewalks before construction (km/km^2)
$f_{est}(TPA)$	Current probability distribution of transportation physical activity (MET-hrs/week)
$f_{cf}(TPA)$	Probability distribution of transportation physical activity in the counterfactual scenario (MET-hrs/week)
$O_{w,before}$	Odds of walking given the density of sidewalks before construction (unitless)
$O_{w,after}$	Odds of walking given the density of sidewalks before construction (unitless)
π_i	Probability that daily walk or bike trip counts always equals zero (unitless)
$E(t_{m,i})$	Expected daily number of trips take using mode *m* for individual *i* (trips)
$g(x)$	Link function (unitless)
$P_{S,M,time-1}$	Modeled prevalence of state *S* in the previous time step in a model with no intermediate disease pathways (unitless)
$P_{S,M+D,time-1}$	Modeled prevalence of state *S* in the previous time step in the adjusted model (unitless)
$Pr(p_m)$	Probability that a trip taken by individual *i* using mode *m* is for purpose *p* (unitless)
$Pr(y_i = p)$	Probability of trip purpose *p* for individual *I* (unitless)
$P_i(S \rightarrow S')$	Probability that individual *i* transitions from state *S* to state *S’* during a time step
$P_{w,before}$	Probability that an individual takes at least one walk trip per week before construction (unitless)

$\boldsymbol{P_{w,after}}$	Probability that an individual takes at least one walk trip per week after construction (unitless)
$\boldsymbol{RR_M(TPA)}$	Relative risk of all-cause mortality as a function of transportation physical activity (unitless)
$\boldsymbol{RR_M(PM)}$	Relative risk of all-cause mortality as a function of transportation $PM_{2.5}$ (unitless)
$\boldsymbol{RR_{S'}\|exposure_{r,i}}$	Relative risk of state *S'* occurring for individual *i* given exposure to risk *r*. activity *i* (unitless)
$\boldsymbol{TPA_i}$	Daily physical activity from walking and biking for individual *i* (minutes)
$\boldsymbol{TT_{m,i}}$	Daily minutes spent traveling using mode *m* for individual *i* (minutes)
$\boldsymbol{x}$	Vector of regression coefficients (unitless)
$\boldsymbol{Z_{FAR}}$	Z-score for retail floor area (unitless)
$\boldsymbol{Z_{intersetion}}$	Z-score for the number of intersections divided by land area (unitless)
$\boldsymbol{Z_{land-use}}$	Z-score land-use diversity (unitless)
$\boldsymbol{Z_{residential}}$	Z-score for the number housing units divided by the residential land area (unitless)

CHAPTER 1: INTRODUCTION

1.1. Overview of this research

Characteristics of the built environment have a well-documented link to transportation behavior. The mix of different land uses, the density of land use, access to destinations, physical design, and availability of public transit services affect the number of trips individuals take, the choice of transportation mode for trips, and characteristics of trips themselves, such as trip length (Ewing & Cervero, 2010). In turn, these transportation choices and trip characteristics impact air quality via emissions from automobiles, physical activity levels via transportation walking and biking, and exposure to injury risk from crashes for all transportation modes. Today, physical inactivity is associated with 234,000 premature deaths per year in the US (US Burden of Disease Collaborators, 2013). Fatal injuries from crashes result in an additional 32,000 annual US deaths (US Burden of Disease Collaborators, 2013). Exposure to ambient air pollution is associated with an additional 108,000 annual premature deaths, nearly half of which are associated with fine particulate matter ($PM_{2.5}$) emitted by motor vehicles and other mobile pollution sources (US Burden of Disease Collaborators, 2013; Caiazzo et al., 2013). These three health risks related to transportation systems—air pollution exposure, physical inactivity, and fatal injuries from crashes—are linked to both characteristics of the transportation system itself as well as characteristics of the built environment that influence transportation choices. While the built environment affects travel behavior, and transportation behaviors impact public health, decisions about transportation systems and the built environment rarely consider health impacts beyond those associated with traffic accidents.

The interplay between transportation systems and built environment characteristics results in complex spatial distributions of transportation health risks across urban areas. For example, automobile emissions are distributed across urban areas in idiosyncratic manners defined by the shape and extent of the roadway network and commuting patterns within a city. Individuals living near major roadways are thus exposed to higher levels of air pollution than other residents (Spira-Cohen et al., 2010). Compact neighborhoods support increased walking and biking for transportation, yet may increase health risks from air pollution (Hankey, Marshall, & Brauer, 2012). Limited methods currently exist to untangle the competing effects of transportation health risks in urban areas at the population level. Models considering a single individual or sub-populations have shown that the health benefits of transportation physical activity can outweigh other risks. For example, Woodcock et al. demonstrated that physical activity benefits to individuals using the London bike share system outweighed risks associated with accidents and air pollution exposure (2014). Population-level models have typically relied on coarse spatial characterization of exposures to quantify risk (Woodcock et al., 2009; Maizlish et al., 2013). In addition, population-scale models typically have considered only a single point in time (Mueller et al., 2015).

Given the spatial heterogeneity and dynamic nature of transportation health risks in urban areas, models that are able to provide dynamic estimates at high spatial resolution are important in untangling competing risks. This research develops and applies a novel dynamic microsimulation model to estimate population-level health impacts of transportation systems at high spatial resolution. This model will support future assessments of transportation health impacts, help improve understanding of the interactions between the built environment and public health, and could be used to incorporate health considerations into routine decision-making practices that share transportation system and the built environment. This research is structured around three objectives:

- **Objective 1:** Apply a dynamic health impact model to estimate the health impacts of increases in transportation physical activity after a change in the built environment, and compare estimates from the dynamic model to estimates from a traditional static model.
- **Objective 2:** Develop and demonstrate a statistical model for characterizing baseline transportation physical activity at the Census block group level by linking behavioral evidence

from the 2009 National Household Travel Survey to data routinely collected in the American Community Survey.

- **Objective 3:** Develop and demonstrate a novel dynamic microsimulation health impact model to estimate population-level health impacts of automobile emissions, physical activity, and fatal crashes at the Census block group scale.

1.2. Historical perspective

A brief review of historical links between public health and urban planning and the subsequent divergence of these disciplines along with the suburbanization of US metropolitan areas provides context for this research. In its formative stages, the field of public health placed a strong emphasis on the built environment as a risk for poor health. The sanitation movement, a formative force in the professionalization of public health in the late 19th century, attributed poor health to poor sanitation conditions based on the theory that foul odors were the mechanism for disease transmission (the “miasma theory”). As the sanitation movement spread in the US public health departments were increasingly tasked with urban sanitation (Andrews, 2006). Scientific advancements, specifically the discovery of microbial pathogens as the mechanism for disease transmission, invalidated the miasma theory that had formed the basis of early sanitation-focused public health efforts. Subsequently, public health shifted its focus away from urban planning and toward disease prevention through individual-level interventions, such as vaccination. By 1925, less than 25% of US cities tasked their public health departments with urban sanitation (Melosi, 1980).

As the focus of public health shifted towards individual-level disease prevention during the 20th century, new environmental health risks were emerging in US cities. The industrialization of US cities brought new urban air quality problems. Lacking a federal regulatory structure to manage air quality, Industrial emissions were often considered within a common-law framework; however, the courts often considered the benefits of industrial activities that generated emissions alongside the harms caused by pollutants (Andrews, 2006). While some cities adopted local air pollution controls, often such policies were successful only in the migration of industries to outlying areas (Colten & Skinner, 1996). Several statewide efforts to regulate air quality emerged as well; however, these regulatory frameworks were generally weak (Tarr, 1985). Common-law precedent, the ability of industry to relocate to avoid local emissions regulations, and the role of upwind pollutions sources made early state and municipal efforts to manage air quality difficult to implement (Tarr, 1985). These difficulties were in stark contrast to the success of the urban sanitation movement, which required actions by municipal governments and had easily identifiable benefits. Air pollution regulations required action by firms and had less discernible immediate benefits. However, in the wake of highly visible air pollution events, federal air quality regulations coalesced in the mid-20th century, building to the passage of the Clean Air Act and subsequent amendments. Implementation of the Clean Air Act greatly improved air quality in cities and further reduced health risks in urban areas (Melosi, 1980). Subsequent environmental regulations on automobile emissions and vehicle efficiency further improved air quality in urban areas (EPA, 2011).

While public health shifted towards a more individual-centered approach and environmental regulations coalesced to address emerging air pollution health risks in US cities, substantial changes in urban development patterns were occurring. Suburbanization began in the US in the 19th century as wealthy enclaves began to emerge outside of central cities, enabled by transportation innovations such as the invention of the streetcar (Fishman, 1989). Interestingly, the same factors that brought about the sanitation movement motivated early suburbanization, at least in part. For example, the first planned community in the US, Riverside, Illinois, was designed by two prominent landscape architects of the day, Frederick Law Olmsted and Calvert Vax, and shared many design characteristics with their grand urban parks. This development was marketed as a means to have the conveniences of urban life along with the healthy environment of country living (Kirkman, 2010).

A second transportation innovation—mass production of the Model T—made automobile ownership affordable to many Americans starting in the 1910s. Investment in infrastructure to support this new form of mobility quickly followed. Federal aid was first provided for roadway construction in 1916; by 1929, nearly all states in the US had levied gasoline taxes to fund roadway construction (Jackson, 1985). In addition, in the early 20th century, new financial policies reduced barriers to home ownership. The Federal Housing Authority was created in 1934 and tasked with reinsuring mortgage loans to make them more affordable (Andrews, 2006). The GI Bill, passed in 1944, further subsidized home ownership for returning veterans from the Second World War. In 1950, construction began on more than one million single-family homes in the US (Melosi, 1980). In 1951, the construction of Levittown, NY, demonstrated how mass production principles could be applied to urban development, providing the foundation for a fundamentally different urban form than previously existed in the US. In 1956, the Federal Highway Act pledged the federal government to build a 42,500-mile interstate highway system (Andrews, 2006). Transportation innovations enabling greater personal mobility through use of automobiles, substantial investment in infrastructure to support this new form of transportation, and financial incentives for homeownership provided a suite of complementary forces supporting large-scale suburbanization in the US.

In contrast to rapid growth of the suburbs, US urban areas were in decline during much of the 20th century. The Federal Housing Authority was granted the power to differentiate loan guarantees based on perceived risk. In practice, this power was often used to make federal loan guarantees difficult, if not impossible, to obtain in neighborhoods with high proportions of minority populations and older housing stock, a process known as redlining (Jackson, 1985). Redlined urban neighborhoods languished while many wealthier urban residents moved to the suburbs. Declining urban tax bases made it difficult for municipal governments and urban school districts to provide quality services. In contrast, suburban governments and schools reaped the benefits of suburbanization in their own districts. School quality is a primary driver of household location choice (Bayoh, Irwin, & Haab 2006). Thus, the coupled process of suburban growth and urban decline was, to some degree, self-reinforcing.

The new urban forms emerging in suburban America differed markedly from traditional urban development patterns. Land-use regulations rooted in nuisance claims in dense urban environments coalesced into broader regulations segregating incompatible land uses. Suburban areas were developed on new sites; however, the same adherence to strict use-based zoning was often applied to suburban development (Duany et al., 2000). Applying land use regulations developed to address incompatible uses in dense urban areas in low-density developments on new land led to highly segregated land uses—a characteristic of the built environment that is associated with increased driving, reduced walking and cycling, and increased trip generation (Ewing & Cervero, 2010).

With the rise of the suburbs and the decline of urban neighborhoods, large shifts were occurring in health risks related to the built environment. Environmental regulations, motivated by public health goals, reduced emissions from point-sources. However, increases in vehicle-miles travelled introduced new air quality issues in cities like Los Angeles. Over time, stricter regulations for motor vehicles helped address poor air quality from automobiles (Andrews, 2006). However, other health risks increased over this period. Increased per capita VMT has caused fatality rates from automobile crashes to remain high despite substantial improvements in vehicle safety and increased efficacy of seat belt laws (Litman, 2014). Today, Americans drive an average of 9,600 miles per year, an increase of over 300% since 1950—the same year in which construction began on more than one million single-family homes (USDOT, 2016).

1.3. Transportation health risks today

With the fundamental shifts in urban form, environmental regulations, and travel behavior that occurred in the 20th century, the nature of health risks in US urban areas changed dramatically. While suburban areas offered an escape from the historically polluted cities, the low-density development and segregated land-use patterns that typified suburban America did not support walking and biking for transportation. As environmental regulations evolved and urban air quality improved, health risks in urban neighborhoods declined. However, emerging health risks from increased automobile dependence remained or worsened. These broad changes in urban form and environmental quality have generated complex spatial distributions of competing transportation health risks in urban areas. Not only do these risks respond to built environment variables in different directions and with different magnitudes, but the nature of risk-risk tradeoffs is temporally dynamic. Further, transportation health risks may also disproportionally impact population with low socio-economic status (SES). Historically, the fields of public health and urban planning emerged in tandem to address waterborne disease risks. However, these fields diverged at the same time as transportation systems and the built environment changed in ways that created new health risks. Possibly as a result of the current separation of urban planning and public health, health-based regulatory frameworks to address the multiple risks that arise from modern urban and transportation systems have yet to emerge.

Although a regulatory framework for substantively considering the health implications of transportation and built environment decisions is lacking, urban and transportation planners are increasingly interested in incorporating health considerations into built environment decisions. Policy frameworks have emerged in both local and state-level transportation agencies (USDOT, 2012; USDOT, 2014). Health impact assessment (HIA), a structured process for incorporating health considerations into decision-making, is gaining prominence in the transportation sector (Dannenberg et al., 2014). However, lacking a compulsory regulatory framework, HIAs are conducted on a largely ad hoc basis. Health-based standards do interact with transportation decision-making in certain cases. For example, air pollution exposure is a more routine consideration, including established processes for hotspot analysis triggered when a region is in violation of national ambient air quality stands (EPA, 2013). In nonattainment areas, the Congestion Mitigation and Air Quality Improvement Program also provides funds for projects to reduce transportation emissions; however, these funds make up only a fraction of transportation funding and are available based on air pollution risks (USDOT, 2016). For crash injury risk, transportation decision-making often considers VMT exogenous in making decisions about road safety, focusing on reducing traffic fatalities per VMT rather than traffic fatalities per person. Thus, increases in per capita VMT due to automobile-dependent urban forms may nullify health gains that would otherwise occur due to increasing vehicle safety (Litman, 2014).

1.4. Air pollution exposure

1.4.1 Health risks of air pollution exposure

Convincing epidemiological evidence links exposure to ambient air pollutants to a range of health impacts. Epidemiological studies that consider acute air pollution exposure (e.g., daily or hourly pollutant concentrations) typically assess disease-related outcomes, such as increased risk of hospitalization for respiratory symptoms in response to higher daily $PM_{2.5}$ concentrations (Brook et al., 2010). Conversely, epidemiological studies that consider chronic air pollution exposures (e.g., annual average concentrations) typically assess mortality outcomes, such as increased risk of lung cancer mortality (Pope et al., 2002). While both acute and chronic exposure to a number of individual pollutants have demonstrated links to health outcomes, chronic exposure to $PM_{2.5}$ has an especially strong link to cardiopulmonary and lung cancer mortality (Pope et al., 2002). Recent scientific reviews conducted by the EPA have concluded that long-term exposure to $PM_{2.5}$ is causally linked to increased mortality (EPA, 2012; EPA, 2009). Interestingly, the effects of long-term exposure to pollutants in ambient air on disease risk is not well understood despite strong links to cause-specific mortality outcomes in large US cohort studies.

Urban air contains a mixture of airborne pollutants. While each pollutant may pose some health risk, multi-pollutant risk assessments typically find substantially higher health impacts for $PM_{2.5}$ exposure relative to other air pollutants (US Burden of Disease Collaborators, 2013). A recent assessment of mortality associated with $PM_{2.5}$ and ozone exposure in the ten most populous US counties found that most of the risk for premature mortality was associated with exposure to $PM_{2.5}$ (Fann et al., 2011). Because of the consistently high health impacts of $PM_{2.5}$ relative to other pollutants in ambient air, the use of $PM_{2.5}$ as a surrogate measure of air quality is common in quantitative risk assessments of air pollution exposure (e.g., MacDonald Gibson, 2013).

1.4.2 Air pollution exposure and the built environment

A large body of work has investigated the connections between characteristics of the built environment and air quality. Broadly, this body of evidence can be divided into two categories: inter-urban studies that compare aggregate built environment measures to average air pollution concentrations between cities and intra-urban studies that compare neighborhood-scale built environment features to air pollution concentrations within a single city. In inter-urban studies, more compact urban forms are often associated with improved air quality (Bereitschaft & Debbage, 2013; Clark et al., 2011). However, intra-urban variations in air quality suggest an opposite relationship—compact neighborhoods often have poorer air quality than less compact neighborhoods in the same city (Mansfield et al,. 2014; Hankey, Marshall, & Brauer, 2012; Hoek et al., 2011; Moore et al., 2007; Ross et al., 2007; Schweitzer & Zhou, 2010). While compact urban forms are associated with reduced total pollutant mass emissions, compact neighborhoods may be located in closer proximity to transportation corridors and thereby suffer from decreased air quality (Spira-Cohen et al., 2010). These effects may be countered via improved vehicle efficiency (e.g., hybrid/electric vehicles or stricter emissions controls); however, studies reaching such conclusions often assume aggressive uptake of these technologies in the vehicle fleet (Song et al., 2008).

Previous research has also revealed relationships between poor air quality and indicators of low SES (Abel & White, 2011; Briggs et al., 2008; Grineski et al., 2013; Buzzelli & Jerrett, 2007; Hajat et al., 2013). For example, in neighborhoods near the Port of Long Beach, parcels with high concentrations of mobile-source $PM_{2.5}$ are more likely to have a high percentage of minority populations (Houston et al., 2014). A study of neighborhood-scale exposure to NO and O_3 in Vancouver, B.C., reached similar conclusions (Marshall et al., 2006). De Ridder et al. found more sprawling future development would increase exposure to O_3 and PM_{10} for individuals living in core urban areas but decrease exposure for those who move from core urban areas to new developments in the urban periphery (2008). A study using high-resolution air quality estimates in Detroit found that mortality and asthma risks from $PM_{2.5}$ exposure were significantly higher in vulnerable than in less-vulnerable populations (Fann et al., 2011). In sum, the spatial distribution of air pollution risks is complex, is associated with built environment characteristics, and may affect vulnerable populations disproportionately.

1.5. Physical inactivity

1.5.1. Health risks of physical inactivity

A growing body of evidence links physical activity to a range of health outcomes, including cardiovascular disease, diabetes, cancers, and all-cause mortality (Aune et al., 2015; Robsahm et al., 2013; Zhong et al., 2015; Kelly et al., 2014). In addition to studies linking total physical activity to health outcomes, a subset of studies has documented a preventive relationship between health outcomes and physical activity accrued specifically from transportation (i.e., walking and cycling for transportation) (Kelly et al., 2014; Furie & Desai 2012). Importantly, epidemiological evidence indicates that chronic exposure to $PM_{2.5}$ and physical inactivity can affect similar health outcomes, including mortality risks from pulmonary and cardiovascular diseases as well as all-cause mortality.

1.5.2. Physical inactivity and the built environment

Multiple studies have demonstrated that characteristics of the built environment influence walking and biking for transportation (Ewing & Cervero, 2010; Bauman et al., 2012). Such studies have used both stated (i.e., collected via surveys) and objectively measured (e.g., with pedometers) physical activity (Hirsh et al., 2013; Cerin et al., 2014). Further, studies have shown that built environment features that encourage transportation physical activity do so independently of effects on recreational activity—that is, that increases in transportation physical activity associated with more walkable neighborhoods to not lead to offsetting reductions in recreational physical activity (Ding & Gebel 2012; Bauman et al., 2012). In addition, studies have shown that a positive relationship between built environment characteristics and physical activity remains when self-selection (i.e., households sorting into neighborhoods that match their preferences for physical activity) is introduced as a control in statistical models (Beenackers et al., 2012; Ding et al., 2012; Saelens et al., 2012; Sallis et al., 2009; Badland et al., 2012). Longitudinal studies also reveal a positive relationship between built environment factors and physical activity after controlling for other factors (Giles-Corti et al., 2013). Additionally, a recent study in Charlotte, NC, compared health outcomes before and after the construction of a light rail line using a propensity score matching approach and showed that changing one's commute to light rail increased physical activity and reduced the risk of obesity (MacDonald et al., 2010).

A complicating factor in the literature is the potential presence of a non-additive, "sum greater than the parts" relationship between built environment factors measured in different dimensions and physical activity outcomes. That is, high residential population density and increased mixing of different land uses may increase physical activity independently; however, the joint effect of the two factors may be greater than the sum of independent effects. To account for such a relationship, a number of studies have employed multi-dimension walkability indices (Frank et al., 2010). Similarly, WalkScore has been used as a multi-dimensional composite measure of walkability (Hirsch et al., 2013). Others studies use multi-level designs to account for potential interactions between built environment factors at the regional and neighborhood scales (Clark et al., 2014). Some studies have developed unique neighborhood typologies using techniques such as cluster analysis to define comparison groups within an urban area (Zahabi et al., 2013). Although cluster analysis and multi-dimension indices may have more power to identify significant relationships, they are unable to identify specific built environment factors that explain observed differences in physical activity levels between neighborhoods. Thus, studies using cluster analysis have limited generalizability while multi-dimension indices mask the effect of specific dimensions, such as increased population density holding all else constant, on physical activity. Because of the complexity of measuring built environment factors associated with walkability, associations between physical activity and built environment measures depend in part on the specific built environment measures employed.

Physical activity levels vary significantly between socio-economic groups in the US: in an analysis of accelerometry data from the 2005–2006 National Health and Nutrition Examination Survey, African-Americans were 36% more likely to be inactive than European-Americans, and those living in low-income households were 94% more likely to be inactive than those living in high-income households (Sisson et al., 2012). While low-SES populations may be more likely to participate in labor-intensive jobs and depend on public transportation for mobility, high-SES populations may be more likely to engage in recreational physical activity. Further, evidence suggests that low- and high-SES populations may respond to neighborhood amenities in different ways: Sallis et al. found that low-income residents in low-walkability neighborhoods have higher levels of transportation physical activity than their high-income counterparts; however, low-income residents in high-walkability neighborhoods have significantly lower transportation physical activity levels than high-income residents (2009). Other evidence in the literature is mixed. Wen et al. found that neighborhood factors do not mediate differences in walking by race (2007). Several studies have also found associations between body mass index, neighborhood design, and access to public transit (MacDonald et al., 2010; Carlson et al., 2012; Hess & Russell, 2012). However, a recent review did not find strong evidence that changes in the built environment improve physical activity in disadvantaged populations (Pearce et al., 2011). While the evidence is mixed, modifiable built environment factors may mediate observed health disparities in vulnerable populations. Thus, exploring the potential mediating effect of the built environment on physical activity has important environmental justice implications.

1.6. Motor vehicle, bicycle, and pedestrian crashes

1.6.1. Health risks of motor vehicle, bicycle, and pedestrian crashes

Compared to epidemiological studies of air pollution and physical activity health risks, epidemiological approaches to assessing health risks from crashes are limited by less readily available data to characterize exposure. For motor vehicle fatalities, exposure is typically characterized by the total length of travel (e.g., VMT); however, data on walking and biking are much more limited. Thus, studies that assess risk for pedestrians and cyclists use less refined measures of exposure, such as number of walking or biking trips (Beck, Dellinger, & O'Neil, 2007). National-level traffic fatality and travel data have been linked in a number of studies to estimate fatality risk as a function of distance traveled and/or trips taken by population sub-groups (Harper, Charters, & Strumpf 2015; Beck, Dellinger, & O'Neil, 2007). National-level studies have found evidence of differential risk for some populations, such as higher crash fatality risk per VMT for younger males who may engage in riskier driving behaviors (Harper, Charters, & Strumpf, 2015). As an alternative to national-level studies, Grabowski and Morrisey used state-level data to show that reductions in gas prices and concomitant increases in VMT explain increased fatality rates (2004). At a more refined spatial scale, a study in San Antonio also revealed a strong relationship between VMT assessed at the neighborhood scale (census block groups) and fatal crashes (Dumbaugh & Rae, 2009).

1.6.2. Motor vehicle, bicycle, and pedestrian crashes and the built environment

Built environment factors play a substantial role in modifying the risk for fatal pedestrian and bicycle crashes but have mixed effects on fatalities from motor vehicle crashes. Area-level studies have found associations between built environment characteristics and risks for pedestrians and cyclists. For example, studies in San Francisco and Portland found that pedestrian injuries were significantly associated with motor vehicle traffic volumes within Census tracts, controlling for other built environment variables (Gladhill & Monsere, 2012; Wier et al., 2009). Associations have also been demonstrated between the total number of pedestrians and reductions in individual risk, a phenomenon known as the safety-in-numbers theory (Jacobsen, 2003). However, the safety in numbers theory has been criticized because it may be that increased walking and biking are responses to unobserved built environment factors that reduce risk rather than the mechanism for risk reduction (Bhatia & Wier, 2011). Conversely, built environment variables, including population density, public transit usage, and volume-to-capacity ratio on streets, have mixed effects on risk estimates (Clark & Cushing, 2004; Simpson et al., 2014). While area-level studies are useful in targeting interventions to reduce pedestrian and cyclist fatalities in high-risk locations, limited conceptualization of individual-level dose (i.e., walk trips per person) in these studies limits their usefulness in population-level assessments of health risks from traffic crashes.

From an environmental justice perspective, individuals who rely on active modes of transportation may be exposed to greater risk compared to individuals with access to a private automobile for mobility— especially if low-income neighborhoods are less walkable than more affluent neighborhoods. However, motorists with long commutes may also be exposed to greater risk from motor vehicle fatalities if fatality risk is a function of VMT. Further, advances in vehicle safety have resulted in heterogeneity within the vehicle fleet: new vehicles are generally safer than older vehicles (Farmer & Lund, 2006). The potential for disparities in risk for road injury is great, especially considering recent trends in the US such as the suburbanization of poverty (Steven & Stoll, 2010). Studies in New York City; British Columbia, Canada; and Chicago have found significant relationships between road injuries and indicators of vulnerability, including minority status, education, unemployment, and income (Ukkusuri, Hasan, & Aziz, 2011; Bell et al., 2012; Cottrill & Thakuriah, 2010). Lower-income individuals, especially those living in low-walkability, suburban, and/or rural neighborhoods with long commutes, may be exposed to greater risks for mortality from road injury than more affluent individuals.

1.7. Frameworks for comparing competing transportation risks

While transportation systems alter health risks through automobile emissions, fatal crashes, and physical activity, quantitative methods to explore the health implications of these risks are limited. Hankey, Marshall, and Brauer estimated the relative health impacts of air pollution exposure and physical activity in Los Angeles (2012). Comparing these two risks, the authors found a nearly one-to-one risk tradeoff between walkable and non-walkable neighborhoods—that is, while residents of walkable neighborhoods are exposed to greater air pollution levels, increased physical activity counterbalances these health risks.. Comparing the health impacts of potential future changes in transportation behaviors, Woodcock et al. used a multi-risk framework to demonstrate that the health benefits of encouraging increased transportation physical activity were greater than the benefits of reducing automobile emissions in San Francisco, London, and Delhi (Maizlish et al., 2013; Woodcock et al., 2009). This same framework was used to estimate the health benefits to individuals who use the London bike share system (Woodcock et al., 2014). Replacing short motor vehicle trips with bicycle trips substantially benefited health for users of the system. Finally, De Nazelle, Rodriguez, and Crawford-Brown developed a microsimulation framework to assess changes in energy expenditures and pollutant inhalation given hypothetical changes to the built environment to find that physical activity and air pollution inhalation may both increase given hypothetical changes to the built environment (2009).

Previous multi-risk frameworks have explored competing transportation risks in urban areas. However, population-level studies have relied on coarse characterization of exposure (e.g., using large gird cells to estimate air pollution exposure) (Maizlish et al., 2013; Woodcock et al., 2009). Other studies have assessed impacts in specific sub-populations, such as users of the London bike share (Woodcock et al., 2014) or individuals (De Nazelle, Rodriguez, & Crawford-Brown, 2009), but have not estimated population-level health impacts of transportation systems. Using survey data collected for a large sample of individuals in Los Angeles, Hankey, Marshall, and Brauer presented a framework that begins to bridge the gap between individual-level and population-level studies, but this framework does not estimate physical activity at the population level to facilitate population-scale risk comparisons (2012). Population-level estimates of health impacts are useful for exploring the role of the built environment in influencing transportation health risks, while individual-level studies offer richer understanding of competing health pathways (e.g., comparing an active to a non-active commuter in a polluted neighborhood). However, individual-level health impact models have not been used to estimate population-level health impacts associated with transportation systems. In other sectors, population-level health impacts of interventions such as smoking cessation and body mass index reduction have been explored using individual-level microsimulation models (Lhiachimi et al., 2010). In sum, while frameworks to explore competing transportation health risks have emerged in recent years, no such framework exists for comparing air pollution, physical inactivity, and fatal injury risk from crashes in a dynamic population-scale model.

This research builds upon previous work assessing the competing health risks of transportation systems by developing an advanced micro-simulation model and applying the model to estimate transportation health risks across the Raleigh-Durham-Chapel Hill metropolitan area. This research is divided into three principal objectives (Figure 1). First, an existing dynamic modeling tool is used to estimate the health benefits of increased physical activity from transportation in a single neighborhood in the study region. These estimates are then compare to estimates obtained using a more traditional risk assessment approach that uses a static calculation of health benefits (Objective 1). Regression models are then used to predict transportation physical activity at the Census block group geography across the study region (Objective 2). Then, a novel dynamic multi-risk micro-simulation model tailored to transportation health risks is developed, combining physical activity, walk and bike trip, VMT, and high-resolution air pollution estimates. This model is then applied across the study region to estimate transportation health risks at the Census block group geography. Finally, estimated health risks are compared between neighborhoods grouped by built environment variables (Objective 3).

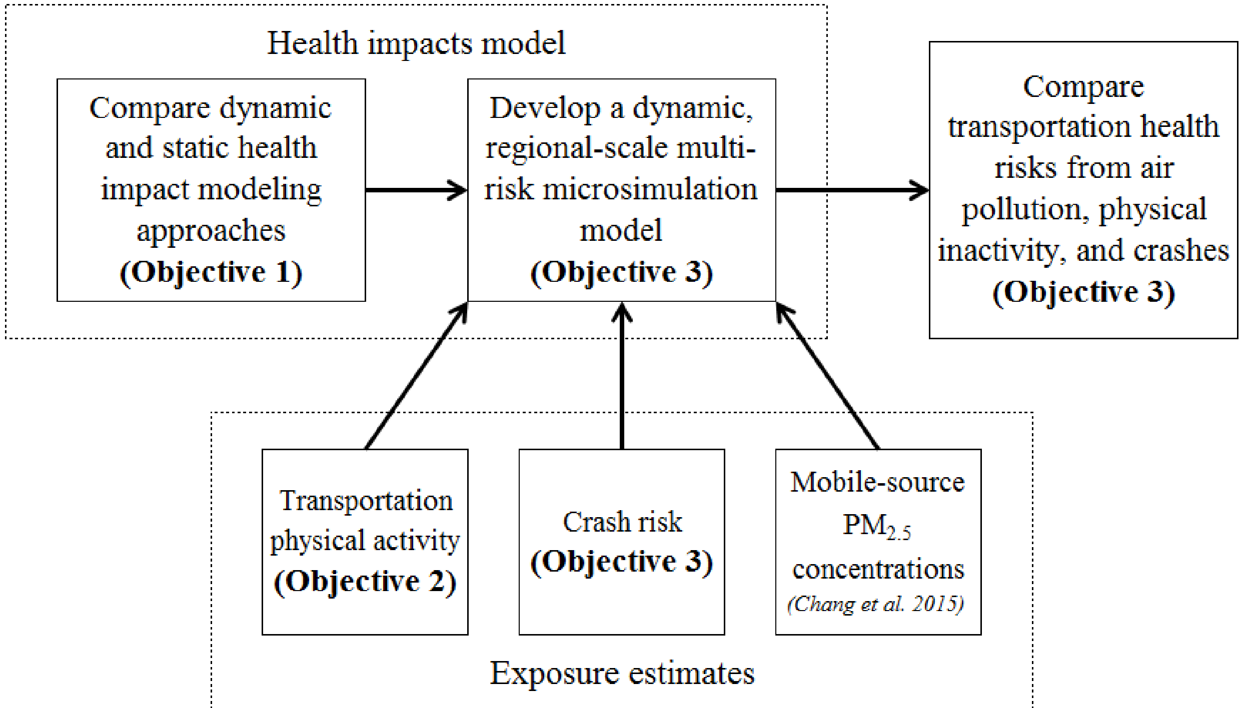

Figure 1.1. Dynamic and static modeling approaches are first compared (Objective 1), exposure to transportation-related health risks are estimated (Objective 2), and novel health impacts model is used to estimate transportation health impacts for different types of neighborhoods (Objective 3).

1.8. Study Region

To demonstrate the methods developed in this thesis, the methods are applied to estimate transportation health risks at the Census block group scale across the Raleigh-Durham-Chapel Hill region. This region is a large urban agglomeration in central North Carolina. The region has several nodes of high-density development surrounded by large suburban areas (Figure 2). The region is highly auto-dependent, with nearly 90% percent of workers commuting using an automobile in 2013 (US Census Bureau 2013).

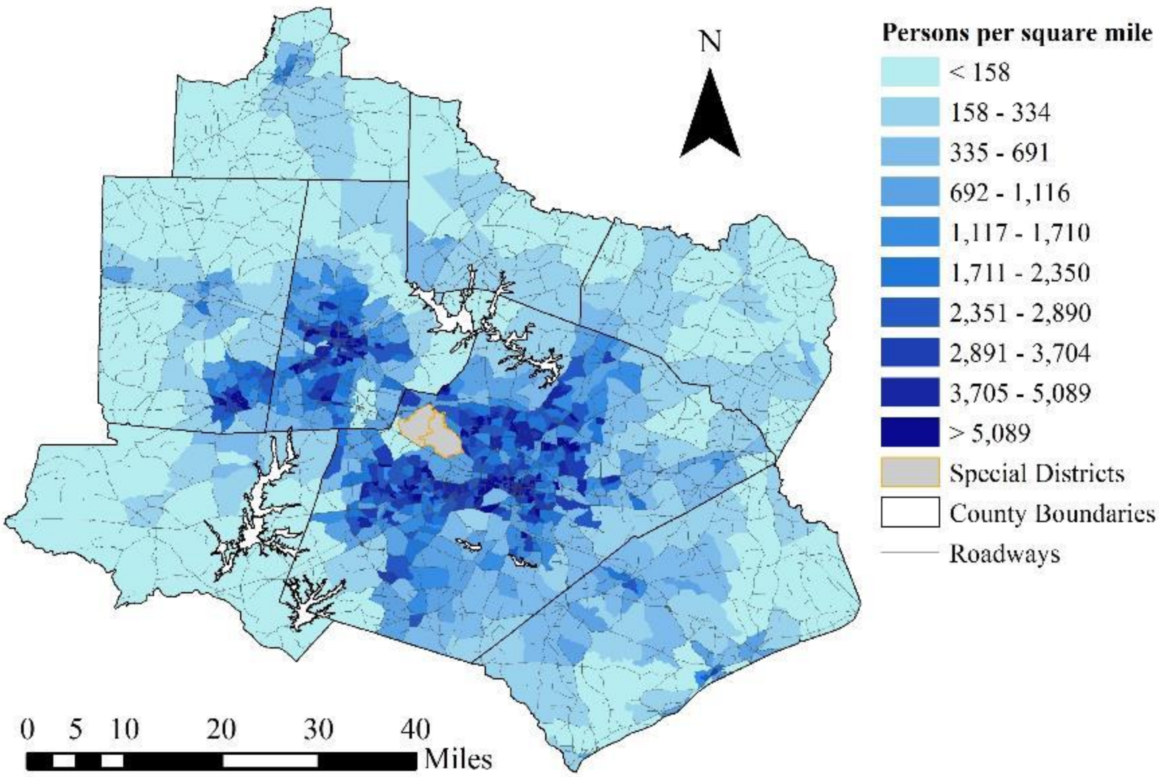

Figure 1.2. Population density in the study region, illustrating multiple nodes of relatively dense development surrounded by large areas of low- to moderate-density development.

1.9. Research Significance

Transportation health risks have significant impacts on population health and are distributed in complex spatial patterns across urban areas. Yet, tools and methods to estimate the health impacts of transportation systems are poorly developed. Previous studies exploring competing transportation health risks in urban areas have used coarse estimates of exposure to transportation risks, employed static health impact models, and focused on individuals or specific sub-populations without translating findings to the population scale. This research builds upon previous work by characterizing exposure at the individual level for all members of the population, estimating health impacts at fine spatial resolution to facilitate neighborhood-level comparisons of risks with built environment factors, and employing an advanced dynamic microsimulation model. In doing so, this research supports more rigorous consideration of transportation health risks and offers more detailed understanding of the complex tradeoffs that occur between competing transportation health risks in urban areas.

CHAPTER 2: HEALTH IMPACTS OF INCREASED PHYSICAL ACTIVITY FROM CHANGES IN TRANSPORTATION INFRASTRUCTURE: QUANTITATIVE ESTIMATES FOR THREE COMMUNITIES[1]

2.1. Introduction

In the United States, approximately 234,000 premature deaths are associated with physical inactivity each year (US Burden of Disease Collaborators, 2013). The built environment influences walking and biking for transportation and, in turn, total physical activity (Ewing & Cervero, 2010; Bauman et al., 2012). Many communities in the United States are designed in ways that do not support walking and biking, thereby contributing to low levels of physical activity (Lee, Ewing, & Sesso, 2009). Recently, transportation agencies across the United States have sought to integrate health considerations into decision-making (USDOT, 2014; USDOT, 2012). Health impact assessment (HIA) has emerged as a systematic framework for considering how decisions, such as modifications to the built environment, may impact public health and has informed a variety of decisions in the transportation sector (National Research Council, 2011; Wernham, 2013). However, most transportation HIAs conducted to date have provided qualitative rather than quantitative estimates of health benefits arising from changes in physical activity (e.g., indicating that physical activity is expected to increase, without estimating the magnitude of the increase) (Bhatia & Seto, 2011). Existing research links the built environment to physical activity levels and health outcomes, but quantitative models to predict the health impacts of modifications to the built environment remain poorly developed (McCormack & Shiell, 2011; MacDonald et al., 2010; Hess & Russell, 2012).

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Within the past four years, two new tools to support quantitative HIAs have emerged. The first tool, the Health Economic Assessment Tool (HEAT) for cycling and walking, was introduced by the World Health Organization in 2011 (Kahlmeier et al., 2014). More recently, the European Union Health Programme released the Dynamic Model for Health Impact Assessment (DYNAMO-HIA) (Lhachimi et al., 2012). These two tools employ fundamentally different methods; while DYNAMO-HIA is dynamic, capable of tracking changes in population health over many years, HEAT is static, providing health impact estimates for a single year. The HEAT method has been used in several HIAs of policies or projects to promote active transportation (walking or cycling instead of driving) (Mueller et al., 2015). DYNAMO-HIA has been applied to estimate the health impacts of a ban on alcohol imports in Sweden, smoking cessation in Great Britain, reduced salt intake in Europe, decreased smoking prevalence in Copenhagen, and body mass index reduction in Netherlands (Lhachimi et al., 2012; Hendriksen et al., 2015; Holm et al., 2014; Boshuizen et al., 2012). However, to our knowledge, DYNAMO-HIA has not yet been applied to predict the health impacts of increased physical activity arising from changes in the built environment. Further, the estimates from these two methods have not been compared.

To demonstrate the use of quantitative tools for estimating the health effects of physical activity in HIAs of the built environment, this paper describes quantitative HIAs of proposed changes to the built environment in three North Carolina communities. All three HIAs used DYNAMO-HIA to estimate the health effects of increased transportation walking time expected to arise due to modifications to the built environment. Changes in premature mortality, coronary heart disease (CHD), type 2 diabetes, hypertension, and stroke were estimated for each community. In addition, each HIA estimated the ratio of health benefits to expected project costs. For one of the case studies, we additionally compared results obtained from DYNAMO-HIA with those obtained from the HEAT model. Our objective in making this comparison was to determine whether the health impact estimates differ when using a dynamic approach (as in DYNAMO-HIA) as compared to a static approach (as in HEAT). We hypothesized that the static approach may overestimate health benefits by failing to account for overall improvements in population health from one year to the next and, as a result, estimating benefits in each year relative to a population for which no benefits have yet accrued. Our overall purpose was twofold: first, to demonstrate that quantitative tools in general may provide objective, evidence-based decision support within the HIA framework and, second, to provide insight into the advantages and disadvantages of emerging quantitative tools and methods to conduct HIAs.

The HIAs presented in this study were conducted as examples to support WalkBikeNC, a statewide bicycle and pedestrian plan developed by the North Carolina Department of Transportation (NCDOT) in 2013 (NCDOT, 2013). WalkBikeNC presents a unified policy framework to support active travel statewide, but it does not propose projects. Instead, specific bicycle and pedestrian infrastructure projects are planned and implemented by local authorities in accordance with WalkBikeNC. Such projects may be included in a range of local plans, including small-area plans, comprehensive transportation plans, and bicycle and pedestrian master plans. The three HIAs described in this paper consider pedestrian infrastructure improvements aligned with the policy framework established in WalkBikeNC at three planning scales: a small-area plan, a comprehensive plan, and a streetscape plan.

2.2 Materials and Methods

All three case studies followed the six steps of HIA proposed by the US National Research Council: (1) screening; (2) scoping; (3) assessment; (4) recommendations; (5) reporting; and (6) monitoring and evaluation (National Research Council, 2011). The first two steps of HIA, screening and scoping, focus on identifying and characterizing health concerns and disparities in the community. The third step, assessment, explores how the decision to be made influences these concerns and disparities through qualitative understanding and/or quantitative modeling of causal pathways as understood in the scientific literature. The conclusions from the assessment stage inform the fourth stage, recommendations. Finally, reporting and monitoring and evaluation aim to engage stakeholders, hold decision-makers accountable, and evaluate the effectiveness of the decision in addressing identified health concerns at some point in the future. Because this paper focuses on improving the assessment stage through the application of quantitative methods, details of steps 4–6 are not presented; these details can be found elsewhere (NCDOT, 2013; MacDonald Gibson et al., 2014). Details on the screening and scoping stages are provided below, because these steps influenced the scope of the assessment phase.

2.2.1 Site Selection (Screening)

Case study sites were selected in coordination with NCDOT. In all three communities, the proposed changes to the built environment were included in adopted local plans but had not received funding as of October 2012 (when this project began). Projects were selected to provide variation across three dimensions: (1) development context (rural, suburban, and urban); (2) planning scale (corridor plan, small-area plan, and comprehensive plan); and (3) geographic region within North Carolina (Piedmont region, coastal region, mountain region). Table A.1 and Figures A.1 through A.3 in Appendix A provide maps, demographic data, and information about the changes to the built environment proposed for each project.

The first HIA is conducted on changes to the built environment proposed in the City of Raleigh's Blue Ridge Road Corridor (BRRC) small-area plan (urban, small-area plan, Piedmont region). The BRRC is located eight kilometers east of downtown Raleigh, the second-largest city in North Carolina and the state capital. The BRRC small-area plan is the result of a planning and visioning process to guide development in the corridor as it urbanizes. The plan includes dense, mixed-use land development, construction of a compact street network, and construction of additional pedestrian and bicycling facilities. We considered the effects on time spent walking for transportation and the resulting health outcomes if the plan were implemented in its entirety (Urban Design Associates, JDavis Architects, M. A. Bryson, RCLCO, & Long Leaf Historic Resources, 2013).

The second HIA is conducted on construction of new sidewalks in the town of Winterville as proposed in the Greenville Metropolitan Planning Organization's Bicycle and Pedestrian Master Plan (suburban, comprehensive plan, coastal region). This plan proposes both pedestrian and bicycle projects throughout the Greenville metropolitan area, a mid-size community in eastern North Carolina. We estimated the health impacts of building all sidewalks proposed in the plan within the municipal boundaries of Winterville, a suburban community on the outskirts of the Greenville region (Greenways Incorporated and Kimley-Horn & Associates, 2011).

The third HIA is conducted on streetscape improvements proposed in the Town of Sparta's Downtown Streetscape Master Plan (rural, corridor plan, mountain region). Sparta is a prototypical rural main-street community, with a small, walkable downtown containing shops and services surrounded by low-density development. We estimated the health impacts of proposed improvements to the downtown streetscape, including improved sidewalks and street crossings (Destination by Design Planning Group, 2012).

2.2.2 Selection of Health Outcomes (Scoping)

Facilitated discussions with local decision-makers and residents in each community confirmed that existing transportation infrastructure (e.g., lack of sidewalks) and overall community design (e.g., lack of destinations within easy walking distance) limit opportunities for walking as a means of transportation. The potential health outcomes that could be affected if new, pedestrian-friendly infrastructure were in place and if, as a result, residents spent more time walking for transportation were then selected from a literature review. The literature review identified several health outcomes for which nonvigorous transportation physical activity has been shown to have a preventive effect: coronary heart disease (CHD), type 2 diabetes mellitus, hypertension, stroke, and premature mortality from all causes (Hu et al., 2005; Furie & Desai, 2012; Kelly et al., 2014). Additionally, these four diseases were identified as existing health concerns related to physical activity levels in each community.

2.2.3 Health Impacts Model (Assessment)

We used DYNAMO-HIA to estimate the health impacts of increased transportation physical activity in all three communities. We then additionally used a modified version of the HEAT model, implemented in Analytica 4.5 (Lumina Decision Systems, Los Gatos, CA) in the BRRC. These two models and their data requirements are described in turn below.

DYNAMO-HIA is a dynamic health impacts model that employs Markov Chain modeling to estimate the effects of a health intervention on a population over time (Lhachimi et al., 2012).

Conceptually, Markov Chain models divide a system into distinct groups of risk factor states linked by transition probabilities, which define the likelihood that a member of one group will transition to another group over time (Figure 2.1). The model moves forward in discrete one-year time steps, estimating the population in each group at time step using the previous group populations and transition probabilities between groups. To estimate the health impacts of an intervention that changes health behaviors, an intervention scenario is specified in which the probabilities of transitioning from a healthy to a diseased state (represented in Figure 1 as P_1, P_2, P_4, and P_5) or from a healthy or diseased state to death (P_3 and P_6-P_9) are altered based on changes in the distribution of risk factors in the population (e.g., amount of time walking for transportation). As the model steps forward through time, changes in these transition probabilities affect the rate at which healthy individuals transition to diseased states and/or death. Alongside the intervention scenario, a baseline scenario is also specified in which transition probabilities are not affected by the intervention. Health impacts are estimated by comparing health outcomes between the two scenarios over time. DYNAMO-HIA requires a large amount of baseline health data: age- and sex-specific population distributions, mortality rates, disease prevalence, disease incidence rates, and risk factor prevalence. In the intervention scenario, a change in risk factor prevalence and/or a transition between risk factor states over time must also be specified. Finally, dose-response functions must be characterized for each health outcome of interest. DYNAMO-HIA is available free of charge (http://www.dynamo-hia.eu/) and may be installed on any Windows-based machine.

We developed DYNAMO-HIA models for each community. Each model included community-specific population and health data as described in Section 2.2.3.1. A baseline, “no-build” scenario and an intervention scenario were specified for each community. In the baseline scenarios, weekly time spent walking for transportation was taken from recent surveys as described in Section 2.2.3.3. In the intervention scenarios, studies linking proposed built environment changes in each community to increases in walking for transportation were used to estimate post-construction walking as described in Section 2.2.3.4. Relative risks linking time spent walking for transportation to modeled health outcomes were taken from epidemiological studies (Figure 2.1). Health impacts were estimated by taking the difference in projected health outcomes between the two scenarios over time each year for 40 years.

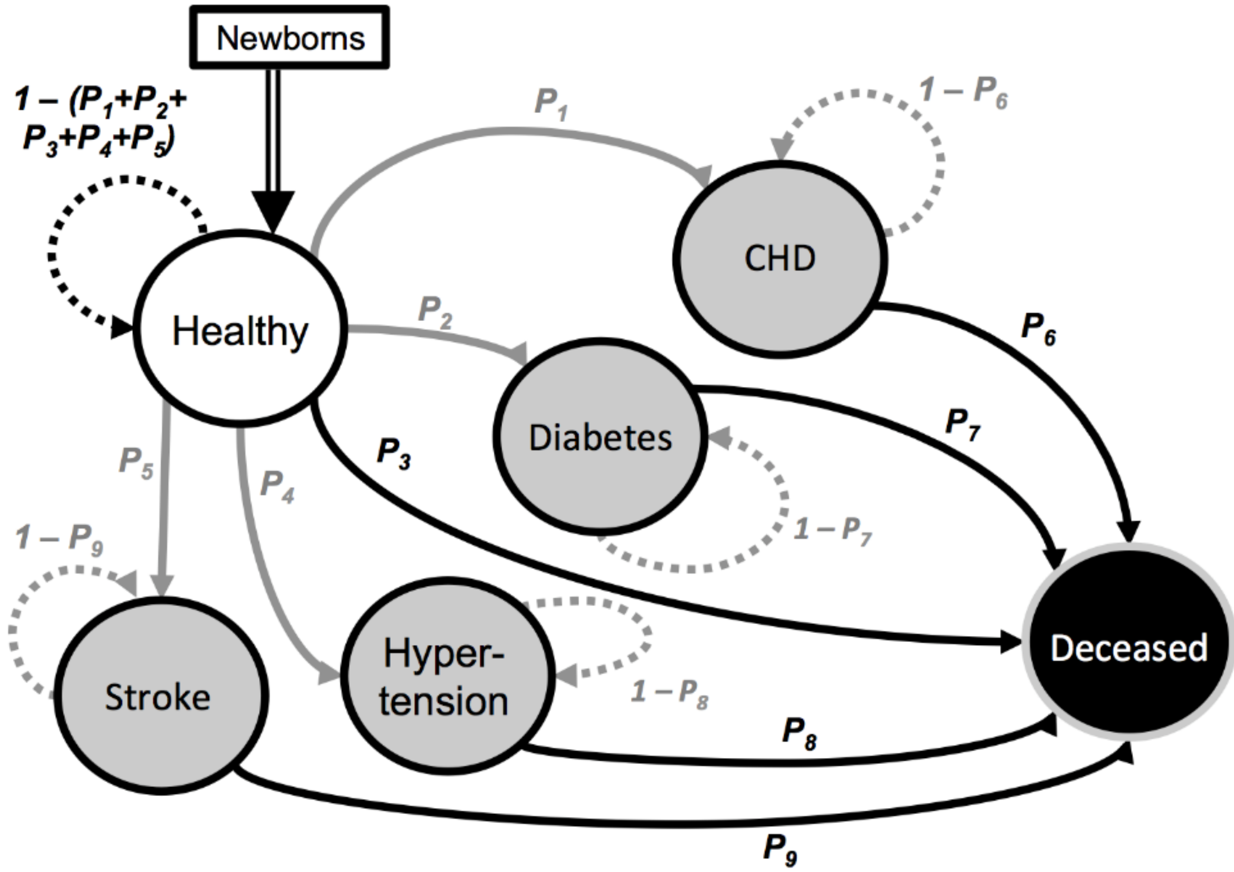

Figure 2.1. DYNAMO-HIA model schematic representing simulation of one time step. Each circle represents a population state. Solid lines represent possible transitions between states at each time step, whereas dotted lines represent staying in the same state during a time step. The variables P_1-P_9 represent transition probabilities between states.

To develop 95% confidence intervals for our health impact estimates, each model was run five times, changing relative risk parameters in the model to the upper and lower bound of the 95% confidence intervals reported in epidemiological studies in each iteration. The first model used central values for all relative risk parameters, the second model used the lower bound of the confidence interval for mortality and central values for all diseases, the third model used the upper bound of the confidence interval for mortality and central values for all diseases, the fourth model used lower bounds for all diseases and the central value for mortality, and the fifth model used upper bounds for all diseases and the central value for mortality. Varying each relative risk parameter in turn and rerunning each model enabled the construction of 95% confidence intervals for all of our results reflecting uncertainty in the relative risk parameters used; however, uncertainty in other model parameters (e.g., magnitude of changes in walking for transportation) is not reflected in these estimates. All confidence intervals reported throughout this paper were developed using this approach.

Unlike DYNAMO-HIA, the HEAT model is static: it estimates a fraction of cases of premature mortality that could be avoided if a population spent more time walking or cycling and assumes that this fraction is constant from year to year. That is, health benefits of increased activity do not accrue from year to year for a given individual. The WHO has made an online tool for automating these calculations (http://www.heatwalkingcycling.org/) available. In order to compare the results obtained with DYNAMO-HIA with those obtained using the HEAT model approach, we reconstructed the HEAT tool using Analytica. This reconstruction additionally includes morbidity, which is not included in the base HEAT model. Details of this reconstruction are provided elsewhere (MacDonald Gibson et al. 2015).

Like DYNAMO-HIA, our reconstructed version of the HEAT model requires baseline data on population size by age and sex, baseline death rates, baseline disease prevalence and incidence rates for each health outcome of interest, and relative risks linking each health outcome to a risk factor (in this case, walking for transportation). In addition, information about the time spent walking for transportation under current conditions and under the intervention scenario is needed. Sources for these data, used in both the DYNAMO-HIA models the reconstructed HEAT model in the BRRC, are described below.

2.2.3.1. Baseline Population and Health Data

We estimated age- and sex-specific population distributions by applying county-level age and sex distributions to refine Census block-group data for each case study location (Figure A.2) (US Census Bureau 2013). Baseline death and birth rates were taken from county-level data obtained from the NC State Center for Health Statistics (NCSCHS, 2009a). We developed age-specific prevalence functions for

CHD, type 2 diabetes mellitus, hypertension, and stroke for each case study location by fitting second-order prevalence functions to data from the Behavioral Risk Factor Surveillance System (BRFSS) survey (NCSCHS, 2009b). Disease prevalence data were not available stratified by both age and sex; thus, we stratified by age only and assumed identical prevalence functions for males and females. Incidence data are not available from the State Center for Health Statistics for the diseases considered in this study. Thus, incidence functions for each case study location were estimated using a differential equation-based method described in Brinks (Appendix A, Section 2.1 and Figure A.4) (Brinks, 2011).

2.2.3.2. Relative Risks

Relative risks of each health outcome as a function of transportation walking were drawn from previous studies (summarized in Figure 2.1). Categorical dose-response functions for type 2 diabetes mellitus and hypertension were taken from a study of US adults that used data from the National Health and Nutrition Examination Survey (Furie & Desai, 2012). To our knowledge, no studies exist linking transportation physical activity levels to CHD or stroke risk in US adults; thus, relative risks were taken from two studies of a large cohort of Finnish adults (Hu et al., 2007; Hu et al., 2005). To estimate the relative risk of premature mortality as a function of time spent walking for transportation, a dose-response function derived in a recent meta-analysis was employed; this same function is used to calculate the relative risk of all-cause mortality in the HEAT model (Kahlmeier et al., 2014; Kelly et al., 2014):

$$RR_{mortality} = 0.89^{\left(\frac{y}{168}\right)} \tag{1.1}$$

where *y* is weekly minutes spent walking for transportation. We used Equation 1 to estimate the relative risk of all-cause mortality for the same exposure categories used in studies linking walking for transportation to disease risk. Specifically, these studies grouped populations into three levels of time spent walking for transportation: a reference category (none), a low category (1–149 min/week), and a high category (150+ min/week). The high category reflects the Centers for Disease Control and Prevention (CDC) minimum recommendation for total adult physical activity (CDC, 2008). Using

Equation 1, we calculated relative risks for all-cause mortality at the midpoint of the low transportation walking category (75 min/week) and at the low point of the high transportation walking category (150 min/week).

Table 2.1. Relative risks

Health Outcome	Sex	Low Category (1-149 minutes walking for transportation per week)	High Category (150+ minutes walking for transportation per week)
All-cause mortality[23]	Combined	0.95 *(0.98-0.92)* [a]	0.90 *(0.96-0.85)*
CHD[24]	Male	0.99 *(1.08-0.91)* [c]	0.99 *(1.10-0.90)* [c]
	Female	0.95 *(1.08-0.83)* [c]	0.80 *(0.92-0.69)* [c]
Type 2 Diabetes[26]	Combined	0.77 *(1.02-0.58)* [b]	0.69 *(0.88-0.54)* [b]
Hypertension[26]	Combined	0.76 *(0.94-0.61)* [b]	0.69 *(0.83-0.58)* [b]
Stroke[25]	Male	0.94 *(1.06-0.83)* [c]	0.88 *(1.02-0.77)* [c]
	Female	0.88 *(1.01-0.77)* [c]	0.87 *(1.01-0.75)* [c]

[a] 95% confidence interval shown for all relative risks
[b] Adjusted for race, education, income, and smoking status
[c] Adjusted for education, smoking status, alcohol consumption, body mass index, systolic blood pressure, cholesterol, history of diabetes, and occupational and leisure-time physical activity

2.2.3.3. Baseline Active Transportation Behavior

In Winterville and Sparta, we estimated baseline transportation physical activity using data from the 2009 North Carolina BRFSS survey (NCSHS, 2009b). In the BRRC, we used an active transportation survey conducted within the neighborhood in 2012 utilizing a widely used and validated physical activity questionnaire (MacDonald Gibson et al., 2015; Craig et al., 2003). Responses to these surveys were recategorized according to the CDC physical activity categories described above.

2.2.3.4. Estimating Changes in Active Transportation Behavior

Due to differences in data availability and the nature of the plans considered, different methods were used in each case study community to estimate how changes in the built environment are expected to affect transportation physical activity.

The method for estimating changes in walking time if the BRRC small-area plan were implemented is described in detail elsewhere (MacDonald Gibson et al., 2015). Briefly, because multiple built environment changes are proposed in addition to pedestrian infrastructure improvements, the net effect of all of these changes on transportation walking is estimated using a multidimensional walkability index that links intersection density, population density, land-use diversity, and retail floor area ratio to walking for transportation (Frank et al., 2010). The walkability index is calculated from:

$$Walkability\ Score = (2 \times Z_{intersetion}) + (Z_{residential}) + (Z_{FAR}) + (Z_{land-use}) \quad (1.2)$$

where Z variables represent normalized versions of intersection density ($Z_{intersetion}$), the number of intersections divided by land area; residential density ($Z_{residential}$), the number of housing units divided by the residential land area; retail floor area (Z_{FAR}), the square footage of retail floor area divided by the square footage of land devoted to retail use; and land-use diversity ($Z_{land-use}$), computed as described in Cervero and Kockelman (1997). Previous studies that have linked transportation walking time to the walkability score were then used to estimate the increase in time spent walking as a result of the increase in walkability score that would occur if the small-area plan were fully implemented (MacDonald Gibson et al., 2015; Sallis et al., 2009).

In Winterville, the proposed changes to the built environment consist solely of new sidewalk construction. Thus, a relationship linking sidewalk density to transportation walking was used to estimate changes in transportation physical activity. A 1 km/km^2 increase in sidewalk density is associated with an increase in the odds of an individual having taken a walking trip in the previous week by 2.3 percent (Fan, 2007). Thus, the odds ratio of walking before and after construction may be expressed as:

$$\frac{O_{w,after}}{O_{w,before}} = 1.023^{(D_{s,after} - D_{s,before})} \quad (1.3)$$

where $O_{w,before}$ is the odds of walking given the density of sidewalks before construction, $D_{s,before}$ (km/km^2), and $O_{w,after}$ is the odds of walking given the density of sidewalks after construction, $D_{s,after}$ (km/km^2). Rearranging Equation and expressing in terms of probabilities, this becomes:

$$\frac{P_{w,after}}{(1-P_{w,after})} = \frac{P_{w,before}\times 1.023^{(D_{s,after}-D_{s,before})}}{(1-P_{w,before})} \tag{1.4}$$

where is $P_{w,after}$ is the probability that an individual takes at least one walk trip per week after construction, and $P_{w,before}$ is the probability that an individual has taken a walking trip in the past week before construction, assumed to be equal to the proportion of the population reporting any walking in the BRFSS. We iteratively solved for $P_{w,after}$ and adjusted the proportion of non-walkers in the population accordingly. We assumed that new walkers were distributed between the low- and high-walk-time categories in the same manner as walkers were distributed between these two categories before construction.

In Sparta, we used changes in a composite pedestrian environment factor (PEF)—which includes sidewalk quality, ease of street crossings, topography, and density of the street grid—to estimate changes in average weekly walking distance (Boarnet, Greenwald, & McMillan, 2008). Each subcategory is assessed on a 3-point scale; the PEF is calculated by adding these four subcategory scores and transforming the result into an ordinal variable (low, medium, or high). After construction of streetscape improvement in Sparta, sidewalk quality and ease of street crossings would improve significantly while topography and the configuration of the street network would remain unchanged. Therefore, we assumed that the sidewalk quality and ease of street crossings subcategories would change from 1 (current conditions) to 3 (post-construction), while the topography and street grid density would remain unchanged. This change in subscores would change the PEF from low to medium. In turn, per-capita weekly walking distance would increase by 0.92 kilometers (Boarnet, Greenwald & McMillan, 2008). Assuming a typical walking speed of 4 kilometers per hour, per-capita transportation walking time would increase by 13.6 minutes per week, on average (Browning et al., 2006). Because this relationship was derived in an urban setting using small geographies, while Sparta is a rural town, we assumed that only individuals living within a 0.4-kilometer buffer of the proposed improvements (25% of the population) would increase their walking. We increased the percentage of population in each walking time bin proportionally so that the average per-capita walking time for individuals living within 0.4 kilometers of the proposed improvements equaled to the preconstruction average plus 13.6 minutes.

2.2.3.5. Economic Valuation

To compare the benefits of estimated health impacts to project costs, we applied economic valuations to each health outcome considered. For mortality, we used the value of a statistical life suggested by the United States Department of Transportation (USDOT) in 2013, $9.1 M USD per avoided premature death (USDOT, 2014). For each disease, we used yearly disease costs estimated by the Milken Institute that combine treatment costs and indirect costs from productivity losses resulting from lost workdays and reduced presenteeism (Figure A.7) (DeVol & Bedroussian, 2007). For the BRRC and Winterville, we estimated project costs using average bid data for North Carolina ($89.57 per linear meter of sidewalk; $142.08 and $150.70 per square meter of poured concrete sidewalk and curb and gutter, respectively) (NCDOT, 2013). For Sparta, we used the cost estimate provided in the plan, $686,157 USD (Destination by Design Planning Group, 2012). Ongoing maintenance costs are not considered. Benefits and costs were discounted to the present using a 5% discount rate per USDOT guidance (US OMB, 1992). A sensitivity analysis was conducted using 3.5% and 7% discount rates based on guidance from the United States Office of Management and Budget and NCDOT, respectively (Figure A.5) (US OMB, 1992; NCDOT, 2012)

2.3. Results

2.3.1. Health Outcomes

To estimate the health impacts of built environment changes in each community, we used DYNAMO-HIA to predict changes in premature mortality and incidence of CHD, type 2 diabetes, hypertension, and stroke over 40 years due to increased walking for transportation. In the BRRC, DYNAMO-HIA estimates a significant reduction in premature all-cause mortality as well as significant preventive effects for hypertension, type 2 diabetes mellitus, and CHD (Figure 2.2). In Sparta, significant reductions in premature mortality, cases of hypertension, and cases of type 2 diabetes mellitus are estimated; however, estimated effects on avoided cases of CHD are minimal. In Winterville, DYNAMO-

HIA estimates small, yet significant, reductions in premature mortality and cases of hypertension and minimal effects on type 2 diabetes and CHD. Across all sites, no significant reductions in cases of stroke are estimated. The total population benefits of avoided mortality and the prevention of hypertension and type 2 diabetes accrue over time but demonstrate diminishing returns (Figure 2.2, Table 2.2). For example, DYNAMO-HIA estimates that the cumulative number of premature deaths avoided in the BRRC will increase from 4.9 (1.8–7.7) ten years after construction to 14 (5.2–23) 40 years after construction (Figure2). Similarly, within ten years of construction, an estimated 12 (4.5–17) and 4.9 (2.6–7.6) cases of hypertension and type 2 diabetes will have been prevented, and these numbers are expected to increase to 32 (12–45) and 16 (8.3–24) within 40 years. Generally, health outcomes for which a strong preventive effect is demonstrated in the literature and for which baseline community prevalence is high (e.g., hypertension) are most influenced by increases in transportation physical activity.

Comparing across sites, DYNAMO-HIA estimates stronger preventive effects on a per-capita basis in the BRRC and Sparta than in Winterville (Figure 2.2). For example, the cumulative cases of premature mortality prevented by year 40 are 0.99 and 0.36 per 1,000 people in the BRRC and Sparta, respectively, as compared to 0.08 per 1,000 people in Winterville. This result occurs because the proposed changes to the built environment in the BRRC and Sparta are estimated to increase transportation walking more in the BRRC and in Sparta than in Winterville (Table 2.2). For example, the average time spent walking per week is expected to increase by 17 minutes in the BRRC and 2.2 minutes in Sparta, in comparison to a smaller increase of 0.7 minutes per week in Winterville (Table 2.2). Additionally, a preventive effect on CHD is only estimated in the BRRC. As shown in Table 2.1, the preventive effect of walking for transportation on CHD is strong only for females in the highest physical activity category. The population in the BRRC has a greater proportion of women compared to the other two sites (Figure A.4) and a greater predicted change in the proportion of the population walking more than 150 minutes per week for transportation (Table 2.2); thus, the effect of increased transportation walking on avoided cases of CHD is significant in the BRRC but not in the other two sites.

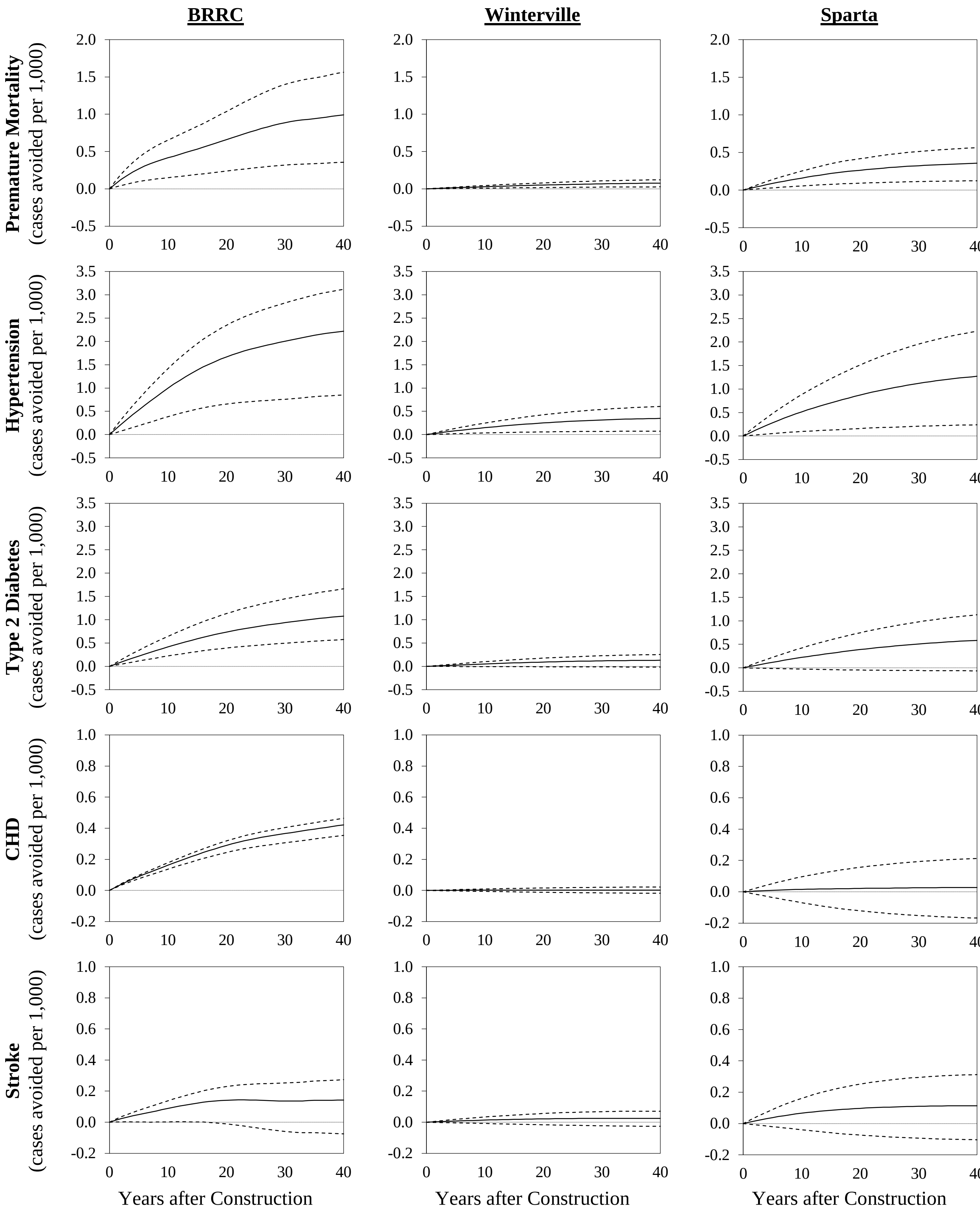

Figure 2.2. Estimated health impacts per 1,000 persons for each community (solid lines), with 95% confidence intervals reflecting uncertainty in relative risk parameters (dashed lines).

Table 2.2. Summary of findings, with 95% confidence intervals based on uncertainty in relative risk parameters

Built Environment Variables	**BRRC**			**Winterville**			**Sparta**		
	Before	After	Change	Before	After	Change	Before	After	Change
Walkability Score	-3.61	0.96	+4.57	-	-	-	-	-	-
Sidewalk density (km/km^2)	-	-	-	0.8	3.8	**+3.0**	-	-	-
PEF (categorical)	-	-	-	-	-	-	Low	Medium	**+1**
Walking Outcomes [a]	Before	After	Change	Before	After	Change	Before	After	Change
No walking (percent)	40.7%	40.7%	**0%**	84.3%	83.4%	**-0.9%**	85.4%	82.4%	**-3.0%**
1-149 min/week (percent)	41.5%	21.2%	**-20.3%**	12.3%	12.9%	**+0.6%**	12.1%	14.6%	**+2.5%**
150+ min/week (percent)	17.8%	38.1%	**+20.3%**	3.4%	3.6%	**+0.2%**	2.5%	3.0%	**+0.5%**
Ave. walk time (min/week)	13.1	30.4	**+17**	12.5	13.2	**+0.7**	10.4	12.6	**+2.2**
	Years After Construction			Years After Construction			Years After Construction		
Health Outcomes [a]	10	20	40	10	20	40	10	20	40
Avoided premature mortality	4.9 *(1.8–7.7)*	8.5 *(3.1–13.3)*	14.3 *(5.2–22.6)*	0.3 *(0.1–0.5)*	0.5 *(0.2–0.9)*	0.9 *(0.3–1.4)*	0.3 *(0.1–0.4)*	0.4 *(0.2–0.7)*	0.5 *(0.2–0.8)*
Avoided cases of CHD	1.9 *(1.6–2.1)*	3.7 *(3.1–4.1)*	6.1 *(5.1–6.7)*	0.0 *(-0.1–0.1)*	0.0 *(-0.1–0.2)*	0.0 *(-0.2–0.3)*	0.0 *(-0.1–0.2)*	0.0 *(-0.2–0.3)*	0.0 *(-0.2–0.3)*
Avoided cases of type 2 diabetes	4.9 *(2.6–7.6)*	9.4 *(5.1–14.5)*	15.6 *(8.3–24.1)*	0.5 *(0.0–1.0)*	1.0 *(-0.1–1.9)*	1.5 *(-0.2–2.9)*	0.4 *(0.0–0.7)*	0.6 *(-0.1–1.2)*	0.8 *(-0.1–1.6)*
Avoided cases of hypertension	11.8 *(4.5–16.7)*	21.4 *(8.4–30.1)*	32.1 *(12.3–45.1)*	1.5 *(0.4–2.5)*	2.7 *(0.6–4.5)*	4.0 *(0.9–6.9)*	0.9 *(0.2–1.5)*	1.4 *(0.3–2.4)*	1.8 *(0.4–3.2)*
Avoided cases of stroke	1.1 *(0.0–1.6)*	1.8 *(-0.1–2.9)*	2.1 *(-1.1–4.0)*	0.1 *(-0.1–0.3)*	0.2 *(-0.2–0.6)*	0.3 *(-0.3–0.8)*	0.1 *(-0.1–0.3)*	0.2 *(-0.1–0.4)*	0.2 *(-0.2–0.5)*
	Years After Construction			Years After Construction			Years After Construction		
Economic Outcomes [b]	10	20	40	10	20	40	10	20	40
Net Present Value (2012 USD)	33.4M *(10.8–53.7)*	50.4M *(18.4–79.0)*	66.8M *(26.8–103)*	-5.1M *(-6.5– -3.9)*	-3.9M *(-5.9– -2.1)*	-2.9M *(-5.3– -0.6)*	1.4M *(0.1–2.5)*	2.2M *(0.5–3.7)*	2.6M *(0.7–4.2)*
Benefit-cost ratio	10.6 *(4.1–16.5)*	15.5 *(6.3–23.7)*	20.2 *(8.7–30.6)*	0.3 *(0.1–0.5)*	0.5 *(0.2–0.7)*	0.6 *(0.3–0.9)*	3.0 *(1.1–4.6)*	4.1 *(1.7–6.3)*	4.7 *(2.1–7.1)*
Time for B:C to exceed 1	1 year *(1–2 years)*			Benefits do not exceed costs			3 years *(2–9 years)*		

[a] Estimates of walking for transportation after construction in Winterville do not add to 100% due to rounding
[b] For all health and economic outcomes, 95% confidence intervals are estimated using the lower and upper bounds of the relative risk parameters as noted in Table 1
[c] 5% discount rate assumed

2.3.2. Economic Valuation

To estimate the economic value of health benefits in each community, we multiplied projected avoided deaths and avoided disease cases per year by their respective economic values. The economic value of estimated health benefits exceeds project construction costs within one year in the BRRC and within three years in Sparta (Table 2.2) assuming a 5% discount rate. Over the 40-year time period considered, the benefit-cost ratios in the BRRC and Sparta are 20.2 (8.7–30.6) and 4.7 (2.1–7.1), respectively. However, the present value of the health benefits in Winterville is less than the estimated project costs: the benefit-to-cost ratio in Winterville over 40 years is 0.6 (0.3–0.9) (Table 2.2). This latter finding results from the design of the Winterville project and the population density in that community; while significant sidewalk construction is proposed, the new sidewalks will be spread over a very large area of relatively low population density, dampening the potential behavioral impact. The net present value of the BRRC and Sparta projects remains positive even when considering a higher discount rate (7%) and remains negative in Winterville even when considering a lower discount rate (3.5%) (Figure A.5).

In all communities, health benefits are overwhelmingly driven by avoided premature mortality (Figure A.5). Avoided premature mortality constitutes 92%, 86%, and 89% of the total net present value of health benefits over 40 years in the BRRC, Winterville, and Sparta, respectively. This result occurs due to the much higher value placed on an avoided premature death, in comparison to the value placed on avoided chronic disease cases (Figure A.7).

2.3.3. Comparison of DYNAMO-HIA and HEAT

To compare the dynamic approach used in DYNAMO-HIA and the static approach used in the HEAT model, we re-estimated health impacts in the BRRC using our reconstructed HEAT model and compared these findings to impacts estimated by our DYNAMO-HIA model. For all health outcomes considered, the HEAT model estimates a higher number of avoided cases per year than the DYNAMO-HIA model (Figure 2.3). The difference between the two approaches increases with time (Figure 2.3). When considering the cumulative health impacts over multiple years, the differences in the two approaches become substantial (Figure 2.4). The reconstructed HEAT model estimates that 41 premature deaths would be prevented over 40 years—2.9 times as many deaths averted as predicted by the DYNAMO-HIA model. Similarly, central estimates of avoided hypertension, type 2 diabetes, CHD, and stroke increase by factors of 3.3, 1.6, 2.5, and 6.7 when using the static approach, in comparison to the dynamic approach (Figure 2.4).

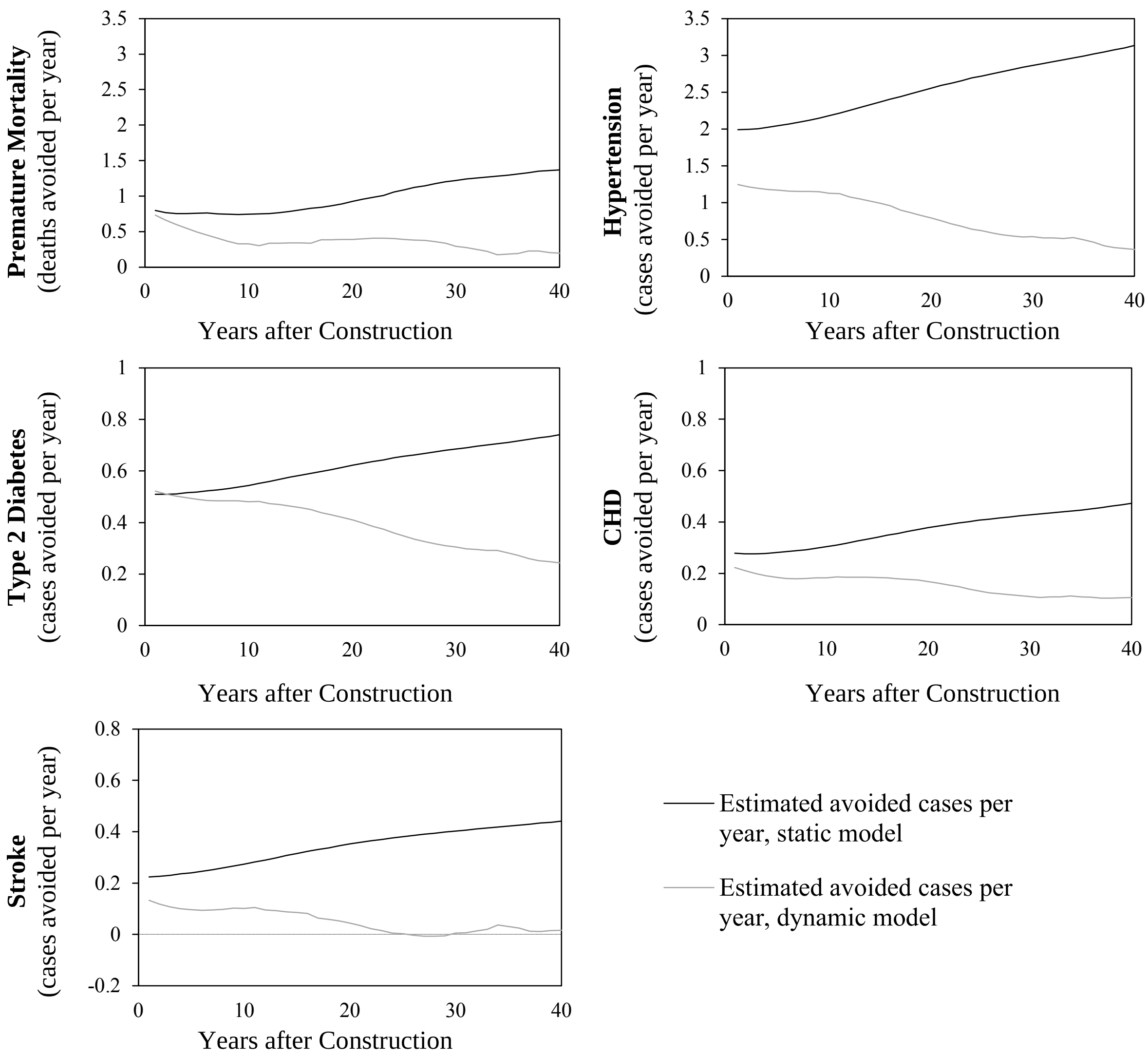

Figure 2.3. Estimated health impacts per year obtained using the HEAT (static) model (solid black lines) and DYNAMO-HIA (dynamic) model (solid grey lines) for the BRRC case study

The static approach overestimates health benefits by failing to account for changing disease prevalence over time. In the static model, avoided cases for each year are estimated for the population as a whole without accounting for population disease prevalence. In contrast, the dynamic model removes individuals who develop a disease from the population that is able to avoid a new case in subsequent years (i.e., individuals who develop a disease transition to diseased states (Figure 2.1), after which they are not included in estimations of new avoided cases). Additionally, the dynamic model references data from the previous year in estimating benefits for a given year whereas the static model has no memory of population health data in the previous year. Thus, relative to the dynamic model, the static model overestimates benefits in the future because it fails to account for changes in disease prevalence over time. In other words, the dynamic model is able to incrementally approach a new steady state in which an intervention has shifted disease incidence functions downwards for a portion of the population; once this steady state is reached, new benefits no longer accrue as lower risk individuals delay the onset of disease but do not completely avoid disease over time. Once these individuals transition into a diseased state, they are no longer included in avoided cases calculations. Static models, however, do not approach a new steady state because benefits are always calculated relative to a population in which no benefits have been accrued and disease prevalence is not accounted for. Thus, benefits will continue to accrue beyond the point at which the dynamic model reaches a new steady state. As a result, the static model increasingly overestimates benefits over time relative to the dynamic model. This behavior is illustrated in Figure 2.3; at each time step, the rate of change in avoided cases of type 2 diabetes stays relatively stable for the static model, increasing slightly as the population grows over time. In the dynamic model, the rate of change in the number of cases avoided decreases over time as the model approaches steady state in which all individuals who walk more have a decreased risk, but still some risk, for developing type 2 diabetes throughout their lifetimes (Figure 2.3).

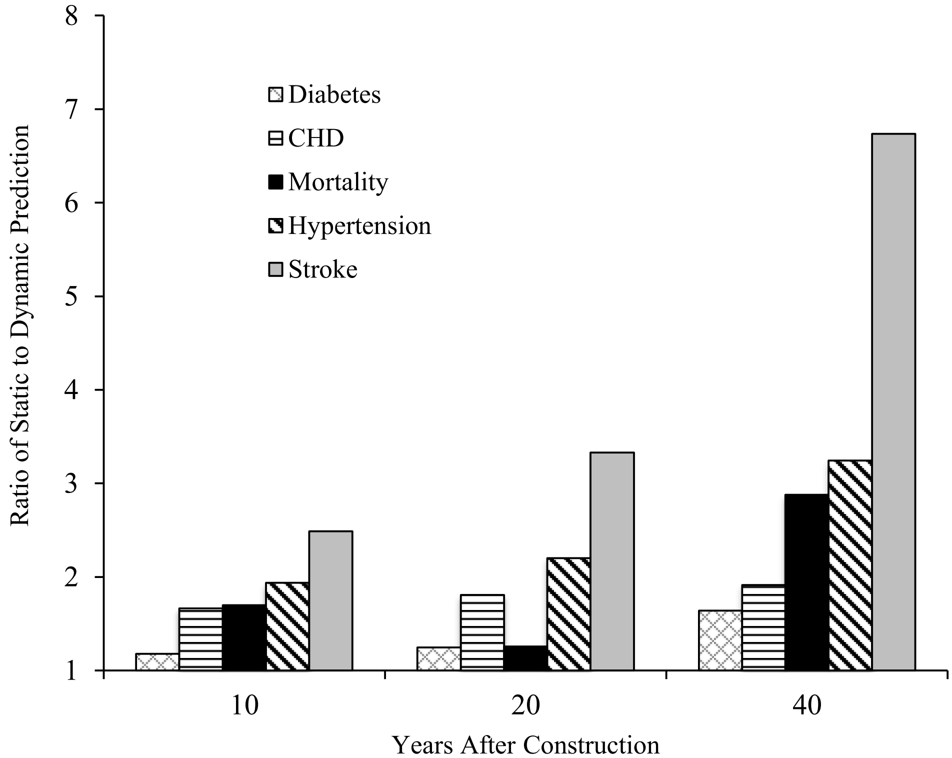

Figure 2.4. Ratio of cumulative health impact estimates from HEAT (static) and DYNAMO-HIA (dynamic) models at 10, 20, and 40 years after construction

2.4. Discussion

Using the dynamic DYNAMO-HIA tool, we predicted that the health benefits of changes to the built environment that support walking for transportation would exceed construction costs in two of the three case study communities. In the urban BRRC neighborhood, the benefit-cost ratio of changes to the built environment that would increase walkability was estimated to be 20 over 40 years. In the small rural town of Sparta, the benefit-cost ratio of proposed improvements to the downtown streetscape reached 4.7 over 40 years. In contrast, the benefit-cost ratio of constructing proposed sidewalks in suburban Winterville reached only 0.6 over 40 years. In addition, our comparison of estimates from the reconstructed HEAT model and estimates from the DYNAMO-HIA model showed that the static approach tends to over-predict benefits when considering effects over multiple years. Thus, if sufficient data and capacity exist, dynamic tools such as DYNAMO-HIA should be used rather than static tools to estimate the health impacts of policies and projects that increase transportation physical activity.

2.4.1. Comparison with Recent Active Transportation HIAs

A number of transportation HIAs using a range of modeling techniques to link changes in the built environment to health benefits from increased transportation physical activity have been completed in recent years (Mueller et al., 2015). To our knowledge, only one example of a dynamic model used to estimate the health benefits of built environment changes exists: a system dynamics model was used in an HIA of large-scale bicycle infrastructure construction in Auckland, New Zealand (Macmillan et al., 2014). This model linked bicycle infrastructure investment scenarios to changes in the perceived safety of bicycling to work and resulting mode shifts to bicycle commuting. Health impacts were then estimated for resulting changes in bicycle crash risk, air pollution exposure, and physical activity levels. Bicycle mode shares were predicted for several investment scenarios, including a business-as-usual scenario. A relative risk function comparing cyclists to non-cyclists was used to estimate changes in mortality from increased physical activity for each scenario over time. Benefit-cost ratios ranged from 6 to 24, driven largely by the value of prevented premature mortality resulting from increased physical activity (Macmillan et al., 2014).

A number of HIAs using static models, including HEAT, have also recently been performed. A study in Dane County, Wisconsin, estimated a benefit-cost ratio of 1.7 for a hypothetical countywide sidewalk construction project. The study used a regression model to link sidewalk presence to time spent walking and biking for transportation. The results of this model were used to estimate transportation physical activity given sidewalk construction across the county. Increased physical activity was then linked to reduced weight gain and ultimately reduced costs associated with obesity using a static model (Guo & Gandavarapu, 2010). An HIA of the construction of a bicycle path in Dublin, Ireland, estimated benefit-cost ratios ranging from 2.2 to 11.8. This HIA used a survey to estimate increased bicycling to work after construction and the HEAT model to estimate health and economic benefits (Deenihan & Caulfield, 2010). Finally, an assessment in Portland, Oregon, used a traffic demand model to estimate increased bicycle commuting due to past and planned investments in bicycle infrastructure throughout the city. Using the HEAT model to estimate benefits from resulting increases in physical activity, benefit-cost ratios ranged from 20 to 53 (Gotschi, 2011). As in our study, avoided premature mortality dominated the monetary value of the health benefits of increased physical activity (Figure A.5).

Previous studies have found benefit-cost ratios for changes in the built environment that support walking and biking for transportation ranging 1.7 to 53. Our results are within this range for the BRRC and Sparta but not in Winterville. The population density in Winterville may be too low for the proposed improvements to be economically viable when considering health benefits alone. This finding demonstrates that the health benefits of changes in the built environment that increase physical activity may not always exceed project costs. Thus, quantitative HIA may be an important tool for prioritizing investments to maximize the overall value of health benefits.

As HIA for active transportation projects and policies is refined, it will be important to consider differential treatment effects for different age groups and to include social equity considerations (Mueller et al., 2015). Physical activity may have a stronger preventive effect for older individuals, and many countries worldwide are seeing shifts in population distribution towards older age groups. The dynamic model used in this assessment is able to easily incorporate age-specific dose-response information, if available. The usefulness of such stratifications is demonstrated in our estimates for CHD: due to differences in population characteristics and predicted changes in behavior across sites, we estimate reduced incidence of CHD in the BRRC but not in Sparta or Winterville. This difference is driven by differential treatment effects at higher doses of transportation walking for men and women (Table 2.1). To increase the consideration of social equity in transportation HIA, scalable models are needed. Using the DYNAMO-HIA model at three different scales, we provide evidence that quantitative assessment methods are robust across scales. If modeling methods are robust at different scales, a series of neighborhood-scale models may be used to compare the health impacts of transportation decisions in neighborhoods with different socioeconomic conditions and may reveal disproportionate impacts. Such an application could better inform investments in active transportation infrastructure to address social equity concerns.

In sum, previous studies provide strong evidence that built environment changes meaningfully impact health outcomes and are often quite economically advantageous. Our application of a novel dynamic model yields findings consistent with the existing literature, building the robustness of the link between the built environment, physical activity, and health benefits. Further, we demonstrate that dynamic models may be applied across a variety of scales and are able to incorporate differential treatment effects for different age groups and for men and women. Thus, dynamic models may help address identified limitations of transportation HIA in practice.

2.4.2. Limitations

Our estimates of post-construction physical activity do not consider activity substitution (i.e., reducing other activities after increasing transportation physical activity) or self-selection (i.e., more active individuals may be more likely to increase transportation physical activity). However, longitudinal evidence suggests that activity substitution is minimal, and increases in physical activity remain when self-selection is accounted for (Sahlqvist et al., 2013; Goodman, Sahlqvist, & Ogilvia, 2014; Badland et al., 2012). In addition, our estimates exclude potential increases in physical activity from walking for leisure and from bicycling and, in this regard, could underestimate health benefits.

Additionally, we consider only one health pathway (physical activity), while transportation influences health in other ways, including exposure to air pollution and crash risk. Other health pathways may respond to built environment changes in opposite directions and with different magnitudes. For example, compact urban forms may increase physical activity but also increase exposure to air pollution (Mansfield et al., 2015). A recent HIA in London found health benefits from increased physical activity but also negative health impacts from increased exposure to air pollution and elevated crash risk for active commuters (Woodcock, Givoni, & Morgan, 2013). However, recent HIAs of active transportation consistently find changes in physical activity to be the largest contributor to estimated health impacts (Mueller et al., 2015).

While DYNAMO-HIA is able to use continuous relative risk functions, continuous prevalence data are also required when doing so and must be characterized using the mean, standard deviation, and skewness of the distribution. Baseline distributions of walking for transportation were noncontinuous (taken from categorical survey responses) and difficult to characterize as continuous distributions due to excess zeroes. Further, continuous dose-response functions were not available linking walking for transportation with CHD, type 2 diabetes, hypertension, or stroke. To overcome these difficulties, the model uses a discrete dose-response function that caps health benefits at 150 minutes of transportation physical activity per week. As a result, the model may underestimate benefits for those accruing more than 150 minutes of transportation physical activity per week. To analyze the potential magnitude of this underestimation, we recomputed the static (HEAT) model predicted mortality reduction using a continuous dose-response function combined with categorical prevalence data using smaller bins (i.e., divided into eleven categories of weekly time spent walking for transportation). The latter model estimates an additional 26 (+63%) avoided deaths after 40 years. However, since both these models are prone to overestimation, this difference may be artificially inflated.

This paper considered only three communities in North Carolina. While representing a range of urban development contexts (rural, suburban, and urban), all three communities had low baseline levels of transportation physical activity and limited public transit service. Further, community-specific disease prevalence and incidence may reflect population characteristics specific to North Carolina. Thus, our findings concerning the relative costs and benefits of the planned infrastructure investments in these three communities may not generalize to highly urban settings with higher baseline levels of transportation physical activity, higher levels of public transit usage, and/or different demographic characteristics than North Carolina. However, the differences revealed comparing estimates from DYNAMO-HIA and the HEAT model stem from the different structures of the modeling approaches themselves and thus may be generalizable across communities of many types.

Finally, disease prevalence and incidence are estimated using county data. However, these data are identical in the baseline and intervention scenarios so any resulting bias is likely minimal.

2.5. Conclusion

Using DYNAMO-HIA to conduct three quantitative HIAs, we demonstrated that investments in infrastructure that supports active transportation may have meaningful impacts on health outcomes via increased transportation physical activity. These health outcomes may also have considerable financial implications: in two of the three cases, the benefits of avoided disease and premature mortality alone exceeded construction costs.

Dynamic health impact models, such as DYNAMO-HIA, offer significant advantages over static models, such as HEAT. Static models may overestimate health benefits by failing to account for changing population health characteristics over time. However, it may be difficult to implement continuous relative risk functions using existing dynamic modeling tools if baseline exposure information is difficult to characterize as continuous distributions or if continuous dose-response information is available only for certain health outcomes. If continuous dose-response functions are discretized into just a few categories, the benefits of physical activity may be underestimated for individuals who are very physically active. Providing greater flexibility in characterizing exposure or allowing continuous dose-response functions to be used alongside categorical exposure data in existing tools would address this shortcoming in practice. Overall, the advantages of dynamic models outweigh the current limitations of available tools.

Quantitative HIA is a feasible tool for objective, evidence-based decision support linking health outcomes to increased—or decreased—physical activity resulting from changes in the built environment. Transportation decision-makers routinely use models to estimate congestion reduction and improvement in traffic safety and translate these outcomes into monetary benefits (Gwee, Currie, & Stanley, 2011). Thus, quantitative HIA combined with economic valuation enables the health benefits of increased transportation physical activity from changes in the built environment to be considered alongside traditional transportation metrics. As transportation agencies search for ways to better integrate health considerations into transportation decision-making, quantitative HIA fills a critical gap, translating investment in infrastructure that supports active travel into a metric that enables direct comparison with other types of projects. Further, quantitative assessments of competing built environment risks, such as physical activity, air pollution, and traffic fatalities, may help align larger planning efforts (e.g., comprehensive plans) with health goals by comparing the public health impacts of alternative future scenarios. Using three cases across North Carolina, we demonstrated that quantitative models linking built environment changes to physical activity and health impacts are feasible, provide meaningful results to decision-makers, and may help prioritize resources in pursuit of public health goals.

CHAPTER 3: ESTIMATING ACTIVE TRANSPORTATION BEHAVIORS TO SUPPORT HEALTH IMPACT ASSESSMENT IN THE UNITED STATES[2]

3.1 Introduction

Physical inactivity is a leading cause of premature mortality in the United States, contributing to an estimated 234,000 premature deaths annually (Murray et al., 2013). In addition, physical inactivity is associated with increased risk for chronic diseases including type 2 diabetes, cardiovascular disease, and colon cancer (Furie & Desai, 2012; Li, Loerbroks, & Angerer, 2013; Robsahm et al., 2013). Recognizing the risks associated with physical inactivity, the Centers for Disease Control and Prevention (CDC) recommends that individuals accrue a minimum of 150 minutes of moderate intensity physical activity per week (CDC, 2008). One important source of physical activity is walking and biking for transportation (known as “active transportation”). For example, a study of respondents to the National Household Travel Survey (NHTS) found that the median time spent walking to or from public transit among individuals who use public transportation was 21 minutes per day (Freeland et al., 2013).

Transportation agencies in the United States are increasingly recognizing the importance of active transportation in pursuit of broader public health goals (USDOT, 2012; USDOT, 2104). To support the incorporation of health considerations into decision-making in sectors such as transportation, health impact assessment (HIA) has emerged in recent years. A number of recent transportation HIAs have sought to estimate the health impacts of investments that support walking and biking for transportation (Mueller et al., 2015). However, active transportation HIAs are often conducted with limited data. While a large body of work has linked active transportation behaviors to characteristics of the built environment

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[2] This chapter previously appeared as an article in Frontiers in Public Health. The original citation is as follows: Mansfield, TJ, MacDonald Gibson, J. Estimating active transportation behaviors to support health impact assessment in the United States. *Front Public Health* (2016) 4(63). doi: 10.3389/fpubh.2016.00063

such as population density, the diversity of land uses, and access to public transit (Ewing & Cervero, 2010), baseline data on walking and biking for transportation are not routinely available at the local level. Baseline active transportation data are important in targeting interventions to increase transportation physical activity and are essential in estimating the expected population-level health benefits of infrastructure and other investments to promote active transportation. Lacking readily available baseline data on walking and biking behaviors, active transportation HIAs must rely on potentially inaccurate estimates or costly primary data collection, the latter of which often is not possible within the budget of the HIA.

While baseline active transportation data are scarce at the local level, a number of US national surveys collect data on transportation behaviors. However, a recent CDC summary of these surveys revealed differences in methods used, geographic scale, and estimates of active transportation (Whitfield, Paul, & Wendel, 2012).

Travel and time-use surveys, including the NHTS and the American Time Use Survey, contain detailed travel information, including the frequency of walking and biking trips for different purposes, but only for a single day (USDOT, 2009; USDOT 2015). Both the National Health and Nutrition Examination Survey and the National Health Interview Survey assess habitual physical activity behaviors, including walking and biking for transportation, and ask respondents to recall activity over the previous week (CDC, 2013a; CDC, 2013b). The American Community Survey (ACS) collects data on typical mode of transportation to work, including walking and biking, but does not gather information from respondents regarding typical walking and biking duration (US Census Bureau, 2009).

The geographic scale of surveillance also varies greatly across surveys. While large national surveys such as the NHTS offer great detail at the individual level, geographic resolution is limited. Conversely, the ACS offers much greater spatial resolution but limited information at the individual level.

Due to the differences in methods and scales across currently available surveys, estimates of the prevalence of walking and biking for transportation in the US population vary widely: in the 2012 ACS, which captures only active commuting behaviors 3.4% or respondents reported walking or biking to work. Conversely, 31.4% of respondents reported some walking or biking in the previous week in the 2011-2012 National Health and Nutrition Examination Survey, which captures all active transportation behaviors (Whitfield, Paul, & Wendel, 2012). Nonetheless, the NHTS and ACS collect a number of shared variables, including individual demographic characteristics, typical transportation mode to work, and basic built environment metrics (USDOT, 2009; US Census Bureau, 2009). These shared variables provide an opportunity to use the NHTS and ACS in tandem to offer a more detailed understanding of walking and biking for transportation at fine spatial resolution.

To address the gap in understanding the influence of transportation choices on physical activity, we use data from the 2009 NHTS to develop a statistical model that estimates weekly .time spent walking and biking for adults in the US as a function of demographic and built environment variables routinely collected in the ACS. We then validate the model using data from a separate household travel survey conducted in the Raleigh, NC, metropolitan area. We demonstrate how the statistical models can be combined with readily available ACS data to estimate baseline active transportation time across the Raleigh-Durham-Chapel Hill, NC, region. Finally, we illustrate how the statistical model could be used to support transportation-related HIAs by applying the model to estimate the health impacts of multiple hypothetical scenarios in which changes to the built environment increase transportation physical activity.

3.2. Materials and methods

Data from the 2009 NHTS were used to estimate a set of regression models: daily walk and bike trip count models, trip purpose probability models, and trip duration models. These models were estimated separately for walk and bike trips for working and non-working adults. These models were then combined to estimate weekly walking and biking time based on individual and built environment data from the ACS. Statistical analysis was performed using Stata 13 (College Station, TX), and the model was applied in the study region using Analytica 4.3 (Los Gatos, CA).

3.2.1. National Household Travel Survey

The NHTS, last administered in 2009, collects travel information from households across United States. Household, personal, and vehicle characteristics are collected via an initial telephone interview.

Subsequently, participants use a travel diary to record all travel for an assigned day, and these travel data are collected in a follow-up phone interview. The 2009 dataset contains information on 1,116,321 trips taken by 308,901 individuals living in 150,147 households and is organized into four files (household file, person file, day trip file, and vehicle file). The data are weighted to match national demographic characteristics.

3.2.1.1. Data preparation

To prepare the 2009 NHTS data for our purposes, we first summed walk and bike trip counts in the day trip file for each individual in the person file and generated two new variables to store walk and bike trip counts in the person file. We then collapsed commute mode to work and trip mode data into four categories: private vehicle (including all vehicle types and carpool), public transit (including fixed-route and paratransit), walk, and bike. In the day trip file, trip purpose was collapsed into five categories (work, shopping, social, recreational, and personal/family business), using roundtrip purpose definitions (the 1990 trip purpose definitions variable). Race and Hispanic status were combined into a single race/ethnicity variable (Hispanic, non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, and non-Hispanic other). The month variable was collapsed into four seasons, and a weekend dummy variable was generated using the travel day of week variables. Finally population density was divided by 1,000. We then merged the person and day trip data files as described in the NHTS supporting documentation (USDOT, 2011). The data were then stratified into two sub-groups: working adults (individuals aged 18 and over who report working in the previous week) and non-working adults (individuals aged 18 and over reporting no work in the previous week).

3.2.1.2. Outliers

Because we focus on routine active travel among US adults, we removed observations from the NHTS that do not represent typical transportation behaviors. In the person file, we dropped individuals who reported being out of town when the survey was administered, commuting to work via airplane or "other" travel modes, or having work commutes lasting longer than 2 hours. From the trip file, we dropped all non-active trips, vacation-related trips, and trips with durations in the highest 1% of the mode-specific trip duration distributions. In total, we removed 4,585 persons and 3,420 active trips from the sample of working adults and 3,632 persons and 2,574 active trips from the sample of non-working adults due to atypical responses (Figure 3.1).

3.2.1.3. Missing data

We dropped observations from the person file if race, education, presence of a medical condition restricting travel variables, or commute mode to work (for working adults only) was missing. Due to missing data, we removed 23,243 persons and 9,682 active trips from the sample of working adults and 2,967 persons and 1,170 active trips from the sample of non-working adults. Commute mode to work was the most common missing variable (15.9% of the remaining sample) due to a skip in the survey questionnaire triggered when the respondent reported not traveling to work in the previous week, potentially indicating that the week was atypical for that individual.

After removing atypical transportation behaviors and observations with missing, the final sample of working adults contained 45,938 trips made by 109,250 persons, and the final sample of non-working adults contained 37,311 trips made by 119,743 persons (Figure 3.1). Descriptive statistics of the final sample are presented Appendix B, Tables B.1 (Person File) and B.2 (Trip File).

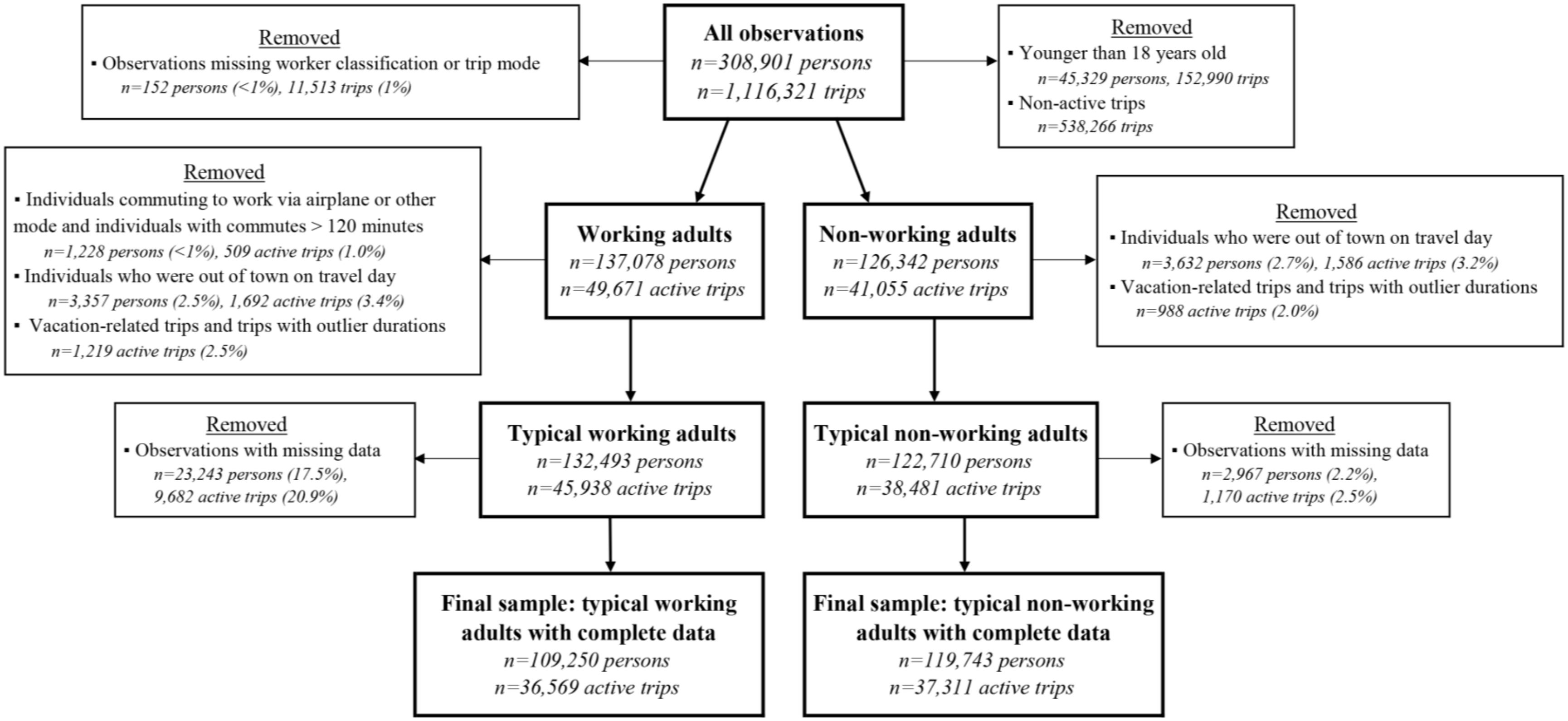


Figure 3.1. Flowchart illustrating data cleaning and stratification of the 2009 NHTS dataset into working and non-working adults.

3.2.2. Transportation physical activity estimation framework

To estimate weekly time spent walking and biking for transportation, count models were first used to estimate the number of walk and bike trips taken by an individual during a typical day (Section 3.2.2.1). Because trip duration in the NHTS varies significantly with trip purpose, the distribution of trips among different purposes is also an important factor in estimating total transportation physical activity. Multinomial logistic regression models were used to predict the probability that a given walk or bike trip was for one of five purposes: 1) commuting to work; 2) shopping; 3) socializing; 4) engaging in recreation; or 5) tending to personal or family business (Section 3.2.2.2). Finally, trip duration was estimated for each trip purpose (Section 3.2.2.3). Estimated trip counts were combined with trip purpose probabilities and purpose-specific duration estimates to predict daily walking and biking time for individuals using Equation 5:

$$TT_{m,i} = \sum_{p=1}^{5} \left(E\left(t_{m,i}\right) \times \left(Pr(p_{m,i}) \times d_{p,m,i}\right)\right) \qquad (2.1)$$

in which $TT_{m,i}$ is daily minutes spent traveling using mode *m* for individual i, $E\left(t_{m,i}\right)$ is the expected daily number of trips take using mode *m* for individual i, $Pr(p_m)$ is the probability that a trip taken by individual *i* using mode *m* is for purpose *p*, and $d_{p,m}$ is trip duration for a trip taken by individual *i* for purpose *p* using mode *m*.

Walking and biking time were combined by multiplying each activity by its intensity, measured by metabolic equivalents (METs). METs measure the intensity of physical activity relative to an individuals' resting metabolic rate, which is equal to one MET. By multiplying the intensity of an activity by its MET value and its duration, total physical activity dose from a variety of activities with differing intensities may be calculated, expressed in METs multiplied by the duration of the activity to obtain MET-hours. Walking and biking for transportation have MET values of 3.5 and 6.8, respectively (Ainsworth et al., 2011). Equation 5 was thus used to transform biking and walking time into a daily physical activity dose:

$$TPA_i = \frac{\left(TT_{m=walk,i} \times 3.5\right) + \left(TT_{m=bike,i} \times 6.8\right)}{60 \frac{minutes}{hour}} \quad (2.2)$$

in which TPA_i is daily physical activity from walking and biking for individual *i* in MET-hours, $TT_{m=walk,\,i}$ is daily time spent walking for transportation for individual *i* in minutes, and $TT_{m=bike,I}$ is daily time spent biking for transportation for individual *i* in minutes.

The following sections describe the three regression models used to estimate $E(t_{m,i})$, $Pr(p_{m,i})$, and $d_{p,m,i}$. For all models, explanatory variables included both individual characteristics (commute mode to work, age, sex, and race) and built environment variables reported in the NHTS (population density and proportion of housing units that are rented in the block group in which the individual resides). Commute mode to work is intuitively related to active transportation behavior. Age, sex, and race are associated with transportation walking and biking (Pucher et al., 2011). Population density has a well-documented relationship with walking and biking for transportation (Ewing & Cervero, 2010). Finally, percent of rental units may be a rough proxy for land-use diversity, also strongly linked to walking and biking for transportation (Ewing & Cervero, 2010). All models included controls for educational attainment, travel day of the week (weekday or weekend), the season in which the survey was administered, whether or not the respondent reported having a medical condition that may restrict travel, whether the interview was conducted with a proxy respondent, whether the metropolitan statistical area in which the respondent resided had heavy rail (which may influence urban form and trip-making in unique ways), and state, Census division, or Census region fixed effects. In all regression models, variables were retained if significant at the 10% level.

3.2.2.1. Daily trip count models

Daily walk and bike trip count data contained high proportions of zeroes and displayed little evidence of overdispersion (Figure B.1). Specification tests (Vuong and Lagrange multiplier) were used to select an appropriate form for the daily trip count models (Cameron & Trivedi, 2005). These specification tests revealed very strong ($p<0.001$) evidence for zero-inflated Poisson models to represent both walk and bike trip counts for working and non-working adults (Figure B.2 and Tables B.3 and B.4). Thus, daily walk and bike trip counts were estimated using the following model (Long & Freese, 2014):

$$Pr(Y_i = y_i|\boldsymbol{x}_i) = \begin{cases} \pi_i + (1-\pi_i)e^{-\lambda_i}, \ if \ y_i = 0 \\ \dfrac{(1-\pi_i)e^{-\lambda_i}{\lambda_i}^{y_i}}{y_i!}, \ if \ y_i > 0 \end{cases} \qquad (2.3)$$
$$\lambda_i = e^{(\alpha + \boldsymbol{x}_i^T \boldsymbol{\beta})}$$

where π_i is the probability that daily walk or bike trip counts always equals zero, $\boldsymbol{x}_i$ is a vector of individual-specific regressors, and $\boldsymbol{\beta}$ is a vector of regression coefficients. Variables were retained in the model if significant at the 10% level and robust standard errors were used.

3.2.2.2. Trip purpose probability models

Multinomial logistic regression models were used to predict the probability of different trip purposes based on individual characteristics and built environment variables. Accordingly, the probability that a trip is for purpose *j* is expressed as (Cameron & Trivedi, 2005):

$$Pr(y_i = p) = \frac{e^{(\boldsymbol{x}_i^T \beta)}}{1 + \sum_{p=1}^{P-1} e^{(\boldsymbol{x}_i^T \beta)}}, \qquad for \ p = 1, \dots, P-1 \qquad (2.4)$$

where $\Pr(y_i = p)$ is the probability of trip purpose *p* for individual *i*, P is the number of outcomes (in this case, five: work commute, shopping, social, personal/family business), $\boldsymbol{x}_i$ is a vector of individual-specific regressors, and β is a vector of regression coefficients.

3.2.2.3. Trip duration models

Generalized estimating equation (GEE) models with a log link were used to estimate trip duration based on individual characteristics and built environment variables. Because an individual may take multiple trips during the day and trip characteristics may be correlated within and across individuals, the data are treated as a panel of individuals observed taking multiple trips. GEE models offer a robust approach to estimating standard errors when using data that are correlated within clusters of observations (in this case, the relatedness of trips within individuals) (Hanley et al., 2003). Trip duration may be influenced by different factors depending on trip purpose; thus, commute mode to work, travel time to work, population density, and percent rental units were interacted with trip purpose in trip duration models for working adults. Population density and percent rental units were interacted with trip purpose in trip duration models for non-working adults. These models may be expressed as (Cameron & Trivedi, 2005):

$$g(d_{m.i}) = \boldsymbol{x}_i^T \boldsymbol{\beta} \tag{2.5}$$

where $d_{m,i}$ is trip duration for individual *i* using mode *m*, $g(d_{m,i})$ is the link function, $\boldsymbol{x}_i^T$ is a vector of trip-specific regressors, and $\boldsymbol{\beta}$ is a vector of estimated coefficients.

3.2.2.4. Marginal effects

Average marginal effects of explanatory variables for each regression model (count, trip purpose, and trip duration) were estimated using the margins command in Stata. To calculate the combined marginal effect of explanatory variables on daily walking and biking time, a model was developed in Analytica that incorporated estimated regression coefficients for each model into Equation 5. Monte Carlo simulation was used to develop standard errors for combined marginal effects.

3.2.2.5. Model validation

To validate model performance, model predictions were compared to results from a 2006 household travel survey conducted in the Raleigh-Durham-Chapel Hill metropolitan area as part of routine transportation planning (Bricka & Dickerson, 2006). Survey respondents provided demographic information and recorded all trips for one weekday. The full validation dataset contained 6,618 workers. We dropped 3,427 individuals due to missing data, largely due to missing race/ethnicity (n=2,789). We then calculated observed daily MET-hours for all individuals with complete data in the validation dataset from their recorded trips using Equation 6. Finally, we used Equation 5 to estimate daily MET-hours for the validation survey ($TPA_{i,est}$) sample and compared model predictions to observed values ($TPA_{i,obs}$).

Descriptive statistics for the validation sample are presented in Tables B.1 and B.2. Compared to the NHTS, respondents in the validation survey reported fewer total walk and bike trips. The validation sample also has higher education levels, fewer proxy respondents, and only contains responses from the winter and spring. However, most differences between the two datasets are included as controls in the NHTS regression models.

3.2.3. Applying the model to estimate physical activity for population subgroups

To estimate weekly transportation physical activity across the Raleigh-Durham-Chapel Hill metropolitan region, we first used Equation 1 to estimate TPA_i for all possible combinations of variables that vary on the individual level and across block groups in the study area. We excluded recreational trip durations when summing total walking and biking time in Equation 5 to focus on purpose-oriented (non-recreational) transportation physical activity. Four of these variables—commute mode to work c (including a category for non-workers), age a, sex s, and race/ethnicity r—vary on the individual level. The fifth variable, g, represents the combined effect of all variables and controls that are measured at the block group—population density, percentage of units that are rentals, travel time to work by mode, and educational attainment. Population density was calculated using block-group population counts obtained from the 2013 ACS and area obtained from Census TIGER files (US Census Bureau, 2013; US Census Bureau, 2014). If household income and/or travel time to work data were missing at the block group level due to sampling limitations, tract-level data were used instead. If tract-level data were also missing, county-level data were used. In the block-group level Census data, time to work for bicyclists is combined with other modes (motorcycle, taxicab, and other). If the reported travel time to work by bicycle, motorcycle, taxicab, and other modes was greater than the travel time reported for private vehicles, the lower of these values was used. Missing data were treated as described above, still using the lower value if travel time reported at the tract or county level exceeded motor vehicle travel time.

Equation 2.1 was used to estimate TPA_i for a typical weekday and for a typical weekend day for all possible unique combination of *c*, *a*, *s*, *r*, and *g*. Weekly estimates were then obtained by multiplying the typical weekday estimate by five and typical weekend estimate by two and then summing the products. These estimates were stored in a five-dimensional matrix, **TPA**. This matrix contained approximately 4 million cells, each containing a unique estimate of TPA_i associated with one of five possible commuting behaviors, one of 96 possible ages, one of two sexes, one of five race/ethnicities, and one of 835 block groups. To reflect the uncertainty of regression coefficients, **TPA** was estimated using Monte Carlo simulation in Analytica. The standard deviation of each estimate was stored in a second matrix, $\mathbf{TPA_{SD}}$, with the same dimensions as the matrix **TPA**. $\mathbf{TPA_{SD}}$, was used to model uncertainty and generate 95% confidence intervals for our estimates using Monte Carlo simulation in Analytica.

3.2.4. Applying physical activity estimates to the population

Once the matrix **TPA** was generated, data from the 2013 ACS were used to develop joint distributions of population characteristics across the four individual dimensions (c, a, s, and r) for each block group in the study area. To do so, the normalized distribution of age by sex was first multiplied by age- and gender-specific labor force participation functions to define the age and sex distribution of workers and non-workers in each block group. Labor force participation rates by sex for each county were taken from the 2013 ACS (US Census Bureau, 2013). These data were smoothed over age by fitting fourth-order splines to the raw data for men and women in each county. Then, the distribution of workers was multiplied by the distribution of reported commute mode to work, creating the five dimensions of c noted previously (private vehicle, transit, walk, bike, and not in labor force). Finally, this distribution was multiplied by the distribution of the population by race/ethnicity in each block group. When performed for all block groups in the study region, this process yielded a matrix **NPD** that contained normalized distributions of the populations in each block group across the same dimensions as **TPA**. Finally, **NPD** was multiplied by a vector **P** containing the aggregate population of each block group in the region. This process resulted in a representation of block group populations distributed across age, sex, race/ethnicity, and commute mode to work (including a category for non-workers) based on the 2013 ACS (24). An example of this procedure for a single block group is provided in Appendix B, Section B.4.

3.2.5. Health impact estimates

We estimated health benefits of walking and biking in the study region by comparing predicted transportation physical activity to a counterfactual scenario in which individuals walked 37.4 minutes per week for transportation—the average level of walking observed in groups of high- and low-income walkable neighborhoods in Baltimore and Seattle (Sallis et al., 2009). This calculation requires an estimate of the relative risk of all-cause mortality as a function of transportation physical activity, denoted as $RR_M(TPA)$. According to a recent meta-analysis (Kelly et al., 2014), this dose-response function can be estimated as:

$$RR_M(TPA) = 0.90^{\left(\frac{TPA}{11.25\ MET-hrs}\right)} \tag{2.6}$$

The fractional change in mortality under the counterfactual scenarios, in comparison to current conditions, was estimated from:

$$AF_{TPA} = \frac{\int_{TPA=0}^{\infty}\left(1 - RR_M(TPA)\right)f_{est}(TPA)dTPA - \int_{TPA=0}^{\infty}(1 - RR_M(TPA))f_{cf}(TPA)dTPA}{1 + \int_{TPA=0}^{\infty}\left(1 - RR_M(TPA)\right)f_{est}(TPA)dTPA} \tag{2.7}$$

where AF_{TPA} is the fraction of mortality avoidable by additional active transportation in the study region, $f_{est}(TPA)$ is the current probability distribution of transportation physical activity as estimated in Equation 2.2, and $f_{cf}(TPA)$ is a probability distribution of transportation physical activity in the counterfactual scenario (Hanley, 2001; Rothman, Greenland, & Lash, 2012). Finally, the total change in mortality was calculated as follows:

$$AM_{TPA} = DR_b \times AF_{TPA} \tag{2.8}$$

where AM_{TPA} is avoided mortality due to active transportation and DR_b is the age- and sex-specific baseline death rate for each county in the study region, taken from the North Carolina State Center for Health Statistics (NSCHS, 2014). To alleviate the small number problem (i.e., age groups with no observed deaths in a given year), a five-year average death rate was calculated for males and females for each age group in each county (Table B.6). Equations 11 and 12 were applied across the same dimensions as **TPA**; thus, health impact estimates may be stratified by age, sex, race/ethnicity, commute mode to work, and block group or any combination of these dimensions. The World Health Organization suggests applying Equation 10 only for bicyclists between the ages of 20 and 64 and walkers between the ages of 20 and 74 (Kahlmeier et al., 2014). Thus, we restricted our calculation of health impacts to these age ranges.

3.2.6. Hypothetical HIA application

To illustrate how our regression models could be applied to support active transportation HIA, we estimated health benefits for three hypothetical interventions to support increased walking and biking for transportation. A recent meta-analyses derived elasticities linking changes in the built environment to changes in transportation behavior (Ewing & Cervero, 2010). According to this meta-analysis, five built environment dimensions—land use density, land use diversity, physical design, access to transit, and access to destinations—can affect transportation behavior and, in turn, transportation physical activity. For example, a 1% increase in the number of intersections per square mile is associated with a 0.39% increase in walking. Similarly, 1% increases in land use diversity and the number of transit stops per square mile are each associated with 0.15% increases in walking. A 1% increase in transit stop coverage also is associated with increasing transit use by 0.29%. In the first scenario, we assume that land-use diversity, transit stop coverage, and intersection density all increase by 10% across the study region, resulting in a 7.9% increase in walking for the entire population. For the second scenario, we assume that the same built environment changes result in 7.9% of current drivers walking instead of driving to work. In the third, we assume that transit coverage increases by 50% across the study region, resulting in 14.5% of current drivers switching to public transit for their work commutes. We then used Equations 2.7 and 2.8, replacing $f_{cf}(TPA)$ with the new counterfactual distributions of transportation physical activity.

3.3. Results

3.3.1. Number of walking and biking trips

To estimate the influence of means of transportation to work, individual characteristics, and built environment variables on the number of daily walking and biking trips, we fitted zero-inflated Poisson regression models to data from the 2009 NHTS. Results show that those who walk, bike, or take public transit to work are significantly more likely to be in the "not always zero" daily walk trip count group, compared to those who drive to work (Table 3.1, logistic model). This effect is strongest for those walking to work (OR=16.6) and also quite strong for those riding transit to work (OR=4.73). Additionally, among individuals walking at least once per day, those who walk to work take 1.68 times as many walk trips as those commuting by private vehicle (Table 3.1, count model). Increased population density and percentage of housing units that are rented are both associated with both increased likelihood of being in the "not always zero" daily walk trip count group and, for individuals in the "not always zero" group, increased daily walk trip counts. For non-working adults, population density and percentage rental units are significantly associated with both increased likelihood of taking at least one walk trip and daily walk trip counts. In sum, walk trip count models show that individuals who walk, ride transit, or, to a lesser extent, bike to work are likely to take more walk trips than those who drive to work. Increased population density and percentage of rental units both have additional significant, albeit small, impacts on daily walk trip counts.

Similarly, individuals who bike or take public transit to work are significantly more likely to be in the "not always zero" daily bike trip count group, compared to those who drive to work (OR=300 and 2.99, respectively) (Table 3.2, logistic model). Increased population density is significantly associated with increased odds of taking at least one bike trip for working adults but not for non-working adults. Among individuals who take at least one bike trip per day, bicycle commuters take 1.48 times as many bike trips as those commuting by car (Table 3.2, count model).

Individual characteristics (age, sex, and race/ethnicity) have mixed associations in both the logistic and count portions of the models. Among employed adults, non-Hispanic Blacks and non-Hispanic Asians are less likely to be in the "not always zero" daily bike trip count group (OR=0.64 and 0.62, respectively). Non-Hispanic Asian individuals are also less likely to be in the "not always zero" daily bike trip count group (OR=0.43); however, those who are in the "not always zero" daily bike trip count group take 1.36 times more bike trips than non-Hispanic Whites (Table 3.2, count model). While gender has no significant effect on walking, men are much more likely to report biking for transportation, regardless of employment status.

Table 3.1. Model for estimating daily number of walking trips

		Odds Ratio	
	Variable	Working Adults [a]	Non-working Adults [a]
Logistic model (probability not always zero)	Mode to Work		
	Private vehicle	*(ref)*	-
	Public transit	4.73***	-
	Walk	16.6***	-
	Bike	2.00**	-
	Population Density	1.01**	1.03***
	Percent Rented	1.01***	1.01***
	Age	1.02**	0.99***
	Age Squared	0.9997**	-
	Race/Ethnicity		
	Non-Hispanic White	*(ref)*	*(ref)*
	Non-Hispanic Black	0.64***	1.03
	Hispanic	0.89	1.21*
	Non-Hispanic Asian	0.62***	0.95
	Non-Hispanic other	0.88	0.83
	Constant	0.027***	0.088***
Count model	Mode to Work		
	Private vehicle	*(ref)*	-
	Public transit	1.09*	-
	Walk	1.68***	-
	Bike	1.27**	-
	Population Density	1.01***	1.01**
	Percent Rented	1.002**	1.004***
	Age	-	1.01**
	Age Squared	-	0.9999**
	Constant	0.78**	0.79*
	N	109,250	119,743
	Wald chi-squared *(df)*	854.05*** *(68)*	646.43*** *(67)*
	McFadden Pseudo R^2 *(adjusted)*	0.15	0.12

***p<0.01 **p<0.05 *p<0.10

[a] Adjusted for education, whether the respondent has a medical condition that limits travel, whether a proxy respondent was used, number of trips taken on travel day, season of travel day, day of week of travel day, presence of heavy rail in metropolitan statistical area, and state fixed effects in both stages (logistic and count model)

Table 3.2. Model for estimating daily number of bike trips

	Variable	Odds Ratio: Working Adults [a]	Odds Ratio: Non-working Adults [a]
Logistic model (probability not always zero)	Mode to Work		
	Private vehicle	*(ref)*	-
	Public transit	2.99***	-
	Walk	1.31	-
	Bike	300***	-
	Population Density	1.04*	-
	Age	-	0.98***
	Sex *(ref: male)*	0.29***	0.23***
	Race/Ethnicity		
	Non-Hispanic White	*(ref)*	*(ref)*
	Non-Hispanic Black	0.61	0.52**
	Hispanic	0.88	0.49**
	Non-Hispanic Asian	0.43**	0.50
	Non-Hispanic other	0.49*	0.56
	Constant	0.0039***	0.059***
Count model	Mode to Work		
	Private vehicle	*(ref)*	-
	Public transit	1.20	-
	Walk	0.91	-
	Bike	1.48***	-
	Sex *(ref: male)*	-	0.73**
	Race/Ethnicity		
	Non-Hispanic White	*(ref)*	*(ref)*
	Non-Hispanic Black	1.22	1.28
	Hispanic	1.02	0.65
	Non-Hispanic Asian	1.36*	1.55***
	Non-Hispanic Other	1.06	0.67
	Constant	1.51***	3.03*
	N	109,250	119,743
	Wald chi-squared *(df)*	79.5*** *(28)*	91.7*** *(26)*
	McFadden Pseudo R^2 *(adjusted)*	0.29	0.12

***p<0.01 **p<0.05 *p<0.10

[a] Adjusted for education, whether the respondent has a medical condition that limits travel, whether a proxy respondent was used, number of trips taken on travel day, season of travel day, day of week of travel day, presence of heavy rail in metropolitan statistical area, and census division fixed effects in both stages (logistic and count model)

3.3.2. Walking and biking trip purposes

To test the influence of explanatory variables on the distribution of walking and biking trip purposes, we fitted multinomial logistic regression models to NHTS data. Relative to a working adult who walks to work, a walk trip taken by an individual who commutes using a private vehicle, public transit, or bike is significantly more likely to be for a non-work purpose (shopping, social, recreational, or personal/family business) (Table 3.3, top portion). For working adults, increased population density is associated with reduced odds that a given walk trip will be for recreation, and increased percentage of housing units that are rented is associated with increased odds that a given walk trip will be for shopping. For non-working adults, increased percentage of rental units is associated with increased odds that a given trip will be for non-recreational purposes (shopping, social, or personal/family business) (Table 3.3, bottom portion).

Relative to a working adult who bikes to work, a bike trip taken by an individual using another commute mode is significantly more likely to be for a non-work purpose (shopping, social, recreational, or other purposes) with two exceptions: no significant difference is found for the likelihood that a transit commuter takes a social bike trip or for the likelihood that someone who walks to work takes a personal/family business bike trip (Table 3.4, top portion). For working adults, built environment variables have no significant effects on bike trip purpose probabilities, while individual characteristics have mixed effects. For non-working adults, the proportion of trips that are for shopping increases significantly with population density, while the proportion of trips for business increases with percentage of rental units (Table 3.4, bottom portion).

Table 3.3. Model for estimating walk trip purpose

Sub-group: Working adults [a]

	Odds Ratio for Trip Purpose *(base outcome: work trip)*			
Variable	Shopping	Social	Recreational	Personal/Family Business
Mode to Work				
Private vehicle	22.7***	35.2***	84.0***	28.1***
Public transit	11.3***	11.9***	12.8***	10.4***
Walk	*(ref)*	*(ref)*	*(ref)*	*(ref)*
Bike	19.5***	26.0***	25.1***	13.1***
Population Density	1.002	1.02	0.965***	0.992
Percent Rent	1.009**	0.998	1.00	1.00
Age	1.003	0.985**	1.01*	0.996
Race/Ethnicity				
Non-Hispanic White	*(ref)*	*(ref)*	*(ref)*	*(ref)*
Non-Hispanic Black	1.12	0.587	0.427**	0.477***
Hispanic	1.04	0.790	0.914	0.752
Non-Hispanic Asian	0.745	0.360***	0.732	0.457**
Non-Hispanic other	0.718	0.713	0.929	0.570
Constant	0.038***	0.049***	0.035***	0.111***
N	33,863			
Wald chi-squared *(df)*	1,610*** *(124)*			McFadden R^2 *(adj.)*: 0.15

Sub-group: Non-working adults [a]

	Odds Ratio for Trip Purpose *(base outcome: recreational trip)*		
Variable	Shopping	Social	Personal/Family Business
Percent Rental	1.02***	1.02***	1.02***
Age	0.994*	0.984***	0.984***
Sex *(ref: male)*	1.10	1.01	1.30*
Race/Ethnicity			
Non-Hispanic White	*(ref)*	*(ref)*	*(ref)*
Non-Hispanic Black	3.32***	1.72**	1.36
Hispanic	1.37	1.00	1.00
Non-Hispanic Asian	0.637	0.403**	0.895
Non-Hispanic other	1.30	0.687	0.842
Constant	0.291***	0.712	0.404**
N	35,330		
Wald chi-squared *(df)*	525.7*** *(84)*		McFadden R^2 *(adj.)*: 0.09

***p<0.01 **p<0.05 *p<0.10

[a] Adjusted for education, whether the respondent has a medical condition that limits travel, whether a proxy respondent was used, number of trips taken on travel day, season of travel day, day of week of travel day, presence of heavy rail in metropolitan statistical area, and census division fixed effects

Table 3.4. Model for estimating bike trip purpose

Sub-group: Working adults [a]

Variable	Odds Ratio for Trip Purpose *(base outcome: work trip)* Shopping	Social	Recreational	Personal/Family Business
Mode to Work				
Private vehicle	21.0***	18.5***	165***	28.9***
Public transit	7.81***	0.908	8.71***	6.23**
Walk	10.0**	15.3***	20.6***	6.60
Bike	*(ref)*	*(ref)*	*(ref)*	*(ref)*
Age	0.934	0.924	0.902	0.806***
Age Squared	1.001	1.001	1.002**	1.002***
Race/Ethnicity				
Non-Hispanic White	*(ref)*	*(ref)*	*(ref)*	*(ref)*
Non-Hispanic Black	3.35*	0.529	2.39	1.70
Hispanic	5.41***	1.93	3.18**	1.10
Non-Hispanic Asian	4.48	0.143	2.51	1.90
Non-Hispanic other	1.05	5.30	4.33	4.09
Constant	0.0044***	0.080	0.0023***	2.19
N	2,706			
Wald chi-squared *(df)*	503.3*** *(100)*			McFadden R^2 *(adj.)*: 0.38

Sub-group: Non-working adults [b]

Variable	Odds Ratio for Trip Purpose *(base outcome: recreational trip)* Shopping	Social	Personal/Family Business
Population Density	1.11**	1.04	0.993
Percent Rental	1.01	1.01	1.02**
Age	1.03***	0.995	0.972***
Race/Ethnicity			
Non-Hispanic White	*(ref)*	*(ref)*	*(ref)*
Non-Hispanic Black	1.86	1.67	0.77
Hispanic	0.518	0.571	0.21*
Non-Hispanic Asian	6.65**	2.25	8.01**
Non-Hispanic Other	0.0304**	0.669	0.0622***
Constant	0.114**	1.49	4.09
N	1,981		
Wald chi-squared *(df)*	327.7*** *(84)*		McFadden R^2 *(adj.)*: 0.28

***p<0.01 **p<0.05 *p<0.10

[a] Adjusted for education, whether the respondent has a medical condition that limits travel, whether a proxy respondent was used, number of trips taken on travel day, season of travel day, day of week of travel day, presence of heavy rail in metropolitan statistical area, and Census region fixed effects

[b] Same adjusted as above, with the exception of census division fixed effects in place of Census region fixed effects

3.3.3. Duration of walking and biking trips

To test the influence of commute mode to work, individual characteristics, and built environment variables on trip durations, we fit GEE models predicting trip duration to the NHTS data. Relative to a walk trip to work by someone who typically walks to work, all other walk trips are longer with the exception of walk trips to work by individuals who typically commute via transit or private vehicle (Table 3.5). Thus, walk trips for purposes other than commuting to work are typically longer than walks to work. Additionally, the significantly shorter walk trips to work for those typically commuting via transit likely reflect walking shorter distances to and/or from transit stops at the beginning and/or end of work commutes. Travel time to work is intuitively associated with the duration of walking trips to work; much smaller but significant associations with other trip types may reflect an unobserved non-aversion for longer trip durations. For non-working adults with no commute to work, shopping, social, and personal/family business walk trips are significantly shorter than recreational trips. Older individuals take longer walk trips, perhaps reflecting decreased walking speed. Additionally, Hispanic and non-Hispanic Blacks take significantly longer walk trips than non-Hispanic White individuals.

Somewhat paradoxically, increased population density and percent rental units are associated with slightly longer walk trips to work. Increased population density is also associated with slightly longer walking trips for social purposes, and increased percent rental units is associated with slightly longer shopping trips. While increases in these built environment variables would seemingly be associated with an increased density of destinations and thereby shorter trip distances, these built environment variables also may be associated with increased replacement of slightly longer duration non-walking trips with walking trips, thus increasing average trip duration. Increased population density and percent rental units are both associated with shorter recreational walking trips, possibly because recreational destinations are closer to residential areas.

Similar associations between trip duration, trip purpose, and built environment variables occur for biking trips (Table 3.6). Some differences exist regarding associations with trip type and mode to work: relative to a bike trip to work by someone who typically cycles to work, a work bike trip by someone who typically drives to work is significantly longer. Bike trips to work by someone who typically walks to work are shorter than those taken by someone who typically bikes to work. Finally, work bike trip duration is not significantly associated with taking public transit to work, likely reflecting the relative rarity of bike trips to access public transit. While population density not associated with bike trip durations, percentage of rental units is negatively associated with the duration of shopping and recreational bike trips for working adults. For non-working adults, shopping, social, and personal/family business bike trips are significantly shorter than the reference category (recreational trips). Among working adults, age exhibits a significant quadratic relationship with bike trip duration. Among working and non-working adults, women take shorter bike trips compared to men.

To illustrate the combined effects of the models summarized in Tables 3.1 through 3.6, Figure 3.2 presents estimates of weekday walking and biking time for a median individual in each commuter category. Generally, individuals who walk to work have much higher average daily walking time than other types of commuters. Similarly, bicycle commuters have higher average daily biking time than all other commuters. Transit commuters have moderate daily average walking times, likely reflecting walk trips to and from transit stops. Bike commuters also have moderate daily average walking times. Daily walking time for individuals who walk to work peaks around age 50 and then decreases slightly with age, while daily biking time peaks at a later age for bicycle commuters. Increases in daily bike time for bike commuters until to around age 75 is a surprising finding, perhaps reflecting strong underlying preferences for biking among those that continue to bike to work at older ages. Both daily walking and biking time increase as population density and percent rental units increase.

Table 3.5. Model for Estimating Walk Trip Duration

Variable	Regression Coefficient	
	Working Adults [a]	Non-working Adults [a]
Trip purpose		
Shopping trip	-	-0.711***
Social trip	-	-0.763***
Recreational trip	-	*(ref)*
Personal/family business trip	-	-0.459***
Interaction: trip purpose with mode to work		
Work trip x private vehicle to work	0.043	-
Work trip x transit to work	-0.404***	-
Work trip x walk to work	*(ref)*	-
Work trip x bike to work	0.388***	-
Shopping trip x private vehicle to work	1.02***	-
Shopping trip x transit to work	1.12***	-
Shopping trip x walk to work	1.16***	-
Shopping trip x bike to work	1.26***	-
Social trip x private vehicle	1.07***	-
Social trip x transit to work	1.03***	-
Social trip x walk to work	1.25***	-
Social trip x bike to work	1.28***	-
Recreational trip x private vehicle to work	2.08***	-
Recreational trip x transit to work	2.05***	-
Recreational trip x walk to work	2.13***	-
Recreational trip x bike to work	2.13***	-
Personal/family business trip x private vehicle	1.30***	-
Personal/family business trip x transit to work	1.21***	-
Personal/family business trip x walk to work	1.29***	-
Personal/family business trip x bike to work	1.32***	-
Interaction: log of time to work with trip purpose		
Log time to work x work trip	0.537***	-
Log time to work x shopping trip	0.063**	-
Log time to work x social trip	0.080***	-
Log time to work x recreational trip	-0.020**	-
Log time to work x personal/family business	0.070***	-
Interaction: population density with trip purpose		
Population density x work trip	0.004*	-
Population density x shopping trip	-0.003	0.001
Population density x social trip	0.008**	0.011***
Population density x recreational trip	-0.004**	-0.003
Population density x personal/family business	-0.001	0.002
Interaction: percent rental units with trip purpose		
Percent rental x work trip	0.002***	-
Percent rental x shopping trip	0.002**	0.003***
Percent rental x social trip	-0.0003	0.001
Percent rental x recreational trip	-0.001*	-0.001
Percent rental x personal/family business trip	-0.0001	-0.0001
Age	0.002***	0.006***
Age Squared	-	-0.0001***
Sex *(ref: male)*	-	-0.083***
Race/Ethnicity		
Non-Hispanic White	*(ref)*	*(ref)*
Non-Hispanic Black	0.084***	0.103***
Hispanic	0.121***	0.136***
Non-Hispanic Asian	0.008	0.036
Non-Hispanic Other	0.006	0.053
Constant	0.94***	3.20***
N (trips)	33,863	35,350
N (individuals)	14,888	14,879
Wald chi-squared *(df)*	4,841*** *(102)*	2,680*** *(81)*

***p<0.01 **p<0.05 *p<0.10

[a] Adjusted for education, whether the respondent has a medical condition, whether a proxy respondent was used, number of trips taken on travel day, season of travel day, day of week of travel day, presence of heavy rail in metropolitan statistical area, and state fixed effects

Table 3.6. Model for Estimating Bike Trip Duration

Variable	Regression Coefficient	
	Working Adults [a]	Non-working Adults [a]
Trip purpose		
Shopping trip	-	-0.579***
Social trip	-	-0.449***
Recreational trip	-	*(ref)*
Personal/family business trip	-	-0.388***
Interaction: trip purpose with mode to work		
Work trip x private vehicle to work	0.378***	-
Work trip x transit to work	0.015	-
Work trip x walk to work	-0.196**	-
Work trip x bike to work	*(ref)*	-
Shopping trip x private vehicle to work	0.987**	-
Shopping trip x transit to work	0.900*	-
Shopping trip x walk to work	0.954**	-
Shopping trip x bike to work	0.970***	-
Social trip x private vehicle	1.59***	-
Social trip x transit to work	1.38***	-
Social trip x walk to work	1.90***	-
Social trip x bike to work	1.58***	-
Recreational trip x private vehicle to work	2.44***	-
Recreational trip x transit to work	2.29***	-
Recreational trip x walk to work	2.75***	-
Recreational trip x bike to work	2.53***	-
Personal/family business trip x private vehicle	1.31***	-
Personal/family business trip x transit to work	0.939**	-
Personal/family business trip x walk to work	1.09***	-
Personal/family business trip x bike to work	1.19***	-
Interaction: log of time to work with trip purpose		
Log time to work x work trip	0.731***	-
Log time to work x shopping trip	0.358***	-
Log time to work x social trip	0.178*	-
Log time to work x recreational trip	0.0460	-
Log time to work x personal/family business	0.297***	-
Interaction: Percent rental units with trip purpose		
Percent rental x work trip	-0.0004	-
Percent rental x shopping trip	-0.005***	-
Percent rental x social trip	-0.003	-
Percent rental x recreational trip	-0.004***	-
Percent rental x personal/family business trip	-0.002	-
Age	0.019**	-
Age Squared	-0.0002*	-
Sex *(ref: male)*	-0.075*	-0.190***
Race/Ethnicity		
Non-Hispanic White	-	*(ref)*
Non-Hispanic Black	-	0.404***
Hispanic	-	0.191*
Non-Hispanic Asian	-	0.280
Non-Hispanic Other	-	0.062
Constant	0.46*	3.33***
N (trips)	2,706	1,981
N (individuals)	1,222	866
Wald chi-squared *(df)*	1,085*** *(53)*	168.8*** *(29)*

***p<0.01 **p<0.05 *p<0.10

[a] Adjusted for education, whether the respondent has a medical condition, whether a proxy respondent was used, number of trips taken on travel day, season of travel day, day of week of travel day, presence of heavy rail in metropolitan statistical area, and state fixed effects

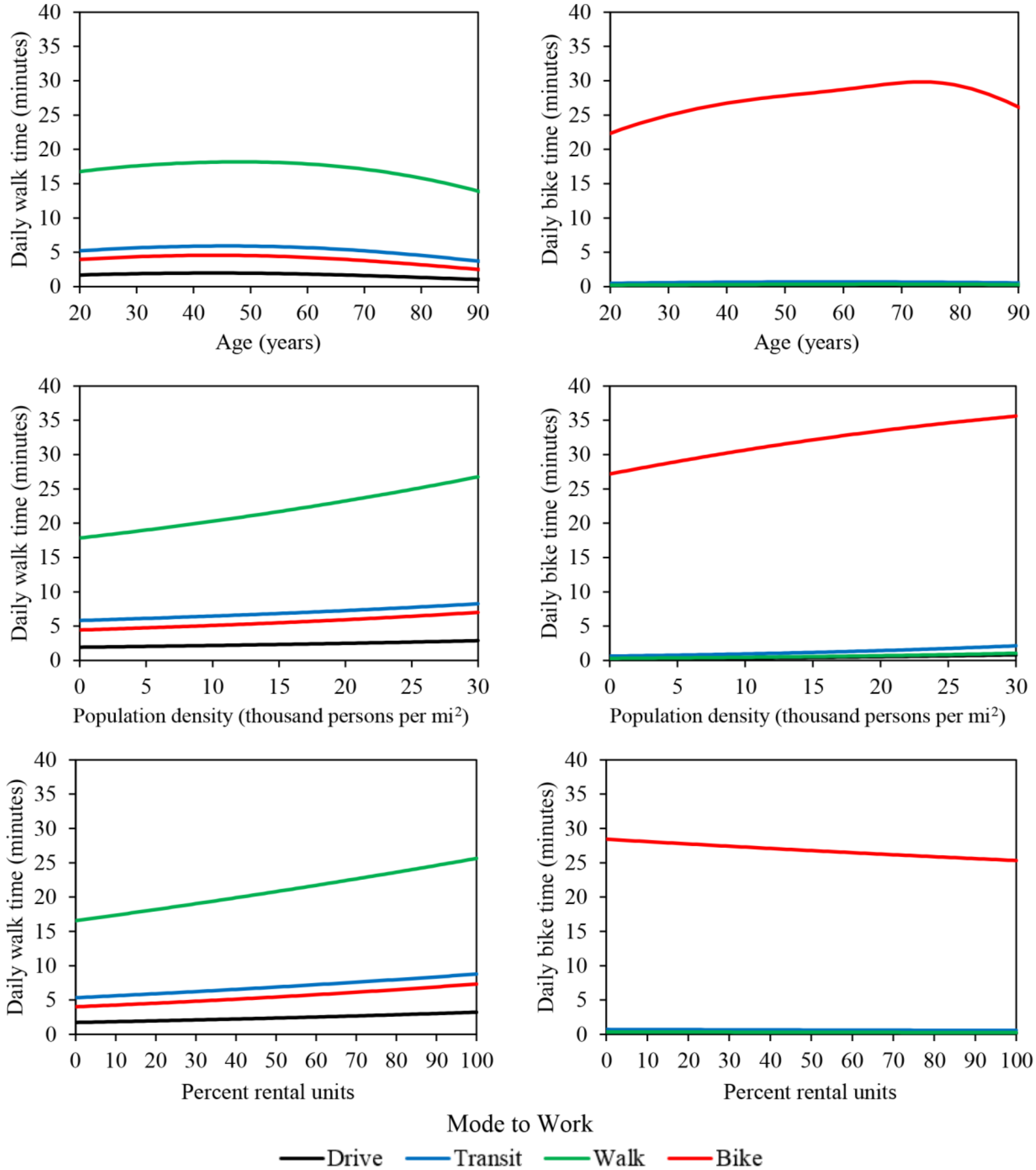


Figure 3.2. Regression estimates of daily walking and biking time as a function of age, population density, and percent rental units. In each plot, median values are used for all other variables.

3.3.4. Effects of commuting method and built environment variables on physical activity

To demonstrate the effect of commuting method, population density, and percent rental units on physical activity, we calculated the average marginal effects of a one-unit change in each of these variables on daily walking and biking times. Average marginal effects for commute mode represent the average increase in daily walking or biking time expected given a switch from the reference category (private vehicle) to a different commuting mode. Average marginal effects for population density and percent rental units both represent the average change in daily walking or biking time given a one unit change in these variables. On average, an individual who walks to work walks an additional 19.8 (95% CI 16.9–23.1) minutes per day compared to an individual who drives to work. Transit and bicycle commuters walk an additional 5.0 (95% CI 3.5–6.4) and 3.9 (95% CI 1.2–8.3) minutes per day, respectively, compared to drivers (Figure 3, top left). The effect of biking to work on daily biking time is stronger than the effect of walking to work on daily walking time: a bicycle commuter bikes an additional 28.0 (95% CI 17.5–38.1) minutes per day compared to drivers. Transit commuters cycle for an additional 0.8 (95% CI 0.1–2.2) minutes per day compared to drivers (Figure 3.3, top right). However, individuals who walk to work do not bike significantly more than drivers. Built environment variables have small but significant effects on daily walking time but no significant effects on daily biking time. For working adults, a one-unit increase in population density (thousands of people per square mile) increases daily walking time by 0.05 (95% CI 0.002–0.1) minutes, and a one-unit increase in percent rental units increases daily walking time by 0.02 (95% CI 0.01–0.04) minutes.

Average marginal effects for individual models (trip count, purpose, and duration) and are presented in Appendix B. Active commuters generally take significantly more walk and/or bike trips per week, but these trips tend to have shorter durations. Thus, the net effect of commute mode to work on weekly walking or biking time (Figure 3.3) is slightly less than the effect of commute mode on the number of weekly walking or biking trips (Figure B.5). For example, a non-Hispanic White individual who walks to work is expected to take 1.6 (1.4–1.7) additional walk trips per day relative to a similar individual who drives to work (Table B.3). For this same individual, the likelihood that a given walk trip would be for work purposes is 38% (33%–43%) greater than their counterpart who drives to work (Figure B.4). Finally, for this individual, a typical work trip would have a duration 5.2 (3.0–7.5) minutes shorter than a recreational trip (Figure B.5). Thus, while active commuters take a much greater number of walk or bike trips per day, it is more likely that trips taken by active commuters will have shorter durations than trips taken by individuals who drive to work due to the shift towards work-related active travel. This nuance highlights the importance of including trip probability models in the initial estimation framework presented in Equation 5.

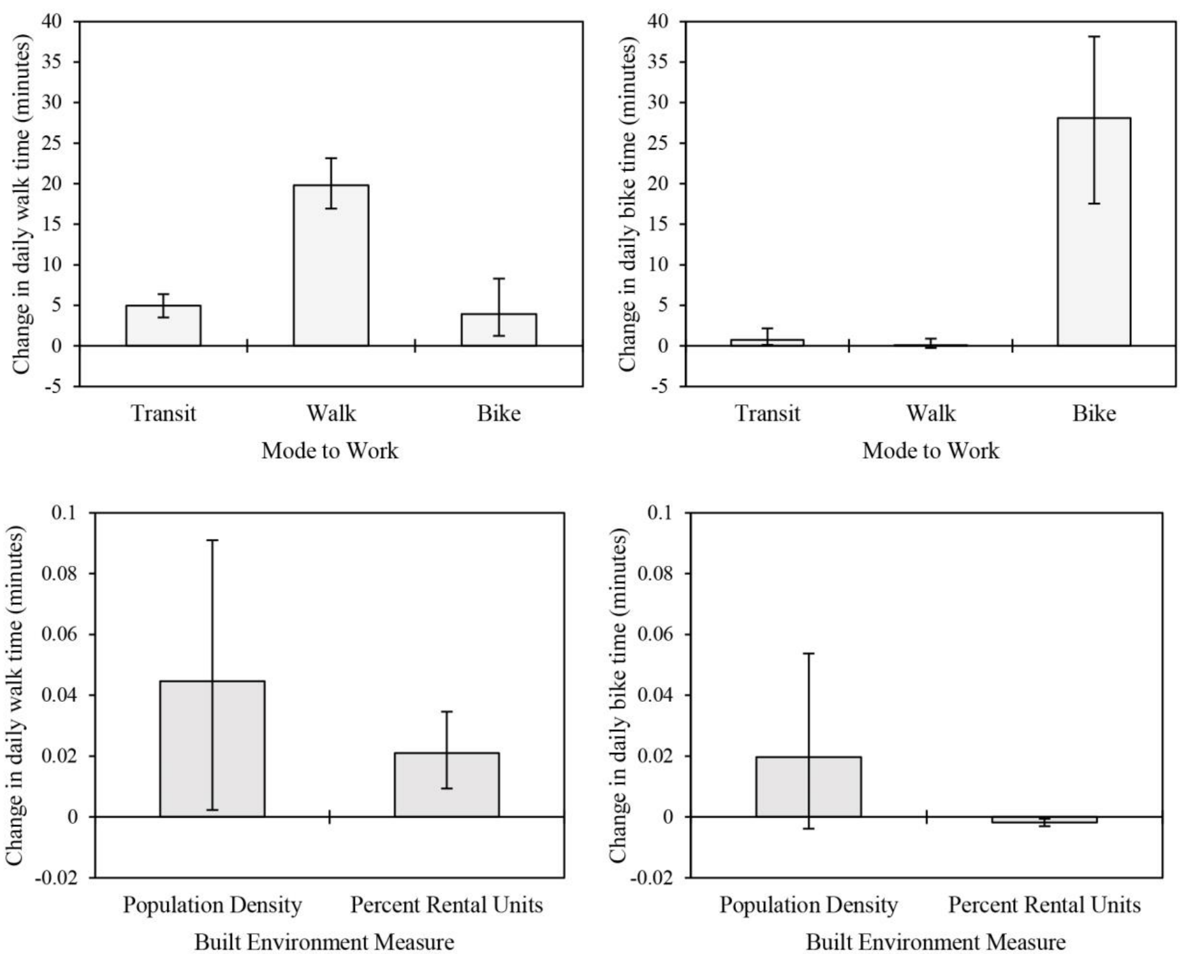


Figure 3.3. Effects of commuting method on daily time spent walking (top left) and biking (top right) relative to the reference category (driving a private vehicle to work), and effects of one-unit changes in built environment measures on daily walking (bottom left) and biking (bottom right) time.

3.3.5. Model validation

To assess the regression models' accuracy, we used the models and Equations 5 and 6 to estimate daily physical activity from walking and biking for all participants in the 2006 Greater Triangle Travel Survey (Bricka & Dickerson, 2013), and we compared the estimates to the survey results. The models estimate an average of 0.22 MET-hours per day of walking and biking for those who drive to work; the averaged observed value for private vehicle commuters is 0.20 MET-hours per day. For transit commuters, the models estimate an average of 0.78 MET-hours per day compared to an average observed value of 1.44 MET-hours per day. For those who walk to work, the models predicts an average of 1.46 MET-hours per day, compared to an average observed value of 1.54 MET-hours per day. Finally, for bike commuters, the model estimates is 3.96 MET-hours per day compared to an average observed value of 5.23 MET-hours.

The square root of model predictions are plotted against the square root of observed values in Figure 3.4 along with lines representing perfect agreement (dashed black line) and predictions within 0.5 (solid black lines), 1 (solid grey lines), and 2 (dashed grey lines) MET-hours per day. Solid black circles, black triangles, grey crosses, and grey circles represent individual estimates within 0.5, 1, 2, or more than 2 MET-hours per day, respectively. Estimated physical activity from walking and biking is within 0.5, 1, and 1.6 MET-hours per day for 83%, 91%, and 95% of observations, respectively. The Triangle Travel Survey contains a large proportion of days with no walking or biking trips, which are clustered along the x-axis. While the NHTS model estimates non-zero transportation physical activity for these days, predictions are less than 0.2 MET-hours per day for 63% of observed zeroes and less than 0.62 MET-hours per day for 95% of observed zeroes.

Overall, the NHTS model performs very well for those who walk or drive to work. However, the model under-estimates physical activity for those who bike or ride transit to work. Under-predictions for transit use may reflect inclusion of more individuals using park-and-ride lots to access transit services in the NHTS dataset than in the Raleigh-Durham-Chapel Hill region, where park-and-ride lots are available only for regional bus service. Under-estimates of physical activity for bicycle commuters may reflect the limited availability of travel time to work information for cyclists in the Triangle Travel Survey.

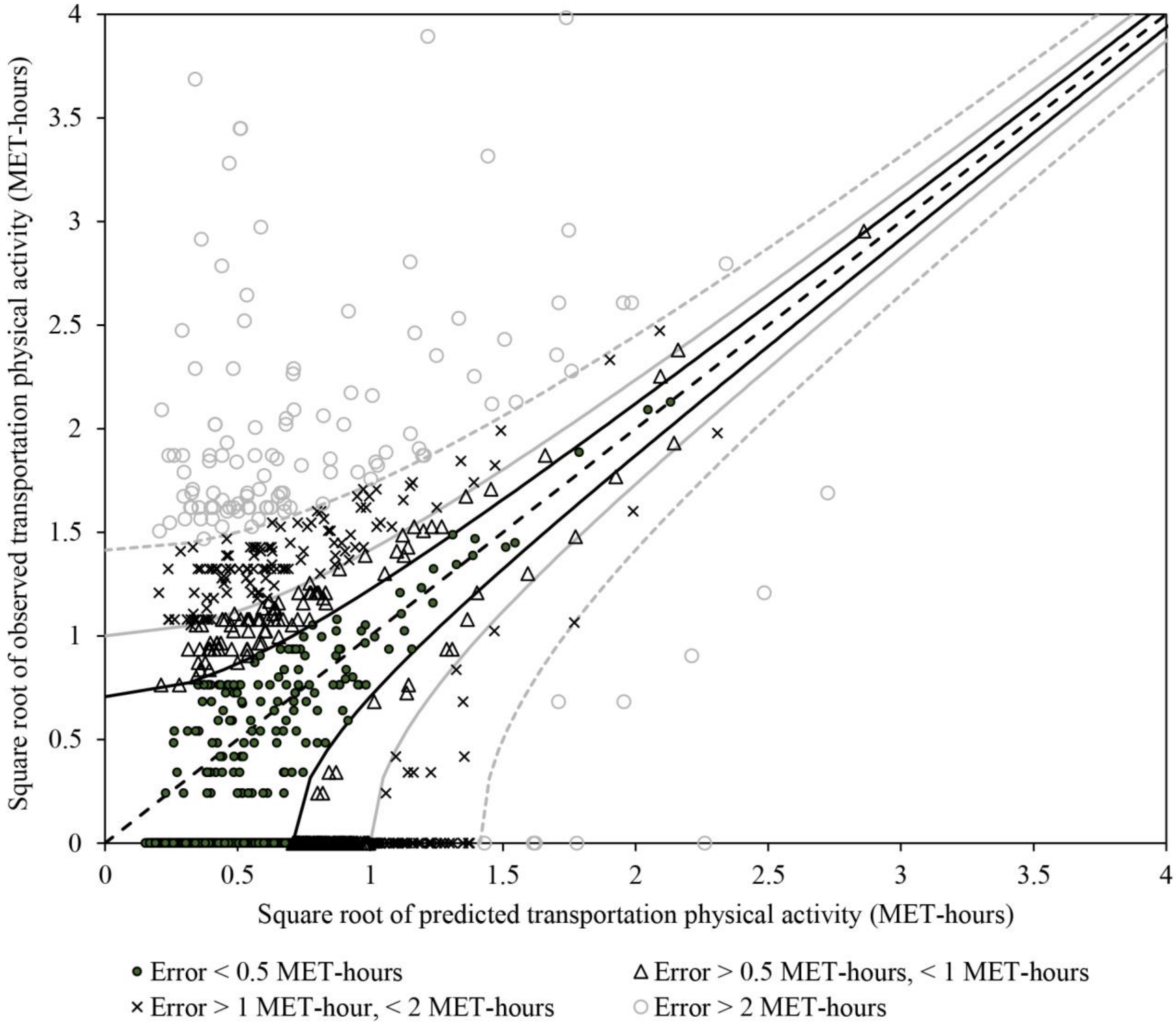


Figure 3.4. Predicted versus observed transportation physical activity for the validation dataset. Dashed black line: perfect agreement. Solid black lines and circular markers: predictions within 0.5 MET-hours per day of observed values. Solid grey lines and triangular markers: predictions within 1 MET-hour per day of observed values. Dashed grey lines and x-shaped markers: predictions within 2 MET-hours per day of observed values. Hollow circle markers: predictions more than 2 MET-hours different than observed values.

3.3.6. Health impacts of active transportation in the case study region

Using Equations 5 and 6, the population-weighted mean transportation physical activity level for the Raleigh-Durham-Chapel Hill region is 1.2 MET-hours per week. Generally, block groups with high population density (Figure 3.5, top left panel) and/or high proportions of the population who walk or bike to work (Figure 3.5, top right panel) tend to also have higher estimated transportation physical activity generally. Averaging estimated transportation physical activity within population density quintiles of block groups confirms this observation: the bottom two quintiles have similar average estimated transportation physical activity while estimated transportation physical activity increases incrementally in the top three quintiles (Table 3.7). Average estimated transportation physical activity in the highest quintile of population is 81% greater than average estimated transportation physical activity in the lowest quintile (Table 3.7).

Estimated transportation physical activity levels were used to estimate the number of premature deaths that could be prevented if all individuals walked 37.4 minutes per week, as observed in walkable neighborhoods in Baltimore and Seattle (Sallis et al., 2009). According to this estimate, 38 (95% CI 15–59) additional premature deaths would have been avoided across the region As shown in Figure 3.5 (bottom right panel), the health risks posed by low transportation physical activity, relative to expected transportation physical activity for walkable neighborhoods, are lowest in block groups with high population density and/or high proportions of the population walking or biking to work. As expected, the spatial pattern of estimated health impacts is roughly the inverse of the spatial pattern of transportation physical activity. Premature mortality that could be avoided if all individuals in the study region walked 37.4 minutes per week decreases with population density, suggesting that population density supports transportation physical activity and reduces health risks associated with low physical activity (Table 3.7). Equivalently, prevented premature mortality is nearly four times greater in the highest population density quintile compared to the lowest.

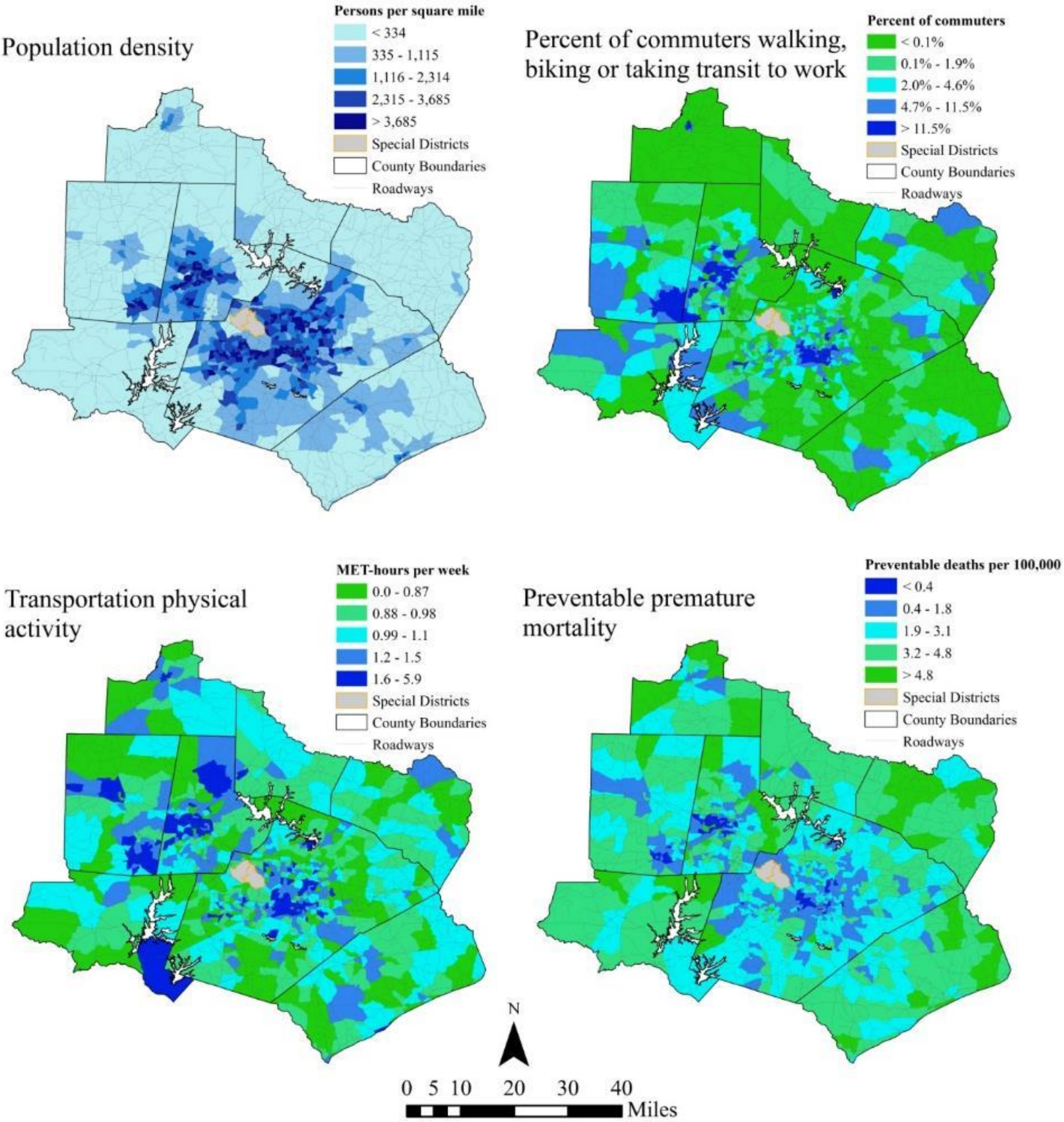


Figure 3.5. Study region population density (top left), proportion of commuters walking or biking to work (top right), estimated weekly transportation physical activity (bottom left), and preventable mortality per 100,000 people in 2013. Special districts indicated in the maps include an international airport and a state park.

Table 3.7. Effects of population density on transportation physical activity and estimates of preventable premature deaths relative to the walkable neighborhoods counterfactual

Quintile of population density (persons/mi^2)	Mean population density (persons/mi^2)	Population	Transportation physical activity (MET-hrs/week)	Preventable mortality (deaths per 100,000)	Preventable mortality (total deaths)
1	165.4	314,734	1.00	3.6	11
2	688.4	369,457	1.01	2.7	9.8
3	1,711	327,809	1.16	2.3	7.7
4	2,913	341,956	1.33	1.8	6.2
5	5,954	311,268	1.81	0.93	2.9
All	2,165	1,656,225	1.20	2.3 (0.88–3.6)	38 (15–59)

3.3.7. Hypothetical HIA application

To demonstrate how our regression models could be used to support active transportation HIA, we developed three hypothetical scenarios in which changes made to the built environment increase transportation physical activity in the Raleigh–Durham–Chapel Hill region. In the first, transportation physical activity is assumed to increase by 7.9% for all individuals in the study region as a result of 10% increases in land-use diversity, transit stop coverage, and intersection density. In the second, 7.9% of drivers begin walking to work, increasing population-average transportation physical activity by 0.34 MET-hrs per week. In the third, 14.5% of drivers switch to commuting by public transit, increasing average transportation physical activity by 0.24 MET-hrs per week (Table 3.8). Compared to baseline conditions, these three scenarios would reduce premature mortality across the region by 3.2 (95% CI 1.3–5.2), 8.0 (95% CI 3.2–12.5), and 6.2 (95% CI 2.6–10.3) deaths per year, respectively. While only illustrative, the application of our regression models to predict health benefits of hypothetical changes in the built environment demonstrates how such models could be used to support quantitative HIAs of built environment changes that support walking and biking for transportation. The first scenario illustrates how our regression models could support the calculation of population-wide increases in physical activity while the second and third illustrate how these models could instead support HIAs of built environment changes that result in shifts of transportation mode used for the work commute.

Table 3.8. Transportation physical activity and health benefits estimated for hypothetical built environment changes

	Scenario 1: Population increase in walking	Scenario 2: Drivers shift to walking	Scenario 3: Drivers shift to transit
Transportation physical activity (MET-hrs/week)	1.32	1.56	1.47
Increase in transportation physical activity, relative to baseline (MET-hrs/week)	0.10	0.34	0.24
Prevented mortality (total deaths)	3.2 (1.3–5.2)	8.0 (3.2–12.5)	6.2 (2.6–10.3)
Prevented mortality (deaths per 100,000)	0.20 (0.08–0.31)	0.96 (0.38–1.5)	0.70 (0.39–1.2)

3.4. Discussion

3.4.1. Overall significance

Using data from the 2009 NHTS, we developed regression models that future analysts can use to predict weekly time spent walking and biking for transportation based on routinely collected demographic and built environment data. These models enabled the development of transportation physical activity predictions across the Raleigh-Durham-Chapel Hill case study region with greater spatial resolution than was previously possible. We showed how the models can be used to estimate the potential health benefits of increasing walking and biking in the case study region: for example, if changes to the built environment induced 14.5% of drivers to commute by public transit, an estimated 6.2 (95% CI 2.6–10.3) premature deaths could have been prevented in 2013. Further, estimates of health impacts for baseline transportation physical activity at the Census block groups scale across the region (Figure 3.5) could be used to target built environment changes to better support walking and biking for transportation. Physical activity estimates at this fine scale of geographic resolution enable better understanding of how risks associated with physical inactivity vary across urban areas. As transportation HIA continues to evolve, more advanced modeling techniques are emerging. While advanced modeling tools offer a number of benefits to transportation HIA, they may have extensive data requirements (Mansfield and MacDonald Gibson, 2015). The estimation approach presented in this paper provides a means to estimate baseline transportation physical activity levels and compare baseline levels across space using readily accessible data.

More broadly, a handful of recent studies have explored the competing health risks posed by transportation systems in urban environments. While compact urban environments support increased walking and biking for transportation, residents of densely populated neighborhoods may be exposed to more air pollution (Hankey, Marshall, & Brauer, 2012; Mansfield et al., 2015). Additionally, active commuters may have increased exposure relative to non-active commuters due to increased inhalation rates (De Nazelle, Rodriguez, & Crawford-Brown, 2009). However, estimates suggest that the benefits of transportation physical activity for active commuters outweigh risks associated with increased air pollution exposure (Woodcock et al., 2014). A previous study in the Raleigh-Durham-Chapel Hill metropolitan area estimated that, in 2010, 47 premature deaths were associated with exposure to fine particulate matter air pollution from motor vehicles (Mansfield et al., 2015). Other recent work provides evidence that residents in denser neighborhoods may face greater health risks from exposure to pollutants in ambient air (Hankey, Marshall, & Brauer, 2012). Thus, physical activity and air pollution exposure may respond to characteristics of the built environment in different directions and with different magnitudes. While a variety of tools and methods exist to estimate air pollution exposures at fine spatial resolutions (Levy et al., 2009; Chang et al., 2015), this study presents a novel estimation framework for estimating active transportation behaviors at fine spatial resolutions across a large metropolitan region. In doing so, we support future research efforts to identify the relationships between the built environment and competing transportation health risks in urban areas. Across urban areas, these competing risks result in a highly heterogeneous riskscape. Quantitative assessments of these risks support informed policy-making to reduce the health risk associated with transportation.

3.4.2. Comparison to previous studies

Previous analyses of the NHTS have found a number of associations between individual characteristics and active transportation behaviors. For example, Pucher et al. found that men are much more likely to cycle at least 30 minutes per day while women are slightly more likely to walk at least 30 minutes per day (2011). Similarly, we find that men are much more likely to take at least one bike trip compared to women (Table 3.2). In contrast to previous work finding that individuals who ride public transit walk 21 minutes per day, we find that individuals who take transit to work walk an additional 4.5 minutes per day compared to individuals who commute using a private vehicle (Freeland et al., 2013). This discrepancy may arise for several reasons. First, our estimate includes individuals who use all forms of public transit, including paratransit services. Since commuters do not have to walk or bike to access demand-responsive services, the average marginal effect of taking public transit to work is attenuated. Second, we include transit commuters who do not walk or bike to access transit (e.g., park-and-ride users). Third, we calculated the marginal effect of riding transit to work relative to driving. Individuals who drive to work still walk and bike for other purposes, and our results show that taking public transit increases the likelihood that a given trip will be for work purposes (Table 3.3). Thus, we estimate the impact of transit commuting to a non-zero baseline and find some evidence that transit users shift the purpose of walk trips towards commuting and away from other purposes. Previous work has also found that individuals who walk to public transportation are more likely to be non-White (Freeland et al., 2013). Counter to this finding, we find that non-Hispanic Blacks and Asians are less likely to take at least one walking trip in a given day (Table 3.1). However, we also find that non-Hispanic Blacks take longer walk trips, counteracting the effect of lower trip counts on daily walking time (Table 3.5). These differences are likely due to our use of commute mode to work as an explanatory variable. Non-White individuals are more likely to ride transit to work; thus, the correlation between race/ethnicity and commute mode to work may attenuate the relationship between race/ethnicity and daily walking trips.

Assessing active transportation behaviors at the neighborhood scale, a number of previous studies have shown that individuals living in more walkable neighborhoods are more physically active than residents in non-walkable neighborhoods (Ewing & Cervero, 2010; Sallis et al., 2009; Cerin 2011; Hirsch et al., 2014). Broadly, our findings are aligned with these previous neighborhood-scale studies. We found strong effects of commute mode choice on daily walking and biking time, as well as small yet significant associations between built environment measures and daily walking time (Table 3.3). Overall, we found the highest population-average levels of physical activity—and, in turn, the lowest burden of preventable premature mortality associated with physical inactivity—in the densest quintile of block groups in the region (Table 3.7). Thus, our regional analysis using a downscaled national survey largely aligns with previous studies conducted at the neighborhood scale.

3.5. Limitations

This analysis considers only physical activity from transportation in estimating preventable mortality relative to counterfactual scenarios in which more people walk for transportation. Because the dose-response function linking transportation physical activity to all-cause mortality (Equation 2.6) is log-linear, the slope of the function decrease as dose increases. Thus, estimated risk reduction for a fixed increase in physical activity is sensitive to the baseline level of physical activity. This may lead us to overestimate preventable mortality. However, the meta-analysis that derived Equation 6 included studies that controlled for physical activity on other domains when estimating the dose-response function for transportation walking and biking (Kelly et al., 2014). Thus, Equation 10 implicitly assumes that there is some unobserved level of non-transportation physical activity in the population. While considering only transportation physical activity is a limitation of our approach, the tendency of this limitation to result in overestimation of preventable mortality is minimized by the use of a dose-response function that accounts for non-transportation physical activity.

Additionally, the 2009 NHTS offers only a snapshot of walking and biking behaviors across the US at a single point in time. The NHTS was previously administered in 2001. Comparisons of walking in biking in the 2001 and 2009 NHTS reveal several small, yet significant, trends in active transportation behaviors (Pucher et al., 2011). However, the data are insufficient to project baseline trends or link these behaviors to exogenous variables. As population cohorts age and economic conditions (e.g., gasoline prices) change, preferences for active transportation may also change. However, our model validation shows that regression estimates from the NHTS have a reasonable predictive validity.

Finally, the generation of block group population distributions across individual-level dimensions assumes that the distributions of different population characteristics are independent when cross-tabulations were not available at the block group level in the ACS (e.g., the distribution of commute mode to work for working adults was assumed to be independent of the distribution of race). Finally, the ACS groups all public transit services into a single category when reporting commute mode to work at the block group geography, including demand-responsive paratransit services in rural areas. These transit services may not be associated with as much walking and biking for transportation as fixed-route transit service in urban areas. Thus, in some rural block groups, this may result in an overestimation of transportation physical activity. Despite limitations associated with the ACS data, our approach offers a much more detailed understanding of active transportation behaviors than is offered by existing routinely collected data sources.

3.6. Conclusions

As understanding of the connections between the built environment and public health evolve, tools and methods to develop robust population-level estimates of physical activity from walking and biking must be developed alongside models to characterize exposure to other transportation health risks, such as air pollution. This study demonstrates a statistical approach to characterizing walking and biking levels across a large metropolitan area using routinely collected data. This approach is useful both for estimating baseline behaviors in support of transportation HIAs and for comparing the magnitude of risks associated with physical inactivity to other competing health risks in urban areas. In a case study application, we used this approach to highlight the potential health benefits of modifying the built environment to support walking, biking, and riding public transit to work. In future work, similar approaches could lead to more detailed understanding of how the design of urban environments affects multiple health risks, including physical inactivity, exposure to air pollution, and traffic accidents. Clarifying the complex interplay of competing health risks associated with transportation systems in urban areas is an important research direction to improve understanding of population-level health impacts of the built environment. Ultimately, tools to support quantitative HIAs can support more robust consideration of multiple health risks when deciding how to shape the built environment.

CHAPTER 4: EXPLORING COMPETING TRANSPORTATION HEALTH RISKS AT THE NEIGHBORHOOD SCALE: DEVELOPMENT AND APPLICATION OF A NOVEL DYNAMIC MICROSIMULATION MODEL[3]

4.1. Introduction

Transportation systems affect exposure to air pollution from automobiles, injuries from motor vehicle, pedestrian, and bicycle crashes, and transportation physical activity meaningfully. In turn, these exposures impact population health. In the United States, air pollution from mobile sources such as automobiles was associated with 53,000 premature deaths in 2005 (Caiazzo, Ashok, Waitz, Yim, & Barrett, 2013). Injuries from motor vehicle, bicycle, and pedestrian crashes led to 32,000 deaths in 2013 (NHTSA, 2016). In contrast to these health risks, transportation systems may provide substantial health benefits if they support increased walking and biking in the population. In 2013, 50% of the United States population did not meet the Centers for Disease Control and Prevention's (CDC) minimum physical activity recommendations (150 minutes of moderate intensity physical activity per week), contributing to 145,000 premature deaths (Murray, 2013). Recent estimates in Raleigh, North Carolina—a typical, largely suburban American city—show that roughly 2 premature deaths per 100,000 persons could have been avoided in 2013 if everyone walked at levels observed in a recent study of walkable neighborhoods in Baltimore and Seattle (Mansfield and MacDonald Gibson, 2016).

These three competing health impacts of transportation systems respond to characteristics of the built environment in different ways. For example, individuals living in walkable neighborhoods are more physically active (Frank et al., 2010); however, compact neighborhoods that support walking and biking may also increase health risks from air pollution exposure (Hankey, Marshall, & Brauer, 2012). The risk of fatal crashes also varies significantly for different modes of travel (motor vehicle, public transit,

[3] This chapter is in preparation for publication as an article in Environmental Sciences and Technology.

walking, or biking) (Beck, Dellinger, & O'Neil, 2007). Because health risks from automobile emissions, crash risk, and transportation physical activity respond to characteristics of the built environment in different ways, the combined health impacts of transportation systems are highly heterogeneous across urban areas, and the net effects of these three risks for different neighborhood designs are poorly understood. The complex riskscape posed by transportation systems in urban areas requires robust assessment methods with high spatial resolution; however, existing tools and methods to estimate competing transportation health risks lack methodological rigor and fail to characterize risks at spatial scales fine enough to explore how health impacts vary relative to characteristics of the built environment. In addition, prevailing approaches, such as the World Health Organization Health and Economic Assessment Tool for Walking and Cycling, are static, failing to track how disease prevalence changes over time in response to changes in risk factor exposure (Mansfield & MacDonald Gibson, 2015; Lhachimi et al., 2012).

To address the need for a dynamic multi-risk transportation health impact assessment approach and to compare the relative magnitude of automobile emissions, crash, and physical inactivity across neighborhood types, we develop a novel, generalizable micro-simulation model. We apply the model to characterize exposure to these three risks at fine spatial resolution across the Raleigh-Durham-Chapel Hill metropolitan area in central North Carolina over a 20-year period. The model offers a better means of assessing the complex, dynamic interplay between exposure to $PM_{2.5}$ from automobiles, transportation physical activity, and fatal crash risks and how these risks impact population health than is possible with previous tools.

4.2. Material and Methods

We developed a novel dynamic micro simulation framework and applied this model to explore competing transportation health risks at the neighborhood scale across the Raleigh-Durham-Chapel Hill metropolitan area (Figure 1). This framework uses a Markov chain model to estimate individual-level health impacts over time which can then be aggregated to the population level. Because this model estimates health impacts at the individual level, demographic data were used to develop a representative population across the study region (Section 4.2.2) and baseline health data were translated to the individual level (Section 4.2.3). Exposures to $PM_{2.5}$ from automobiles, transportation physical activity, and fatal crash risks were then estimated at the individual level across the study region (Section 4.2.4). Finally, the model was used in estimate individual-level health impacts associated with these exposures (Section 4.2.5) and these impacts were aggregated to the population level and compared between groups of neighborhoods (Section 4.2.6).

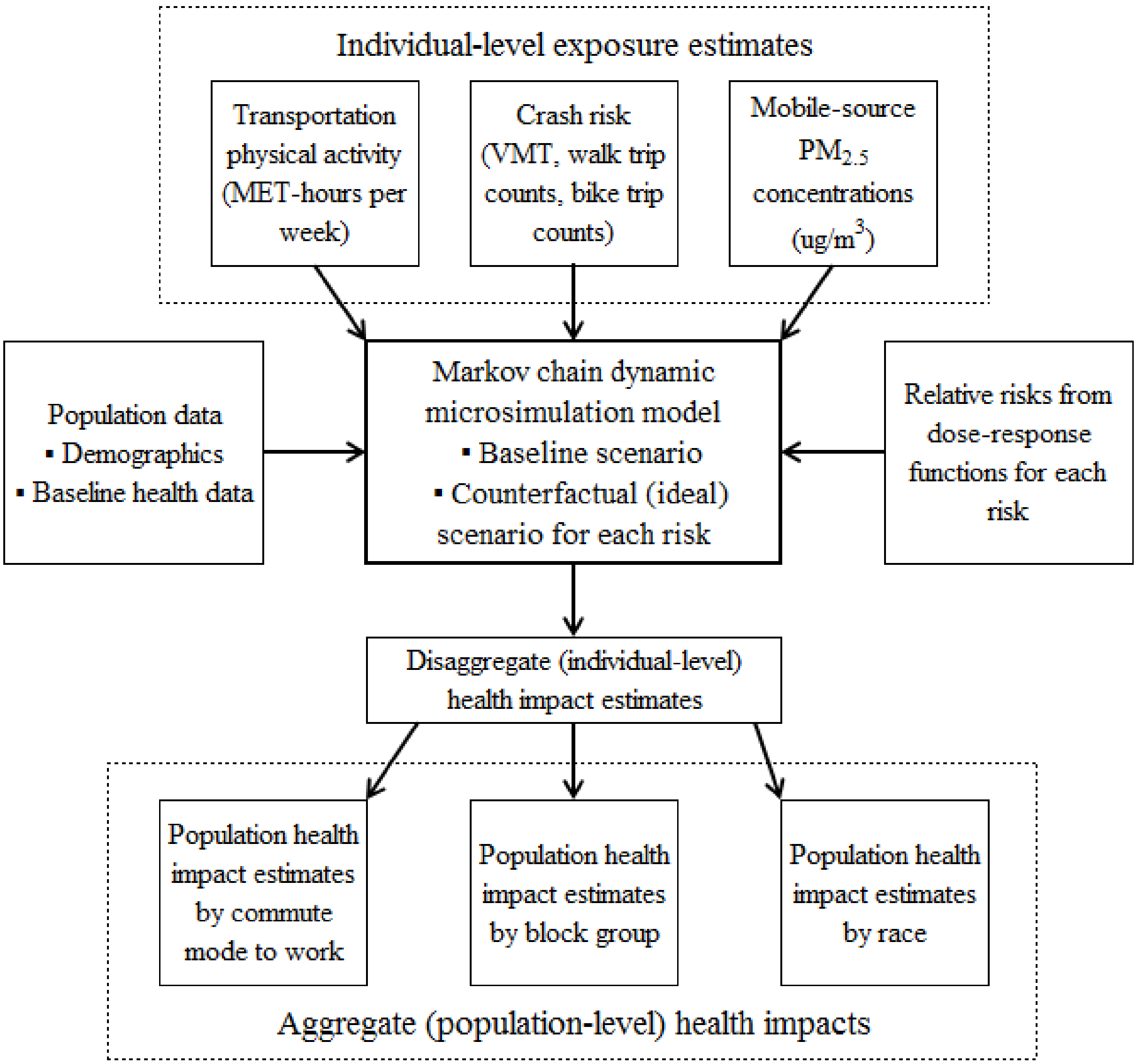


Figure 4.1. Individual-level exposure estimates are combined with demographic, health, and relative risk information to estimate health impacts at the individual level using a dynamic microsimulation model and these estimates are aggregate to explore population-scale health impacts.

4.2.1. Study area

Raleigh-Durham-Chapel Hill is a rapidly growing urban agglomeration in central North Carolina. The study region spans eight counties and had a 2013 population of 1,656,452 persons. The region has a highly polycentric urban form, with multiple nodes of urban activity surrounded by largely suburban neighborhoods (Figure 4.2).

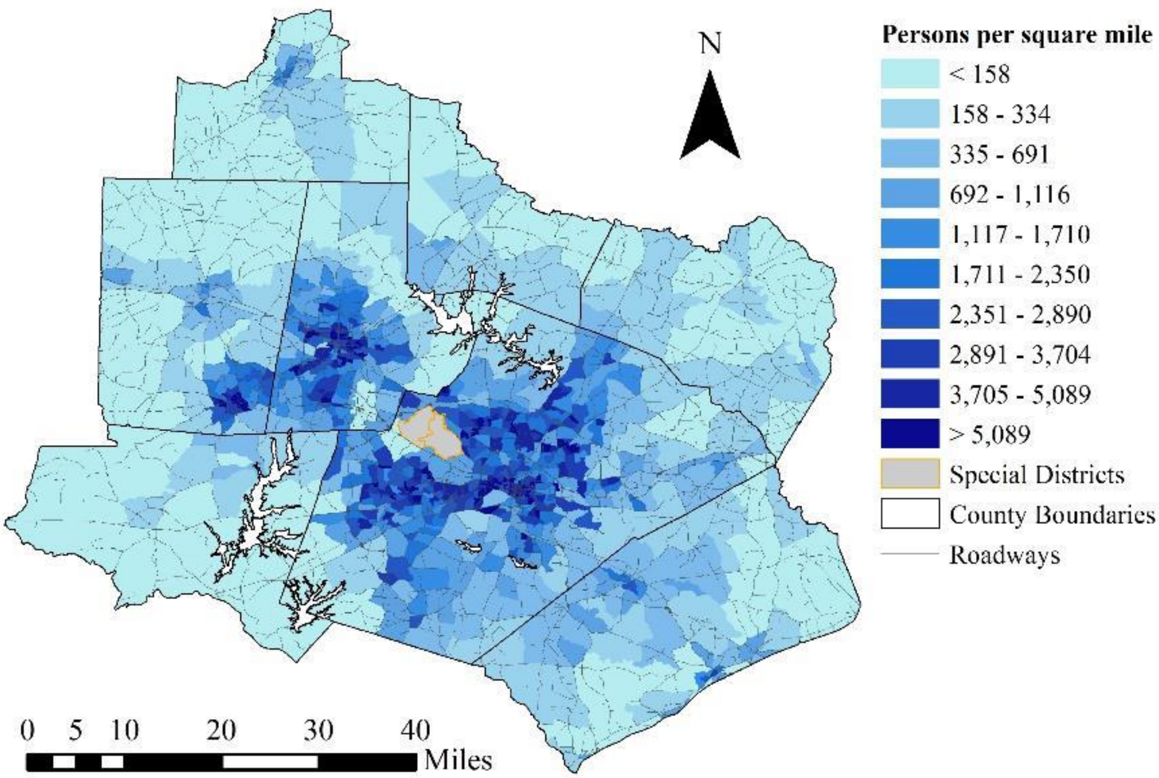


Figure 4.2. Population density in the study region, illustrating multiple nodes of relatively dense development surrounded by large areas of low- to moderate-density development.

4.2.2 Demographic data

First, population by age and sex at the Census block group geography were obtained from the 2013 American Community Survey (ACS) (Census Bureau, 2016). Because estimates of transportation physical activity are based on working status and commute to work, these data were split into workers and non-workers using labor force participation data at the Census tract geography. For non-workers, the age- and sex- distribution within each Census block group was multiplied by the distribution of race in each Census block group, resulting in the four-dimensional matrix **NW** with dimensions age a, sex s, race r, and block group b. For workers, reported commute mode to work, race/ethnicity, and education were obtained for all block groups in the study region from the 2013 ACS. Commute mode to work is associated with age, sex, and race; however, cross-tabulations of these data are not available for Census block groups. To include relationships between these demographic variables, we employed a two-stage iterative proportional fitting procedure, first described in Deming and Stephen (1940). Iterative proportional fitting was performed using the mipfp package in R 3.2.

Briefly, we first estimated the joint probability distribution of commute mode to work, $P(m \cap a \cap s \cap r)$, with commute mode m, age a, sex s, and race r for all Census tracts in the study region. An initial uniform probability distribution, $P(m \cap a \cap s \cap r)$, was first adjusted to match Census tract-level cross-tabulations of mode and age, mode and sex, and mode and race using the iterative proportional fitting algorithm. The resulting distribution, $P'(m \cap a \cap s \cap r)$, as an estimate of the joint probability distribution of m, a, s, and r at the Census tract level. Next, we adjusted $P'(m \cap a \cap s \cap r)$ using the cross tabulations of age and sex, and distributions of mode to work and race at the block group level. The resulting distribution, $P''(m \cap a \cap s \cap r)$ is consistent with distributions reported at the Census block group geography in the 2013 ACS while taking into account observed relationships between commute mode to work and age, sex, and race at the Census tract geography. The total working population in each block group was then multiplied by $P''(m \cap a \cap s \cap r)$ to obtain a representative population of workers, **W**, in each block group. The matrix **NW** was then combined with **W**, adding an extra category in the commute mode to work dimension to store non-workers to develop the population matrix **P**. Finally, the population of workers and non-workers were split into one-year age categories, assuming that individuals are distributed uniformly within each age category.

Finally, observed age-and sex-specific labor force participation rates for the study region were used to estimate T_w, the rate at which young adults transition into the workforce between the ages of 15 and 25. T_w is used to model labor force transitions as younger individuals age and enter the workforce (Appendix C, Section C.1).

4.2.3. Baseline health data

Statewide baseline age- and sex-specific cause-specific mortality data for 2013 were obtained from the North Carolina State Center for Health Statistics (NCSCHS) (2016). Death rates were calculated by dividing mortality counts by age- and sex-specific population estimated from the North Carolina Office of State Budget and Management (2016). Mortality causes were divided into six categories, based on ICD-10 codes: 1) cardiovascular mortality (ICD-10 I10-13, I20-25, and I60-69); 2) other cardiopulmonary mortality (ICD-10 J00-99, I00-09, I14-19, I26-29, I30-59, I70-99); 3) lung cancer mortality (ICD-10 C34); 4) other non-accidental mortality (ICD-10 A00-C33, C35-E09, E15-I99, K00-T98); 5) accidental mortality (ICD-10 V00-Y99); and 6) diabetes mortality (ICD-10 E10-E14).

The World Health Organization *DisMod II* tool was used to generate age- and sex-specific disease prevalence functions, $P_{d,a,s}$, and incidence functions, $I_{d,a,s}$, for type 2 diabetes and cardiovascular disease. Estimates of $RR_{m,d}|d$, the risk of increased disease-related mortality in a population with a disease relative to the risk of mortality from the same disease in the general population, were also calculated using *DisMod II*. Briefly, *DisMod II* uses a differential equations model to develop internally consistent epidemiological parameters when certain data are missing, such as disease incidence. For our purposes, we inputted the age structure of the population, observed all-cause mortality rates in the population, observed mortality rates in the population from the disease for which we were estimating incidence, and disease prevalence as reported in the 2013 Behavioral Risk Factor Surveillance System (BRFSS). Because the BRFSS asks respondents if they have ever been diagnosed with these diseases, we assumed that there is no remission and model the incidence of having ever been diagnosed with these diseases. Using these data, we generated estimates of $P_{d,a,s}$, $I_{d,a,s}$, and of $RR_{m,d}|d$ for cardiovascular disease and type 2 diabetes (Appendix C, Section C.2).

Finally, 2009-2013 average birthrates for the study region were obtained from the North Carolina Center for Health Statistics (NCSCHS 2016).

4.2.4. Exposures

4.2.4.1. Mobile-source $PM_{2.5}$

We used concentrations of fine particulate matter ($PM_{2.5}$) from mobile sources estimated for Census blocks across the using an advanced line source dispersion model estimated by Chang et al. (Chang et al., 2015). The most recent available estimate of annual average $PM_{2.5}$ performed by is for 2011; thus we use this data though the rest of our data are from 2013. We use 2010 Census block populations, the most recent block population estimates available, to developed population-weighted average $PM_{2.5}$ concentrations from all block groups in the region.

4.2.4.2. Transportation physical activity

We used regression models derived from the 2009 National Household Travel Survey (NHTS) to estimate transportation physical activity across the study region using data from the 2013 ACS as described in Mansfield and MacDonald Gibson (2016). Briefly, these regression models estimate weekly time spent walking and biking based on reported commute mode to work, individual characteristics (age, gender, and race/ethnicity) and built environment variables (population density and percent of housing units that are rented). Using these regression models, transportation physical activity was estimated for all possible combinations of individual-level variables (age, sex, race, and mode to work) for each block group in the study regions. These estimates were stored in a five-dimensional matrix, **TPA**, with the same dimensions as the population matrix **P** described previously.

4.2.4.3. Motor vehicle, pedestrian, and bicycle crashes

To estimate individual-level risks for fatal motor vehicle, pedestrian, and bicycle crashes, we used regression models derived from the 2009 NHTS. Estimates of weekly walking and biking trips were the first component of the transportation physical activity estimation framework described in Mansfield and MacDonald Gibson and in Section 3.2.2 of this dissertation (2016). The same data were used to develop a generalized linear model (GLM) estimating yearly vehicle-miles travelled based on individual characteristics, commute mode to work, and built environment variables. Data from NHTS were prepared as described Mansfield and MacDonald Gibson and in Section 3.2.1 of this dissertation (2016). A GLM model was then estimated predicting yearly vehicle-miles travelled (the *yearmile* variable in the NHTS):

$$g(VMT_{est.i}) = \boldsymbol{x}_i^T \boldsymbol{\beta} \tag{4.1}$$

where $VMT_{est,i}$ is estimated yearly VMT for individual i, $g\left(VMT_{est,i}\right)$ is the link function, $\boldsymbol{x}_i^T$ is a vector of regressors, and $\boldsymbol{\beta}$ is a vector of estimated coefficients.

4.2.5. Health impact model

We developed a novel Markov chain-based microsimulation model to dynamically estimate the health impacts of transportation health risks in the study region over time. Briefly, Markov chain models divide a population into a discrete set of states and estimate occupancy in these states over time based on a set of transition probabilities. For our purposes, the population is divided into three distinct states each representing a specific health status (healthy state *h*, cardiovascular disease state *cvd*, and type 2 diabetes state *d*). Mortality is modeled using six additional cause-specific mortality states, $m_{1\text{-}6}$. As the model steps forward through time, populations transition between states based on a set of transition probabilities, $P_i(S_{i,time=t} \rightarrow S'_{i,time=t+1})$ (Figure 4.3). In each time step, the model estimates transitions for all cells in the matrix **P** used to store the study area, notated using the subscript *i* for all population states and transition probabilities. The model was developed and executed in *Analytica* 4.5 (Lumina Decision Systems, Los Gatos, CA).

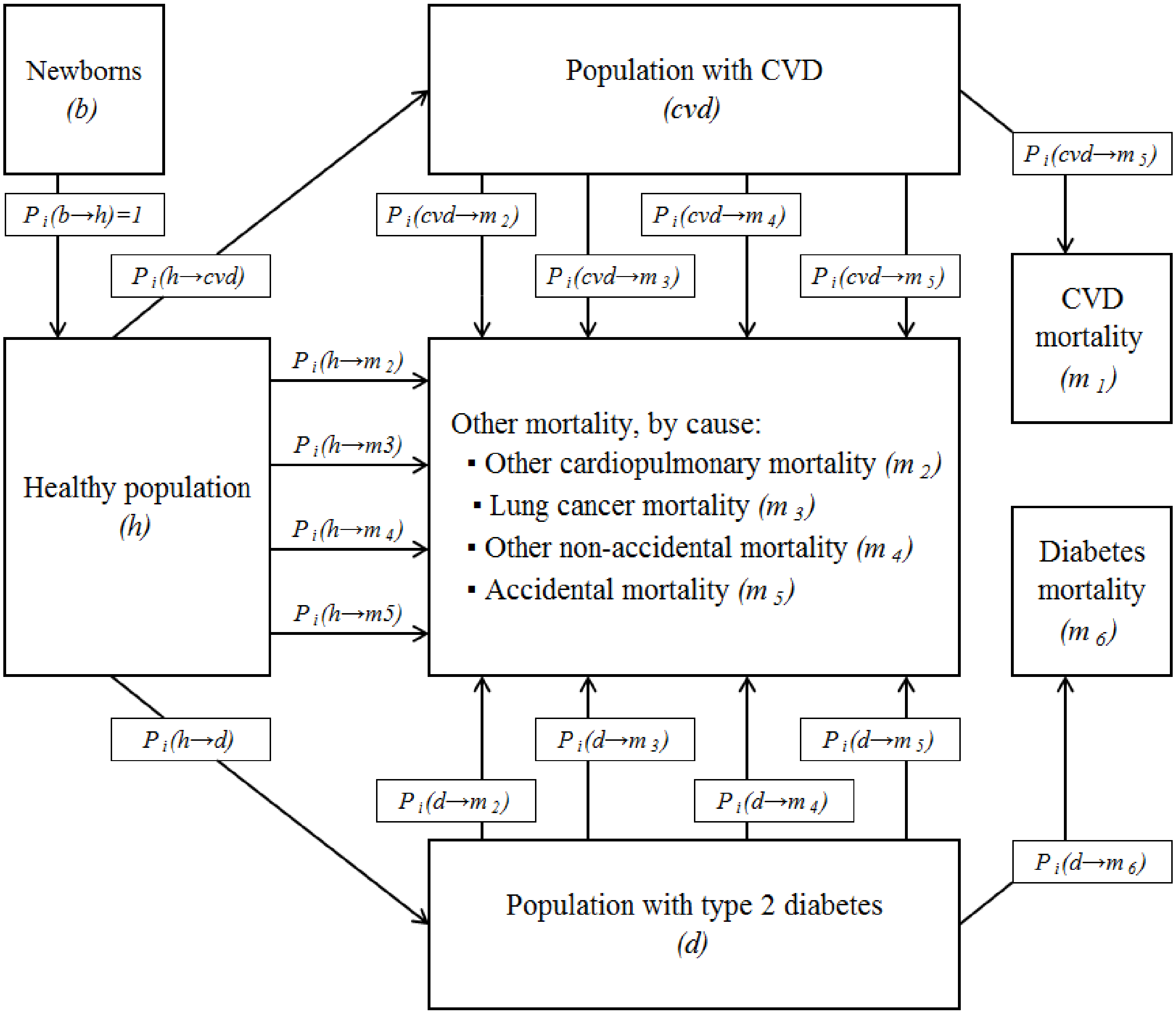


Figure 4.3. Population states (*h*, *cvd*, and *d*), mortality states ($m_{1\text{-}6}$), and transition probabilities $P_i(S \to S')$ in the Markov chain health impacts model.

4.2.5.1 Baseline transitions

The initial distribution of the population between states was obtained by multiplying **P** by age- and sex-specific prevalence functions for cardiovascular disease and type 2 diabetes. Transition probabilities between all states were defined by converting observed death rates and estimated incidence rates into probabilities as follows:

$$P_i\left(S_{i,time=t} \to S'_{i,time=t+1}\right) = 1 - e^{-r_{s',i}} \qquad (4.2)$$

where $P_i(S_{i,time=t} \rightarrow S'_{i,time=t+1})$ is the probability that individual *i* transitions from state *S* to state S' during a time step and $r_{s',i}$ is observed rate at which transition state S' occurs for individual i. For mortality, $r_{s',i}$ is equal to age-specific death rates for each mortality cause obtained from statewide mortality data. For disease incidence, $r_{s',i}$ is equal to age- and sex- specific incidence functions estimated as described in Section 4.2.3. Baseline transition rates between all states are detailed in Appendix C, Section C.3.

4.2.5.2 Linking exposures to transition probabilities

For each cell in **P**, exposures were estimated as described in Section 4.2.4. Exposure to $PM_{2.5}$ varies across only the block group dimension (i.e., all individuals living in a single block group are assumed to have the same exposure to $PM_{2.5}$) while transportation physical activity and crash risk vary across all dimensions of **P**. For each of these exposures, baseline (observed) exposures are compared to an ideal counterfactual scenario. For $PM_{2.5}$, this counterfactual is no exposure (i.e., no air pollution from automobiles). For physical activity, the counterfactual scenario is that everyone walks for transportation 37.4 minutes per week, the average walking time observed for individuals living in walkable neighborhoods in Seattle and Baltimore (Sallis et al. 2009). Finally, the counterfactual scenario for crashes is zero mortalities, the goal of policy efforts such as the Vision Zero Initiative (Johansson, 2009). Changes in population states over time in response to counterfactual exposure scenarios are modeled by changing transition probabilities based on epidemiological evidence linking exposure to a health outcome. Equation 4.2 becomes:

$$P_i\left(S_{i,time=t} \rightarrow S'_{i,time=t+1}\right) = 1 - e^{-r_{s',i} \times RR_{S'}|exposure_{r,i}} \tag{4.3}$$

where $RR_{S'}|exposure_{r,i}$ is the relative risk of state S' occurring for individual *i* given exposure to risk *r*. $RR_{S'}|exposure_{r,i}$ was estimated using dose-response functions for each risk (Table 5.1). Epidemiological evidence suggests that the dose response function linking physical inactivity to all-cause mortality and type 2 diabetes incidence is log-linear (Kelly et al. 2014, Aune et al. 2015). We assumed a log-linear function for cardiovascular disease incidence as well. Because observed transportation physical activity levels are non-zero, we calculate relative risks for the counterfactual scenario relative to estimated baseline levels. Thus, relative risks for physical inactivity were modeled as follows:

$$RR_{S,PI} = 0.90^{\frac{TPA_{est,i} - TPA_{cf}}{11.25}} \tag{4.4}$$

where $RR_{S,PI}$ is the relative risk of state S from physical inactivity, $TPA_{est,i}$ is estimated weekly transportation physical activity for individual i, and TPA_{cf} is the counterfactual level of transportation physical activity (37.4 minutes of walking per week).

For exposure to air pollution, we assumed linear dose-response functions as described in Pope et al. (2002):

$$RR_{S,PM} = 1 - \frac{(1 - RR_s) \times PM_{est,b}}{10} \tag{4.5}$$

where $RR_{S,PM}$ is the relative risk of state S from exposure to $PM_{2.5}$, RR_s is the relative risk for state s (Table 1), and $PM_{est,b}$ is the estimated $PM_{2.5}$ concentration from automobiles in block group b.

Finally, fatal crash risks were modeled as function of estimated vehicle-miles travelled (motor vehicle crashes), weekly walk trips (pedestrian fatalities), and weekly bike trips (cyclist fatalities). Because epidemiological evidence estimates crash risk directly as a function of exposure rather than relative to other types of mortality, fatal crash risk is modeled as a component of accidental mortality, rather than a modifier of accident mortality risk (Harper et al., 2015; Beck et al., 2007):

$$P_i(S_i \rightarrow m_5) = r_{i,m5} - \left(r_{VMT} \times VMT_{est,i} - r_w \times w_{est,i} - r_b \times b_{est,i}\right) \tag{4.6}$$

where $P_i(S_i \rightarrow m_5)$ is the probability that individual i transitions into the accidental mortality state, $r_{i,m5}$ is the observed accidental mortality rate for individual i, r_{VMT} is the fatality rate per VMT, $VMT_{est,i}$ is estimated yearly VMT for individual i, r_w is the fatality rate per walk trip, $w_{est,i}$ is the estimated number of weekly walk trips for individual i, r_b is the fatality rate per bike trip, and $b_{est,i}$ is the estimated number of weekly bike trips taken by individual i.

Table 4.1. Relative risk functions (for $PM_{2.5}$ and physical inactivity) and fatality rates (for crashes) linking exposure to changes mortality risk and disease incidence

Risk	Health Outcome	Relative Risk	Standard error	Source
$PM_{2.5}$	Cardiopulmonary mortality	1.09 per 10 µg/m^3	0.0332	Pope et al., 2002
	Lung cancer mortality	1.14 per 10 µg/m^3	0.0485	
	All other non-accidental mortality	1.01 per 10 µg/m^3	0.0281	
Physical Inactivity	All non-accidental mortality	0.90 per 11.25 MET-hrs	0.0255	Kelly et al., 2014
	Cardiovascular disease incidence	0.84 per 10.5 MET-hrs	0.0281	Li, Loerbroks, & Angerer, 2013
	Type 2 diabetes incidence	0.73 per 22.5 MET-hrs	0.0485	Aune et al., 2015
Crashes	Motor vehicle fatalities, ages 20-24	1.33 per 100 million VMT	n.r. [a]	Harper et al., 2015
	Motor vehicle fatalities, ages 25-34	1.47 per 100 million VMT		
	Motor vehicle fatalities, ages 35-44	0.99 per 100 million VMT		
	Motor vehicle fatalities, ages 45-54	1.03 per 100 million VMT		
	Motor vehicle fatalities, ages 55-64	1.17 per 100 million VMT		
	Motor vehicle fatalities, ages 65-74	2.72 per 100 million VMT		
	Pedestrian fatalities, ages 20-24	12.4 per 100 million walk trips	n.r. [a]	Beck et al., 2007
	Pedestrian fatalities, ages 25-64	15.7 per 100 million walk trips		
	Pedestrian fatalities, ages 65-74	29.8 per 100 million bike trips		
	Cyclist fatalities, ages 20-24	30.9 per 100 million bike trips	n.r. [a]	Beck et al., 2007
	Cyclist fatalities, ages 25-64	34.4 per 100 million bike trips		
	Cyclist fatalities, ages 65-74	41.7 per 100 million bike trips		

[a] Standard errors not reported

4.2.5.3 Adjustment to avoid double-counting

Physical activity has a preventive effect on both disease incidence and all-cause mortality. To avoid double-counting health benefits, we adjusted $RR_{S'}|exposure_{r,i}$ for CVD and diabetes when estimating the health impacts of transportation physical activity. To do so, we compared the predicted distribution of disease prevalence in the full model during previous time step of the simulation to the distribution of disease prevalence in a simplified model in which no intermediate diseases (CVD and diabetes) were modeled during the previous time step. An adjustment factor was developed to ensure that mortality in the full model equaled mortality in the simple model to maintain consistency with epidemiological studies linking physical activity and studies linking physical activity with reduced disease incidence. This adjustment factor was calculated as:

$$Adj_{i,S} = \frac{P_{S,M,time-1}}{P_{S,M+D,time-1}} + \left(\left(1 - P_{S,M,time-1}\right) - \left(1 - P_{S,M+D,time-1}\right)\right) \times 1 - e^{-r_{s',i} \times RR_{S'}|exposure_{r,i}} \quad (4.7)$$

where $P_{S,M,time-1}$ is the modeled prevalence of state *S* (either CVD or diabetes) in the previous time step in a model with no intermediate disease pathways and $P_{S,M+D,time-1}$is the modeled prevalence of state *S* (either CVD or diabetes) in the adjusted model. For the adjusted model predicting the health impacts of transportation physical activity, Equation 4.3 becomes:

$$P_i\left(S_{i,time=t} \rightarrow S'_{i,time=t+1}\right) = 1 - e^{-r_{s',i} \times RR_{S'}|exposure_{r,i} \times Adj_{i,S}} \quad (4.8)$$

Inclusion of this adjustment allows the health impact model to simultaneously estimate the impact of a change in exposure on disease incidence and mortality without double-counting impacts on mortality.

4.2.5.4 Health impacts

To determine the health impacts of each exposure, we calculated the difference in each modeled state between the ideal counterfactual scenario for each risk and the baseline model (i.e., $RR_{S'}|exposure_{r,j} = 1$ for all risks). Death rates were obtained by taking the difference in each mortality state between each time step and the preceding time step. To obtain estimates of health impacts at the population level or for specific subgroups, health impacts were aggregated across dimensions of **P** as needed (e.g. to estimate the health impacts of observed transportation physical activity levels relative to the ideal counterfactual by commute mode to work, impacts were summed for all ages, races, and block group).

4.2.5.5. Model validation

To validate our micro-simulation model, we artificially aged a cohort of 1,000 individuals matching baseline population characteristics 100 years using baseline epidemiological data. Because population health data are not available over sufficiently long time scales to validate the model directly, we instead compared population health outcomes over time as the validation cohort ages to observed age-specific population health outcomes in the population in 2013. Comparing model predictions to observed values for the validation cohort provides a test of the internal consistency of the model; that is, how well estimated underlying epidemiological data, such as disease incidence functions, combine to predict health outcomes over time relative to observed outcomes within specific age groups in the population.

4.2.6. Neighborhood scale risk comparisons

To explore the relationship between transportation health risks and characteristics of the built environment, we first divided block groups into the study region into groups with similar built environment characteristics. We then compared mean exposure to transportation health risks and estimated health outcomes between these groups, conceptualizing the built environment as a treatment that varies between, but is constant within, groups of neighborhoods.

4.2.6.1 Built environment measures

We developed groups of neighborhoods sharing similar built environment characteristics using the a slightly modified version of the walkability index first developed by Frank et al. (Frank et al., 2010). The index combines four dimensions of the built environment understood to influence walkability: the diversity of land uses, net residential density, retail floor area ratio (the ratio of retail square footage to the area of retail parcels), and the density of intersections. Because retail floor area ratio data were not available for the study region, we omitted this term in calculating the walkability index as in Hankey et al. (2012). Land use diversity was calculated as described in Cervero and Kockelman using parcel-level land use data for the region (1997). Population density was used in place of net residential density and was calculated by dividing the number of persons residing in each block group in the 2013 American Community Survey by the total land area of each block group. Intersection density data were obtained from the Center for Neighborhood Technology (CNT 2016).

4.2.6.2 Comparisons between groups

To compare exposures to transportation health risks and estimated health impact associated with these exposures, we tested the difference in means between all pairs of block groups using Tukey's honest significant difference test (Tukey, 1949).

4.3. Results

4.3.1. VMT regression model

To estimate yearly VMT per capita, we used data from the 2009 NHTS to fit a GLM regression model. Commute mode to work has a significant effect on yearly VMT (Table 4.2). Built environment variables (population density and percent rental units) have significant effects in the expected direction (Table 4.2). Individual characteristics (age, sex, and race) have largely significant effects as well (Table 4.2). On average, a woman who takes public transit to work drives 6,860 fewer miles per year compared to a woman who drives to work. Additionally, an increase in population density of 1,000 persons per square mile reduces VMT by 261 miles per person per year (Figure 4.4).

Table 4.2. Regression model for estimating VMT

Variable	Regression Coefficient	
	Working Adults [a]	Non-working Adults [a]
Mode to Work		
Private vehicle	*(ref)*	-
Public transit	-0.812***	-
Walk	-0.491***	-
Bike	-0.669***	-
Population density	-0.020***	-0.019***
Percent rental units	-0.001**	-0.002***
Age	0.044***	0.035***
Age squared	-0.001***	-0.0004***
Sex *(ref: male)*	-0.332***	-0.447***
Race/Ethnicity		
Non-Hispanic White	*(ref)*	*(ref)*
Non-Hispanic Black	-0.073*	-0.100*
Hispanic	-0.051	-0.108*
Non-Hispanic Asian	-0.242***	-0.394***
Non-Hispanic Other	0.011	0
Constant	8.70***	8.65***
N	88,658	79,135

***p<0.01 **p<0.05 *p<0.10

[a] Adjusted for education, whether the respondent has a medical condition that limits travel, whether a proxy respondent was used, number of trips taken on travel day, presence of heavy rail in metropolitan statistical area, and state fixed effects

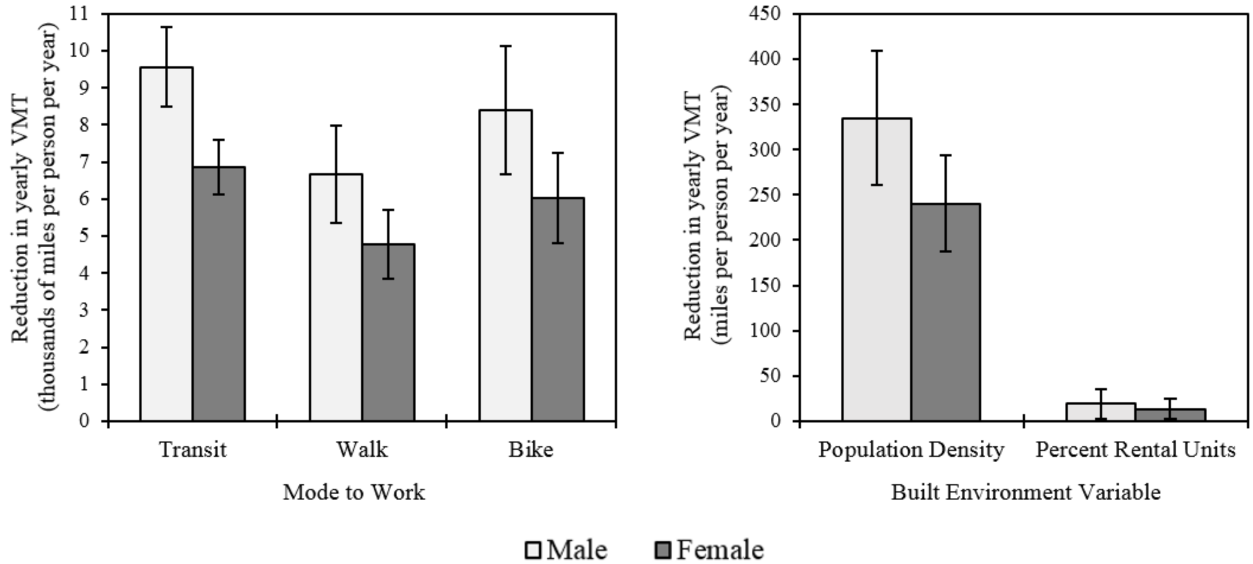


Figure 4.4. Average marginal effects (reductions) of a change in mode to work (left) and a one-unit change in built environment variables (right) on yearly VMT for women and men.

4.3.2. Health impacts model validation

To provide a means to quantify the impacts of transportation infrastructure and neighborhood design on risks from physical inactivity, fatal crashes, and air pollution exposure, we developed a novel dynamic simulation model, and we validated the model by running a simulation for 100 years with a single cohort matching the demographic profile of the region in 2013. Our model predicts diabetes and CVD prevalence within the range of values in the 2013 BRFSS survey for both diseases for four age groups: 18-34, 35-44, 45-54, and 55-64. Our model predicts CVD prevalence within the BRFSS margin of error in the 65-74 year-old age group and slightly under-predicts diabetes prevalence relative to the BRFSS. Our model under-predicts relative to BRFSS values for both diseases in the 75 and older age group (Figure 4.5). Relative to observed death rate data, our model tends to under-predict death rates at younger ages and slightly over-predict mortality at older ages (Figure 4.5). However, baseline death rates are fairly low through the age range in which our model under-predicts; thus, bias introduces by under-prediction in this range likely has little impact on model estimates at the population level. Critically, the model performs very well between the ages of 20 and 74—the age range for which epidemiological evidence is linking transportation physical activity to mortality risk is well-established in the literature (Kahlmeier et al., 2014). Overall, model validation demonstrates that our model provides estimates that are reasonably consistent with observed epidemiological data, especially for the age range for which transportation health impacts are estimated.

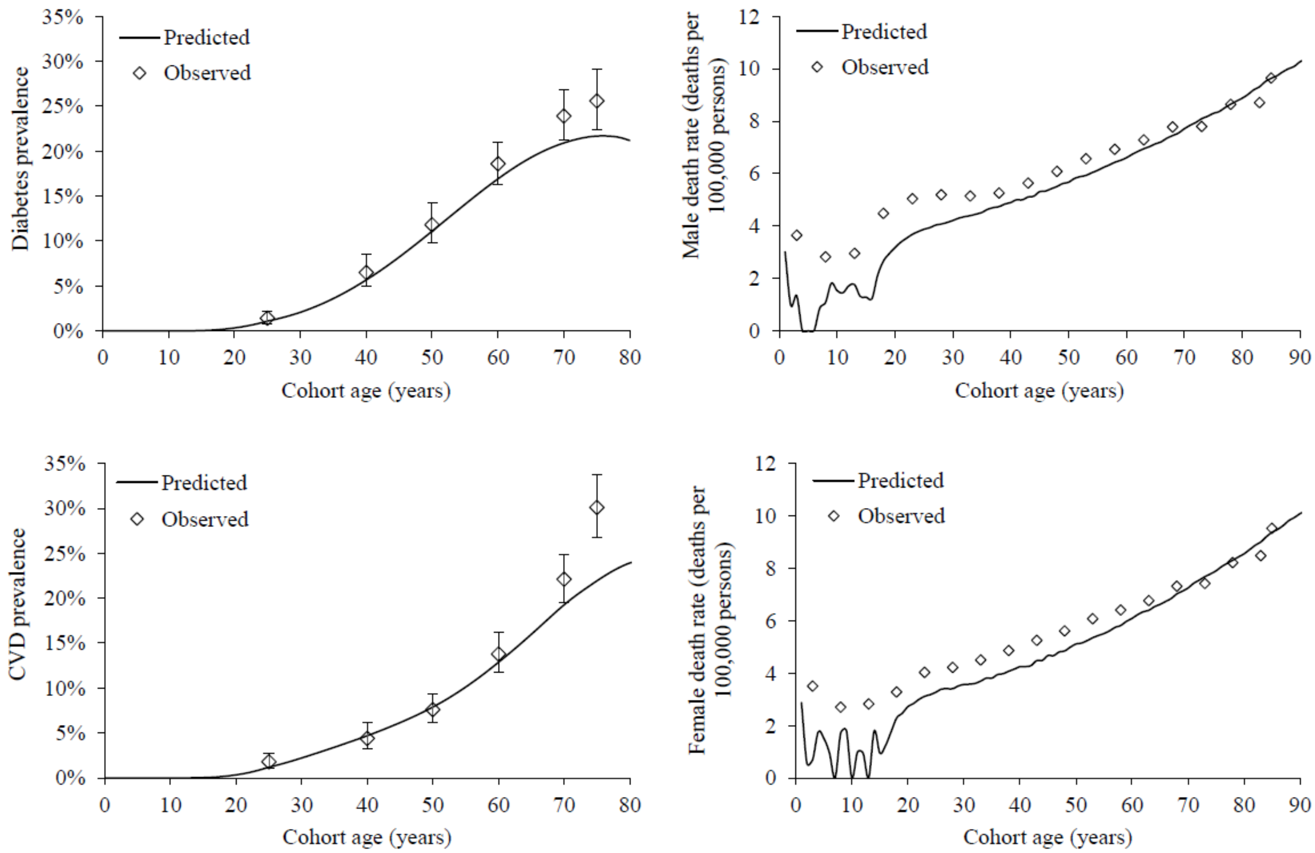


Figure 4.5. Model predicted values (solid lines) versus observed data (markers) for diabetes and CVD prevalence (left) and log-transformed death rates for men and women (right)

4.3.3. Transportation-related exposures

To derive exposure estimates to input to the health impact assessment model (Figure 4.1, top level) in the Raleigh-Durham-Chapel Hill region, we assessed exposure at the Census block group scale using recent estimates of $PM_{2.5}$ from automobiles and regression models predicting transportation physical activity, walking trips, biking trips, and VMT. Generally, $PM_{2.5}$ concentrations are highest in the most densely populated block groups and along transportation corridors (Figure 4.6, top left). Transportation physical activity is also highest in the most compact areas. Interestingly, moderately high transportation physical activity levels are also predicted in a handful of less central block groups, many of which contain small communities with traditional walkable downtowns (Figure 4.6, top right). Yearly walking and biking trips per capita share a similar spatial pattern, although the distribution of biking trips is relatively high in both urban and rural locations, but relatively low in many of the suburban block groups that encircle central Raleigh and Durham (Figure 4.6 middle right and bottom left). Predicted per capita VMT is lowest in compact block groups, once again with a handful of rural block groups containing small towns with low predicted per capita VMT (Figure 4.6, middle left). In general, neighborhoods with the highest air pollution exposures but low per-capita VMT and higher physical activity tend to be located centrally. Conversely, neighborhoods located along transportation corridors and many neighborhoods in southwestern Wake County have not only high risk for $PM_{2.5}$ exposure but also high exposure to VMT and physical inactivity.

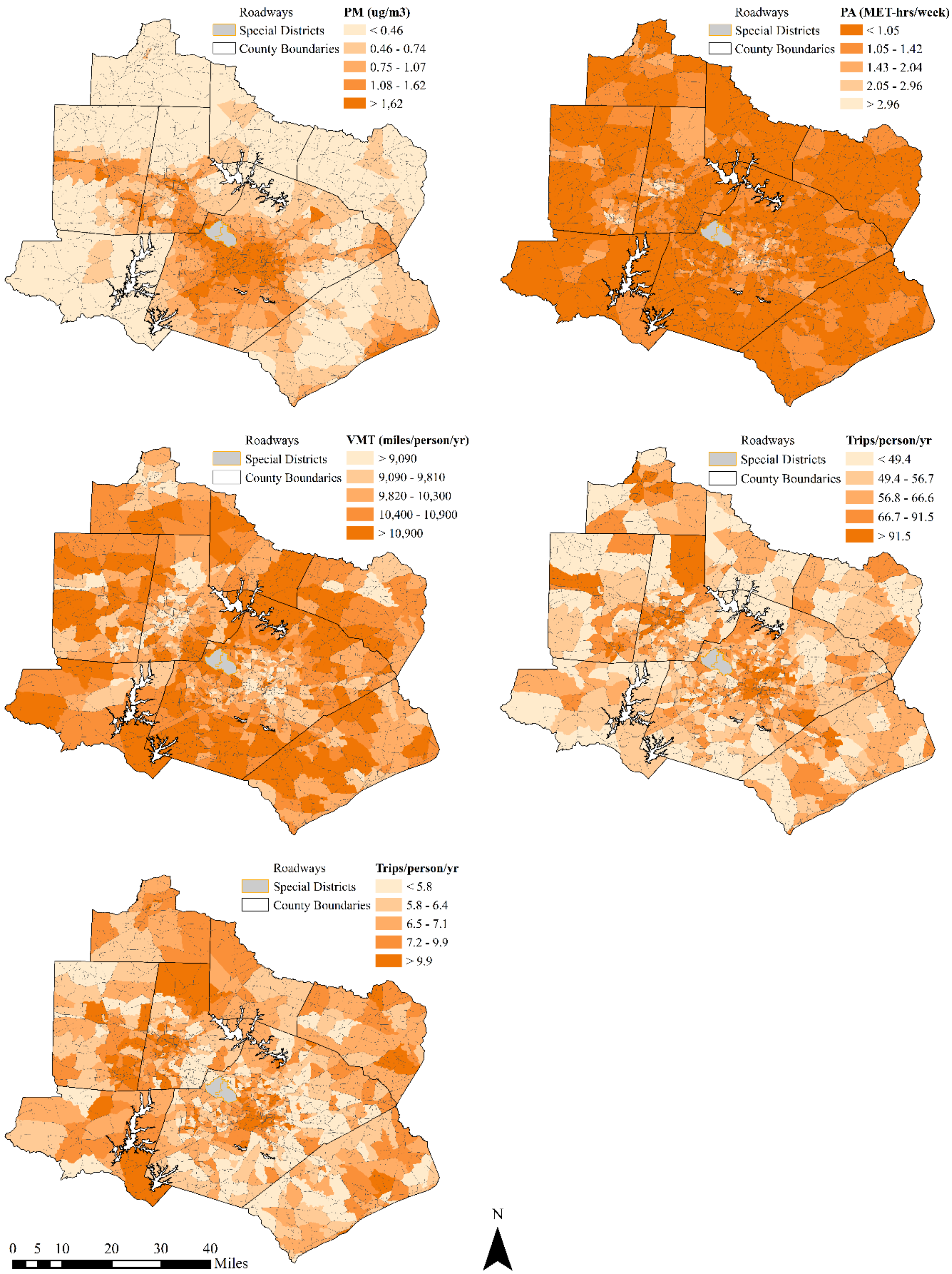


Figure 4.6. Distribution of $PM_{2.5}$ from automobiles (top left), transportation physical activity (top right), per capita yearly VMT (middle left), walk trips (middle right), and bike trips (bottom left). For all exposures, darker coloring indicates high risk.

To assess the relationship between transportation risks and the built environment, we compared exposure between neighborhoods grouped by walkability. Block groups are placed in five groups based on their walkability index scores: low walkability (LW), medium-low walkability (MLW), medium walkability (MW), medium-high walkability (MH), and high walkability (HW). Block groups in the lowest quintile of walkability scores are placed in the LW group, those in the second lowest in the MLW group, and so on. $PM_{2.5}$ concentration is lowest in the LW group and highest in the HW group (Figure 4.7). Transportation physical activity is not substantially different between the LW and MW groups; however, transportation physical activity is significantly higher in the HW group. Walk trips display a similar relationship while bike trips are significantly different between the three groups. Finally, VMT decreases slightly as walkability increases (Figure 4.8). While the distribution of exposure within each neighborhood group is wide, significant differences exist comparing mean exposure levels between groups (Table 4.3).

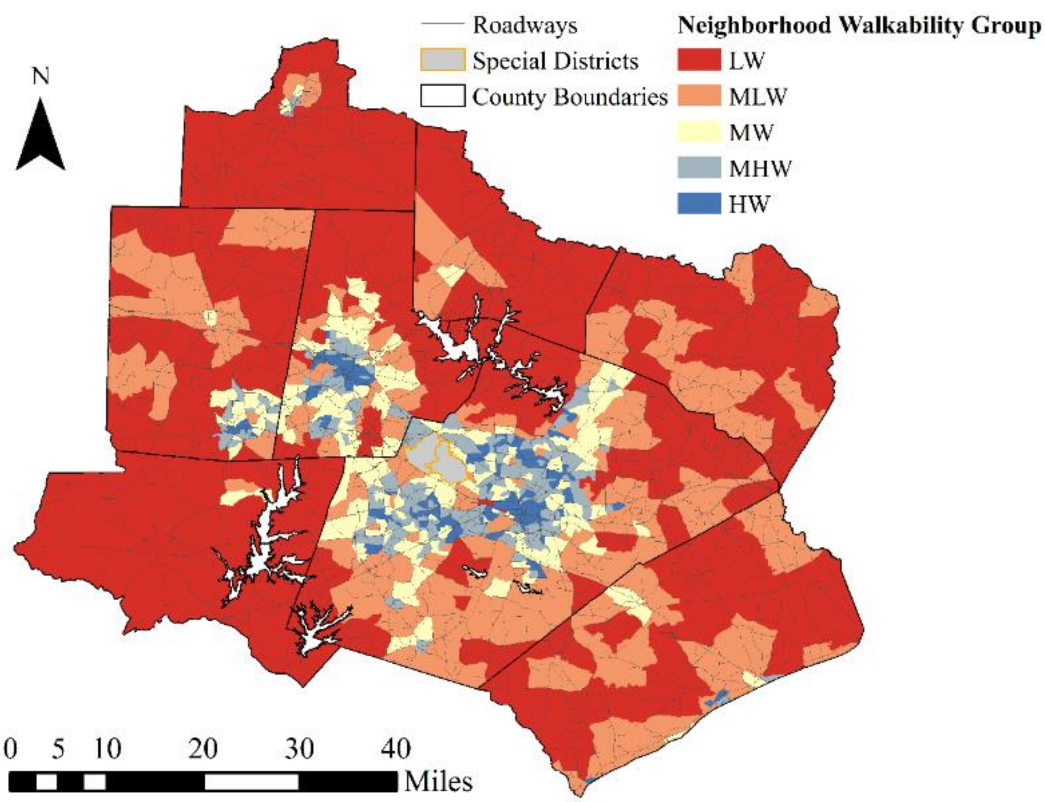


Figure 4.7. Neighborhood groups (LW, MLW, MW, MHW, and HW) defined by quintiles of the walkability index

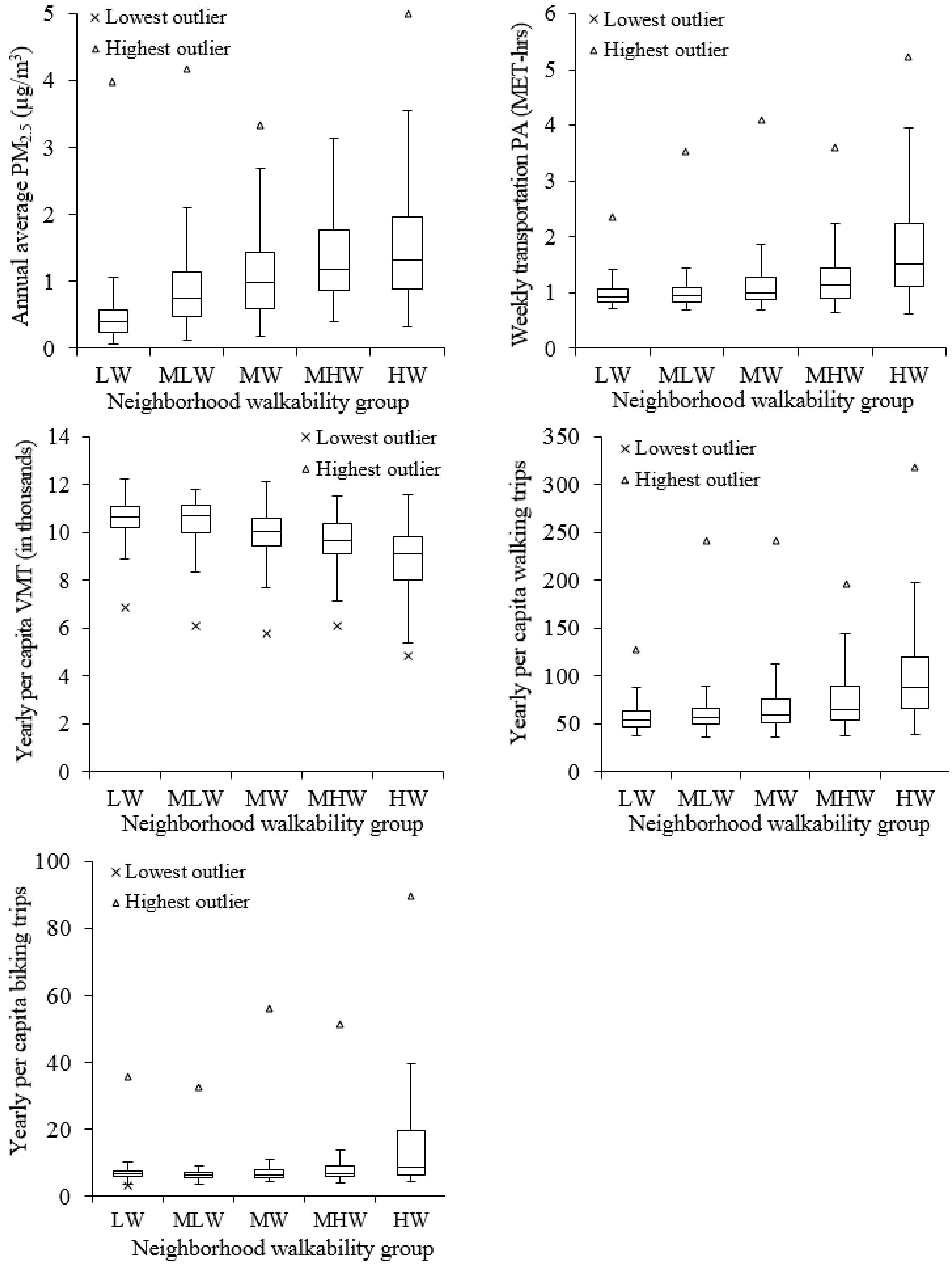


Figure 4.8. Box plots illustrating the distributions of each transportation health risk within the LW, MLW, MW, MHW, and HW neighborhood groups.

While the distributions of exposure levels for each risk within each group are wide (Figure 4.8), the majority of pairwise differences between groups are significant (Table 4.3). Notably, difference in mean $PM_{2.5}$ exposure are significantly different between all pairs of neighborhood groups aside from the MHW and HW groups. All pairs of neighborhoods at least two groups apart (e.g., LW versus MW) have significantly different levels of transportation physical activity, while differences between adjacent groups are mixed. The HW group has significantly higher transportation physical activity than the MHW group. All differences in VMT are significant aside from the LW and MLW group. Differences in walking trips have the same significance patterns as transportation physical activity. Finally bike trips are significantly higher only in the most walkable neighborhood groups (Table 4.3).

Table 4.3. Means and pairwise comparisons of transportation risks between neighborhood groups

Neighborhood Walkability Group	$PM_{2.5}$ (μg/m^3)	Physical activity (MET-hrs/week)	VMT (miles/year)	Walking trips (trips/year)	Biking trips (trips/year)
Mean exposure by group					
LW	0.50	1.00	10,568	57	8
MLW	0.85	1.02	10,491	61	7
MW	1.14	1.16	9,962	68	9
MHW	1.47	1.28	9,621	74	10
HW	1.51	1.79	8,890	99	15
Difference in means between pairs of neighborhood groups [a]					
LW vs MLW	0.35**	0.02	-77.69	3.42	-0.46
LW vs MW	0.64**	0.17*	-606.0**	10.3*	1.25
LW vs MHW	0.97**	0.28**	-947.8**	16.2**	2.15
LW vs HW	1.01**	0.79**	-1678**	41.5**	7.80**
MLW vs MW	0.29**	0.15	-528.3**	6.88	1.71
MLW vs MHW	0.62**	0.26**	-870.1**	12.8**	2.61*
MLW vs HW	0.66**	0.77**	-1600**	38.0**	8.25**
MW vs MHW	0.33**	0.11	-341.8*	5.94	0.91
MW vs HW	0.37**	0.62**	-1072**	31.2**	6.55**
MHW vs HW	0.04	0.51**	-730.3**	25.2**	5.64**

[a] Significance of pairwise difference adjusted using the Tukey honest significance difference test
**p<0.01 *p<0.05

4.3.4. Transportation health impacts

To estimate population-level health impacts resulting from transportation-related exposures, we developed a novel dynamic micro simulation model. In the aggregate, we estimate that an average of 22.0 premature deaths per 100,000 persons per year are associated with $PM_{2.5}$ from automobiles, physical inactivity, and fatal crashes in the region over 20 years. Fatal crashes account for 14.8 premature deaths per 100,000 persons per year (67% of the total burden of disease), physical inactivity 5.2 (24% of the total), and exposure to $PM_{2.5}$ from automobiles 1.9 (9% of the total) (Figure 4.9). Transportation physical activity below the counterfactual scenario (37.4 minutes of walking per week) is associated with 112 excess cases each of diabetes and CVD per 100,000 persons 20 years in the future (Figure 4.9). Interestingly, mortality attributable to transportation health risks stays relatively constant over time while the number of new excess of CVD and diabetes associated with low transportation physical activity decreases over time. As the counterfactual population ages, higher levels of transportation physical activity assumed in this population (37.4 minutes of walking per week) shift disease incidence functions for CVD and diabetes downward. In response, the model moves towards a new steady state in which fewer individuals transition into the CVD and diabetes states (*cvd* and *d* in Figure 4.3). Over time, the number of new avoided cases of CVD and diabetes per year approaches zero as the distribution of the population between the healthy state, the CVD state, and the diabetes states (h, *cvd* and *d* in Figure 5.3) adjusts in response to transition probabilities affected by a change in exposure ($P_j(h \rightarrow cvd)$ and $P_j(h \rightarrow d)$ in Figure 4.3). The ability of dynamic models to estimate health impacts that vary over time have been previously demonstrated and is an advantage of dynamic models compared to static health impact models (Mansfield & MacDonald Gibson, 2015).

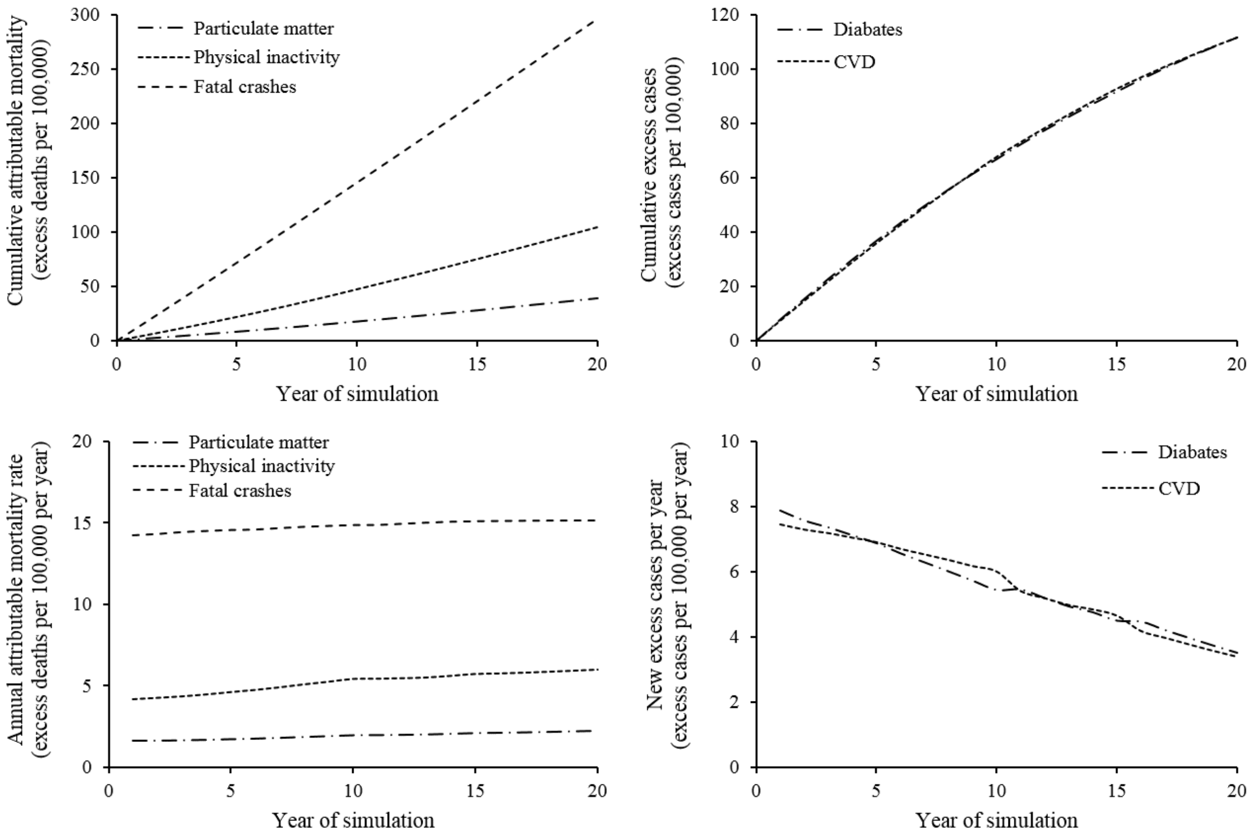


Figure 4.9. Estimated cumulative mortality (top left) and excess cases of CVD and diabetes (top right) per 100,000 persons and excess deaths (bottom left) and new cases of CVD and diabetes bottom right) per year per 100,000 persons in the study region associated with transportation health risks.

Combined transportation health risks are lowest in the most walkable neighborhoods in the region compared to the least walkable neighborhoods (Figure 4.10). While $PM_{2.5}$ concentrations are highest in the most walkable neighborhoods, increases in transportation physical activity and reductions in per capita VMT counteract increased health risks from $PM_{2.5}$, resulting in net health benefits in the most walkable neighborhoods (Figure 4.10). Interestingly, the health impacts of $PM_{2.5}$ exposure are slightly lower in the HW group compared to the MHW group, while $PM_{2.5}$ concentrations are highest in the HW group (Table 4.2). This effect is likely due to a slightly younger population (with lower baseline death rates) in the most walkable neighborhoods in the region, resulting in slightly lower population health impacts form $PM_{2.5}$ exposure in these neighborhoods. Pairwise comparisons of death rates between neighborhood walkability groups shows that combined health risks are significantly lower in the most walkable group of neighborhoods compared to all other groups (Table 4.8). Excess premature mortality associated with $PM_{2.5}$ is significantly higher in the most walkable groups of neighborhoods compared to the least walkable groups, but does not differ significantly within the highest two walkability groups. Excess premature mortality associated with low transportation physical activity is significant between all groups. Similarly, reductions in crash mortality are significant as walkability increases aside from the differences between the HW and MHW group. Comparing the LW and HW groups, transportation-related premature mortality in the most walkable neighborhoods is lower on average than in the least walkable neighborhoods by 4.2, 4.5, and 4.9 persons per 100,000 per year 5, 10, and 20 years into the future.

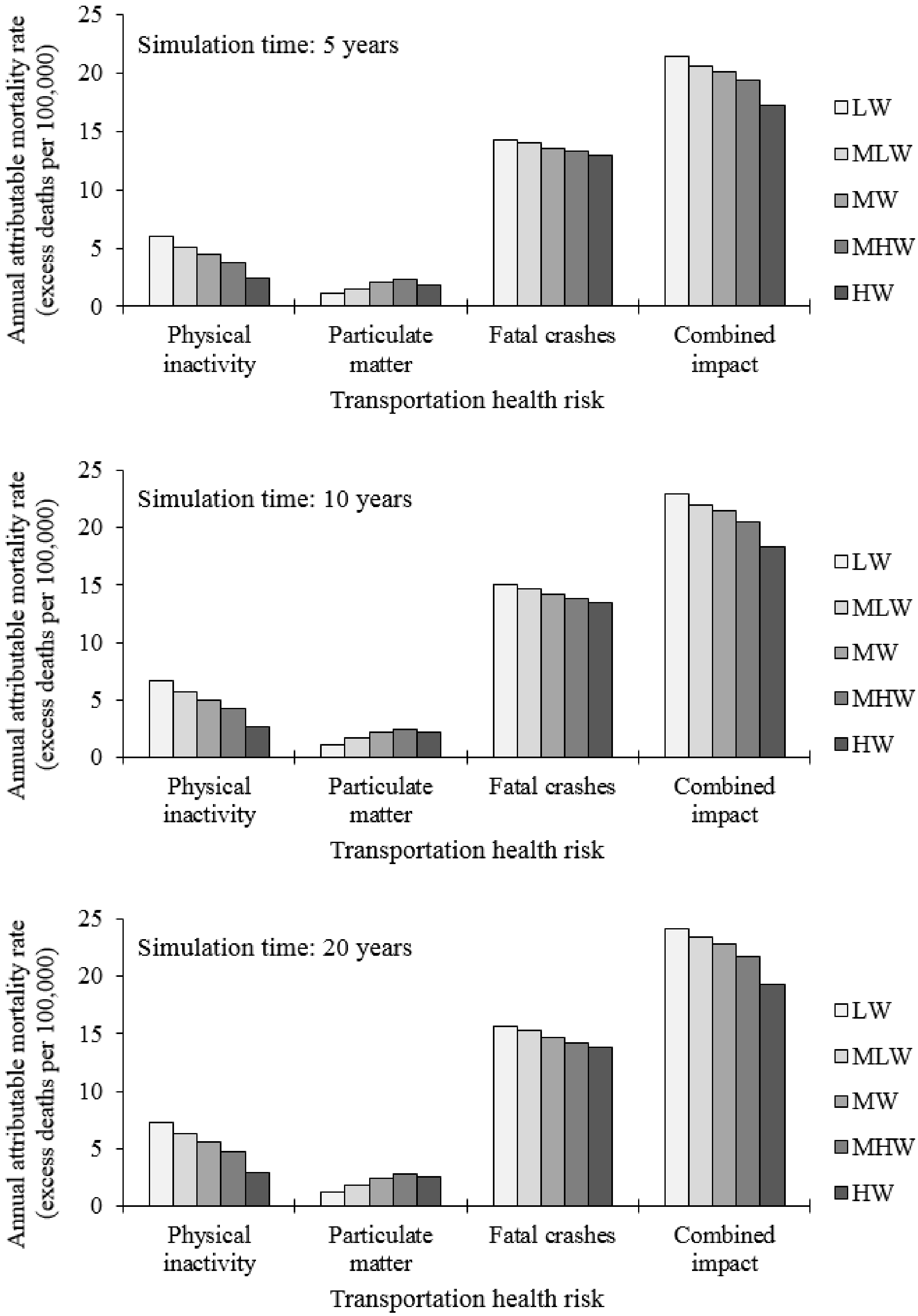


Figure 4.10. Mean excess death rates (premature deaths per 100,000) associated with transportation health risks in each neighborhood group 5, 10, and 20 years from the beginning of the simulation.

Table 4.4. Means and pairwise comparisons of transportation health impacts between neighborhood groups, year 10 of simulation

Neighborhood Walkability Group	Mortality (excess deaths per 100,000 per year)				Morbidity (excess new cases per 100,000 per year)	
	$PM_{2.5}$	Physical inactivity	Fatal crashes	Combined	CVD	Diabetes
Mean impact by group						
LW	1.15	6.66	15.0	22.9	7.4	6.2
MLW	1.68	5.66	14.6	22.0	7.1	6.1
MW	2.24	5.01	14.2	21.5	6.5	5.8
MHW	2.48	4.20	13.9	20.5	5.8	5.4
HW	2.14	2.70	13.5	18.4	2.9	2.7
Difference in means between pairs of neighborhood groups [a]						
LW vs MLW	0.52**	-1.00**	-0.40**	-0.87	-0.38	-0.13
LW vs MW	1.09**	-1.65**	-0.83**	-1.39**	-0.97	-0.58
LW vs MHW	1.33**	-2.45**	-1.19**	-2.32**	-1.61**	-0.98
LW vs HW	0.99**	-3.95**	-1.53**	-4.49**	-4.52**	-3.75**
MLW vs MW	0.56**	-0.65	-0.43**	-0.52	-0.59	-0.45
MLW vs MHW	0.81**	-1.46**	-0.79**	-1.44**	-1.23*	-0.85
MLW vs HW	0.47*	-2.96**	-1.12**	-3.61**	-4.15**	-3.62**
MW vs MHW	0.24	-0.81*	-0.36**	-0.93	-0.64	-0.40
MW vs HW	-0.10	-2.31**	-0.70**	-3.10**	-3.55**	-3.17**
MHW vs HW	-0.34	-1.50**	-0.33**	-2.17**	-2.91**	-2.77**

[a] Significance of pairwise difference adjusted using the Tukey honest significance difference test
**p<0.01 *p<0.05

Incidence of CVD and diabetes are also substantially lower in the most walkable neighborhoods compared to the least walkable group (Figure 4.11). In year 10 of the simulation, transportation physical activity in the most walkable group of neighborhoods is estimated to prevent 4.5 new cases of CVD and 3.8 new cases of diabetes per 100,000 persons per year (Table 4.4). Cumulatively, the most walkable neighborhoods are estimated to have 27 fewer cases of CVD and 26 fewer cases of diabetes per 100,000 persons after 5 years, 51 fewer cases of CVD and 46 fewer cases of diabetes after 10 years, and 87 fewer cases of CVD and 78 fewer cases of diabetes after 20 years (Figure 4.11, top plots). While the cumulative difference in cases of diabetes and CVD between the most and least walkable neighborhoods grow over the simulation time frame, the number of new cases avoided per year approaches zero (Figure 4.11, bottom plots). Changes in transportation physical activity shift the incidence functions of these diseases downward, creating a new population steady state in which fewer individuals become sick over time. The dynamic model used to estimate health impacts in this study is able to capture this behavior.

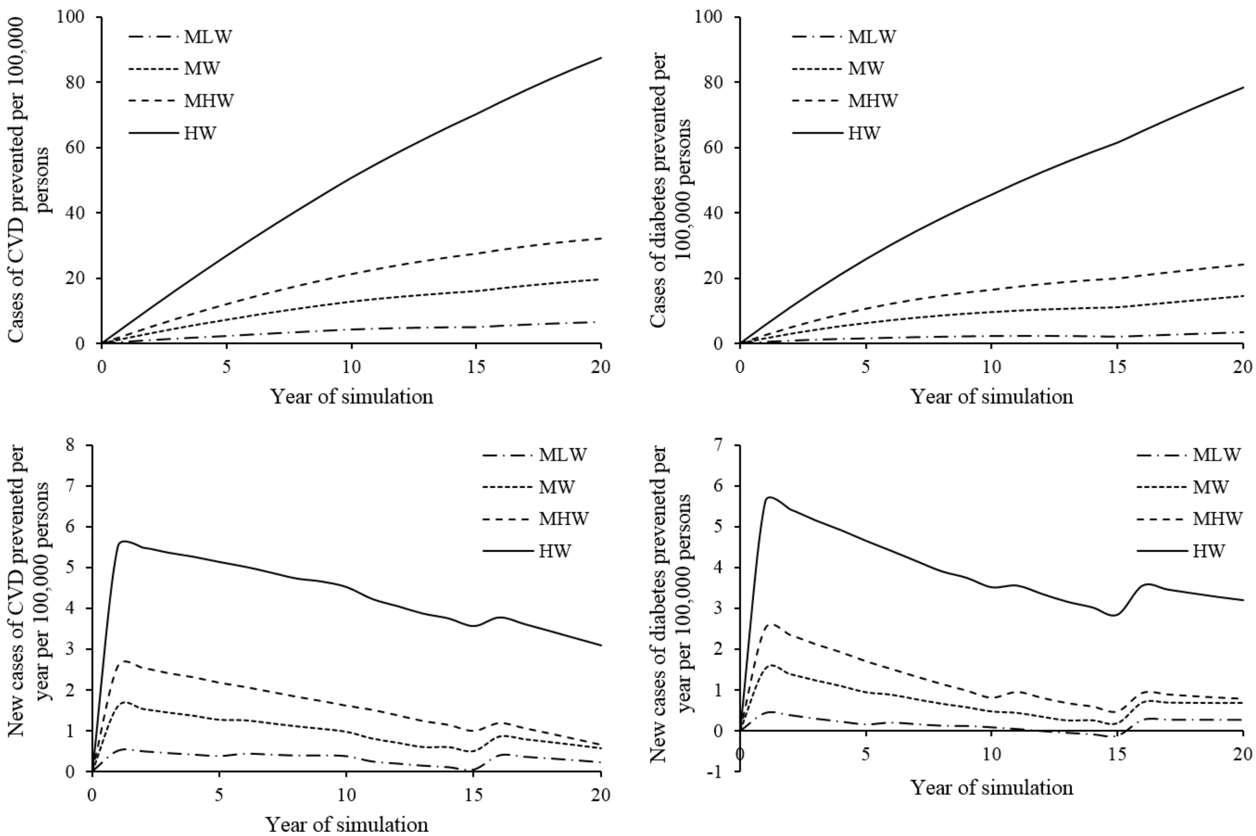


Figure 4.11. Cumulative cases of CVD (top left) and diabetes (top right) per 100,000 persons avoided over time and number of new cases of CVD (bottom left) and diabetes (bottom right) per year per 100,000 persons in each neighborhood group relative to the lowest walkability group.

Comparing transportation health risks by commuting mode to work, we predict substantial health benefits for those who bike to work compared to those who drive to work (Figure 4.12). While crash risk increases slightly for bike commuters, the health benefits of physical activity far outweigh these risks on an individual level. A similar, albeit much less strong effect, is also predicted for those who walk to work. Interestingly, transit users also face fewer health risks than drivers, although benefits are driven largely by lower fatal crash risk for transit users (Figure 4.12).

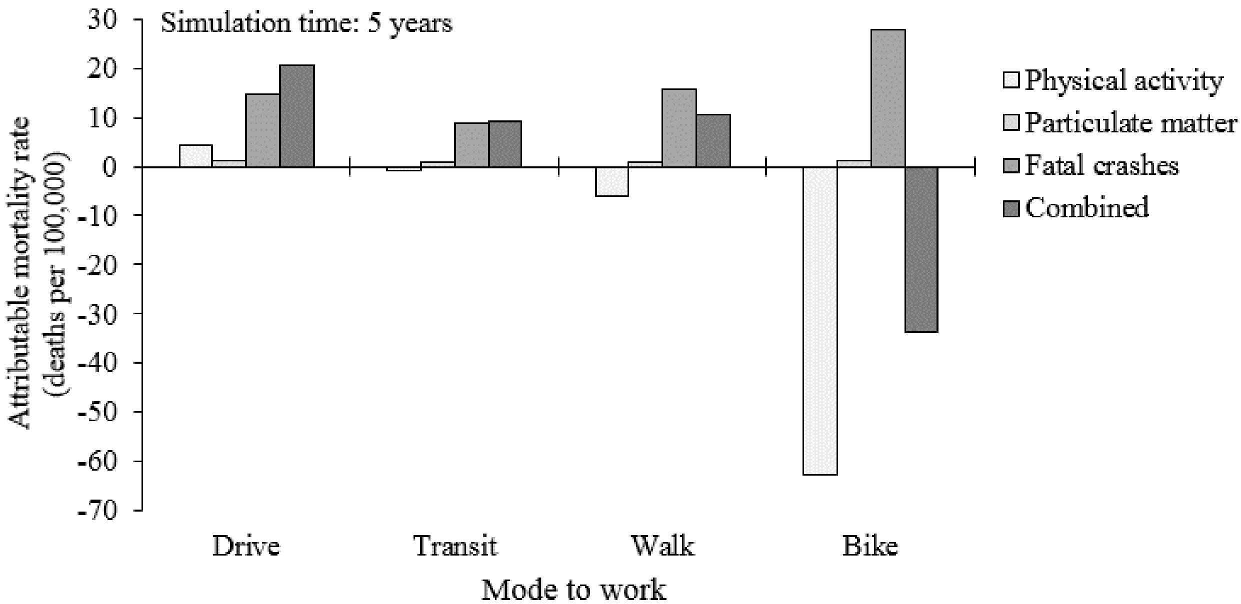


Figure 4.12. Attributable mortality rates by transportation risk and mode to work. Negative attributable mortality rates indicate health benefits relative to the counterfactual scenario (i.e., baseline physical activity exceeding 37.4 minutes per week)

Finally, transportation health risks vary considerably by age. While the risk of fatal crashes per unit travelled increases slightly with age (Table 4.1), mortality from crashes is an acute event. On the other hand, physical inactivity and $PM_{2.5}$ exposure modify underlying health risks that increase substantially with age. Thus, the health impacts of physical inactivity and exposure to $PM_{2.5}$ from automobiles are concentrated in the oldest age group (65-74) whereas premature mortality from crashes is relatively consistent across all three age groups impacted (Figure 4.13, left four groups of columns). A less pronounced difference between age groups is estimated for avoided cases of CVD and diabetes (Figure 4.13, right two groups of columns).

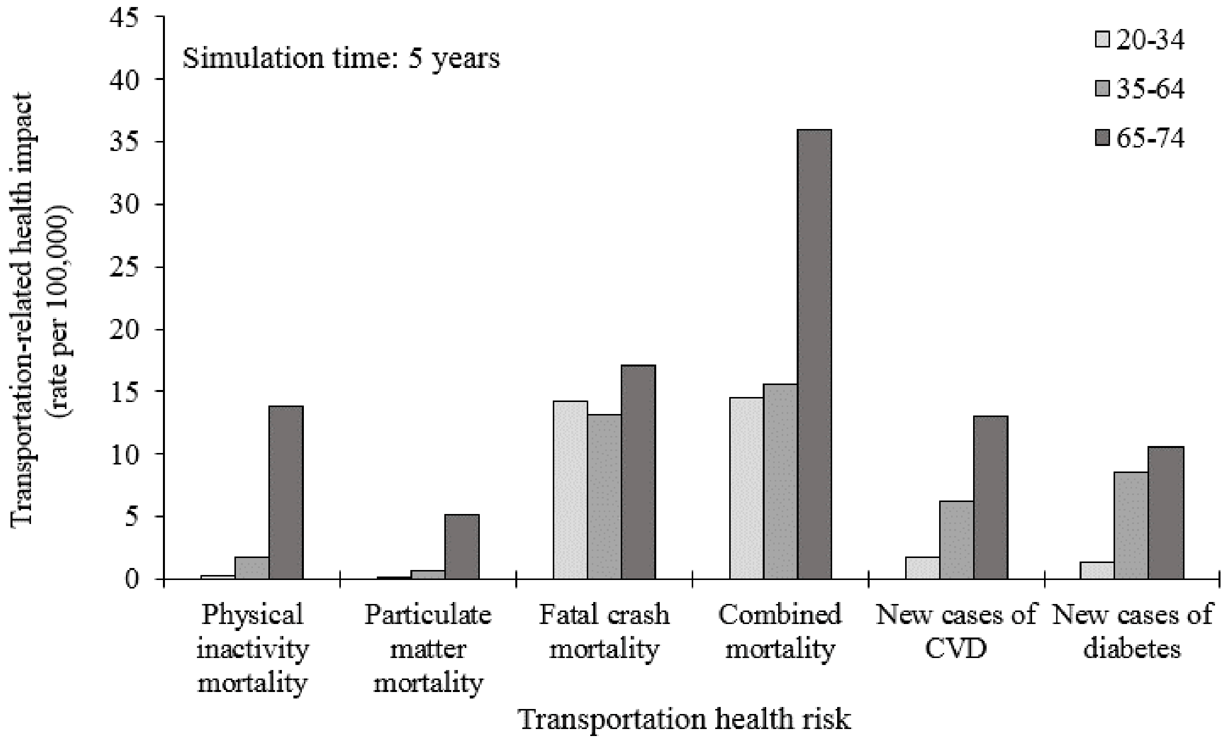


Figure 4.13. Transportation-related death rates (left four groups of columns) and excess cases of CVD and diabetes per year (right two groups of columns) by age group.

4.4. Discussion

Using a novel multi-risk dynamic health impact assessment model, we found that the net health risks of transportation systems are lowest in the most walkable neighborhoods in the Raleigh-Durham-Chapel Hill metropolitan region. In the most walkable quintile of neighborhoods, combined transportation health impacts are lower than in the least walkable quintile of neighborhoods (4.5 fewer premature deaths per 100,000 persons per year). While exposure to $PM_{2.5}$ increases in more walkable neighborhoods, increases in population-average transportation physical activity and decreases in fatal automobile crash risks outweigh health impacts associated with $PM_{2.5}$ exposure. We also found that physical inactivity and air pollution exposure risks from transportation networks that encourage driving in personal automobiles increase mortality risks by 33% compared to estimates that consider crash risks alone. Thus, considering all three risk factors—physical inactivity and air pollution along with crash risks—is vital for characterizing the costs and benefits of transportation network designs that offer varying levels of support for active transportation.

The modeling framework developed in this study is offers a more rigorous understanding of competing transportation health risks in urban areas than previous studies. Previous studies exploring competing transportation health risks have relied exclusively on static health impact models (Maizlish et al., 2013; Hankey et al., 2012). Dynamic health impact models offer several advantages over static modeling approaches, including accounting for changes in population characteristics over time and better capturing long-term changes in population health outcomes as changes in disease incidence and mortality rates shift disease prevalence over time (Mansfield and MacDonald Gibson, 2015). Dynamic health impact models have been employed in non-transportation sectors such as analyses of the benefits of smoking cessation programs (Lhiachimi et al., 2012); however, this study is the first comprehensive application of a dynamic health impact model to explore spatial variation in transportation health risks across a large metropolitan area.

More broadly, our findings build on an emerging body of evidence showing the overall health benefits of walkable neighborhoods. In Los Angeles, Hankey et al. estimated a roughly one-to-one tradeoff between the benefits (increased physical activity) and risks (exposure to air pollution) of walkable neighborhoods using a static model (2012). Using a dynamic simulation model, we showed a stronger effect of neighborhood walkability on physical activity, leading to a net decrease in health risk in the most walkable neighborhoods. In contrast to Hankey et al., which used ambient $PM_{2.5}$ concentrations with low spatial resolution to characterize exposure, we used $PM_{2.5}$ concentrations predicted at high spatial resolution and only from automobiles. We also used estimates of transportation physical activity across the entire population using previously validated regression models while Hankey et al. used observed physical activity data and considered only a subset of the population for which these data were collected. Using different methods in a different geographic context, we showed stronger benefits of walkable neighborhoods than Hankey et al. in Los Angeles (2012).

Woodcock et al. used a multi-risk framework to demonstrate the health benefits of future scenarios that encouraged increased active travel in San Francisco, London, and Delhi (Woodcock et al., 2009; Maizlish et al., 2013). In these studies, future scenarios that assumed higher levels of transportation physical activity had greater health benefits than future scenarios focused on reducing vehicle emissions without encouraging more active travel. While adopting a multi-risk framework, these studies did not consider small-scale neighborhood-level variations in health risks. Using this same framework, Woodcock et al. estimated the health benefits to users of the London bike share system (Woodcock et al., 2014). Replacing short, non-active trips with bicycle trips substantially benefitted bike share users. While modeled at the individual level, this study considered only a subset of the population (bike share users) and did not generalize to the population level. The micro simulation modeling framework used in our study models health impacts at the individual level for the entire population, thereby facilitating translation of model estimates to the population level and enabling neighborhood-level risk comparisons. We show similarly strong health benefits on the individual level (Figure 4.10), but a weaker—although significant—benefit of walkable neighborhoods assessed at the population scale (Figure 4.8, Table 5.4). This result is intuitive—while transportation physical activity is associated with built environment characteristics, individual preferences also play a role. In highly walkable urban environments, some individuals will still choose to participate in transportation physical activity sparingly. Conversely, exposure to $PM_{2.5}$ from automobiles does not vary based on individual characteristics within a neighborhood. Thus, at the population level the health benefits of more walkable neighborhoods are attenuated while health risks associated with $PM_{2.5}$ are not. We estimated that the health benefits of walkable neighborhoods persist at the population-level despite attenuation related to individual preferences for active travel.

The modeling framework employed in this paper is well-suited to integrate with recent innovations in transportation demand modeling. Traditional four-step travel demand models first generate trips at the household level, distribute these trips across space, assign modes to these trips, and finally assign these trips onto the transportation network. Four-step models can be used to support health impact assessments of transportation air quality impacts (Mansfield et al., 2014). However, the usefulness of four-step models is limited when considering other transportation health risks: four-step models divide an urban area into “transportation analysis zones” (TAZs). Four-step models trips estimate between, but not within, TAZs; thus, active trips with short distances (i.e., occurring entirely within a TAZ) are not modeled. Four-step transportation demand models are increasingly being replaced with activity-based transportation demand models, which offer more much finer geographic resolution and provide detailed estimations of travel behaviors at the individual level (TRB, 2015). A necessary step when building an activity-based travel demand model is the generation of a synthetic population for which the model will estimate travel behaviors. An emerging literature explores the development of synthetic populations in urban areas for this purpose (Zhu & Ferreira, 2014). Critically, the microsimulation framework used in this research could easily use the same synthetic population as activity-based transportation demand models. Detailed predictions of individual-level travel behaviors (including trip modes, distances, and locations in an urban area) could easily be used to characterize individual-level exposure in the model used in this dissertation. Thus, this work provides a framework that could support the integration of detailed population-level health impacts into routine travel demand modeling activities as activity-based travel demand models gain prominence in the field.

While we considered three transportation risks in a unified analysis framework, underlying epidemiological evidence varies slightly for these risks. Exposure to pollution in ambient air has been linked to cause-specific mortality in a number of large cohort studies (Pope et al., 2002); however, links between chronic exposure to air pollution and disease incidence are not well understood. Conversely, physical activity has a demonstrated preventive effect on disease incidence and all-cause mortality but no evidence exists linking physical activity to cause-specific mortality (Kelly et al., 2014). Epidemiological studies considering injury risk from crashes are limited, and exposure is typically defined coarsely in these studies (e.g., crash risk per number of walking or biking trips) (Beck et al., 2007). However, the modeling framework used in this study offers an approach to incorporate epidemiological evidence on both disease incidence and cause-specific mortality without double-counting benefits, which minimizes bias introduced by this limitation. We also assumed that commute mode choice—which has a substantial effect on estimated transportation physical activity—and exposure to $PM_{2.5}$ are constant over time. While this approach estimates the long-term population health impacts of built environment characteristics as they exist today, it does not consider possible external policy variables (e.g., the incorporation of zero-emission electric vehicles into the vehicle fleet) that will affect modeled health outcomes. However, the dynamic modeling framework developed in this study is able to incorporate such external policy variables given estimates of how these variables affect exposure (i.e., yearly mobile-source $PM_{2.5}$ concentrations that are sensitive to future changes in the vehicle fleet). Existing work shows that aggressive adoption of low-emissions vehicles dramatically reduces health impacts in the long-term (Song et al., 2008). Thus, incorporating this information into the modeling framework presented in this study would likely strengthen our primary finding that the health benefits of walkable neighborhoods outweigh concomitant health risks.

4.5. Conclusions

In this study, we developed a generalizable modeling framework to estimate the health risks arising from three potentially competing risk factors associated with the design of neighborhoods and transportation systems: physical inactivity, air pollution exposure, and fatal crashes. We found that in walkable neighborhoods, the benefits of transportation physical activity outweigh the health risks of $PM_{2.5}$ from automobiles and fatal injuries from crashes. While the risks of injury due to crashes are commonly considered in making investment decisions about transportation networks, air pollution exposure is considered only when national ambient air quality standards are violated, and physical inactivity is rarely considered (Gwee, Currie, & Stanley, 2011). Transportation and land-use decisions influence transportation behaviors at the project scale (e.g., providing infrastructure that supports all modes of travel), in project programming (e.g., prioritizing funding projects that positively impact population health) and in long-range planning (e.g., integrated transportation-land use planning efforts). Changes in transportation behaviors have meaningful population health impacts, and we demonstrate that these impacts are quantifiable across a large metropolitan region. Thus, this study provides strong evidence for the inclusion of additional health considerations when making decisions about transportation systems. Transportation agencies at the state and local level in the United States have recently demonstrated strong desires to better incorporate health into transportation decisions. However, the lack of robust methods to do so has limited the breadth and effectiveness of existing policy efforts. The framework demonstrated in this paper has substantial promise to immediately support the incorporation of health into transportation decision-making at a variety of scales and in a number of settings.

CHAPTER 5: CONCLUDING REMARKS

5.1. Key Findings

This dissertation has addressed several gaps in current understanding of how transportation systems impact public health and how these health impacts vary with characteristics of the built environment. First, this work demonstrates that dynamic simulation models offer several important advantages over traditional static approaches, including more accurate estimation of disease prevention due to increased physical activity and consideration of dynamic factors such as aging and temporal changes in disease prevalence (Chapter 2). Second, this work offers an approach to develop high-resolution estimates of transportation physical activity levels using behavioral evidence from the 2009 National Household Travel Survey (Chapter 3). Finally, a novel dynamic microsimulation framework was developed specifically for transportation health risks and then applied using high-resolution estimates of exposure of $PM_{2.5}$ from automobiles, transportation physical activity, and fatal crash risk across the Raleigh-Durham-Chapel Hill metropolitan area (Chapter 4). This model integrates state-of-the-science methods to characterize exposure to transportation health risks at high spatial resolution with an advanced dynamic health impacts model.

The health impacts of transportation have been an area of increased research focus in recent years (Mueller et al, 2105). However, existing research has often relied on coarse characterization of transportation health risks (e.g., using air quality models with low spatial resolution) (Maizlich et al., 2013). Studies using more detailed exposure data have typically focused on specific population sub-groups, such as users of the London bike share system (Woodcock et al., 2014). Finally, nearly all existing work on the health impacts of transportation has used static models to estimate health impacts for only one point in time. By integrating high-resolution models of exposure with a dynamic microsimulation health impacts model, this research fills in a number of methodological gaps. Critically, this work finds that health benefits (increased transportation physical activity and decreased motor vehicle crash risk) in the most walkable neighborhoods in the study region outweigh concomitant health risks (increased exposure to $PM_{2.5}$ and increased pedestrian and bicycle crash risk). These results are consistent with other studies exploring competing transportation health risks (Hankey, Marsahll, & Brauer, 2102) but build on this prior work provides a rigorous estimate of population-scale health benefits of walkable neighborhoods by characterizing exposure at high resolution, estimating health impacts on the individual level, and considering the dynamic effects of changes in health status.

5.2. Policy implications

US transportation agencies are expressing increased interest in integrating health considerations into decision-making (USDOT, 2014; USDOT, 2012). Additionally, the use of HIA has been growing rapidly in the transportation sector (Dannenberg et al., 2014). While a handful of existing policy mechanisms exists to consider health impacts in transportation decision-making, applications of these mechanisms are limited. In air quality nonattainment areas (areas not meeting the requirements of the Clean Air Act), funds from the Congestion Mitigation and Air Quality Improvement Program may be used to fund transportation projects that improve air quality and improve public health (USDOT, 2016). Additionally, new highway and transit projects that may increase emissions from diesel vehicles in nonattainment and maintenance areas are now required to conduct quantitative PM hot-spot analyses at the project scale (EPA, 2015). Similar stipulations exist for CO emissions from a wider range of projects in nonattainment and maintenance areas (EPA, 2015). Finally, many transportation agencies seek to reduce fatal crash rates on a per-VMT basis, failing to consider that increases in VMT offset the benefits of programs that reduce per-VMT health risks (Litman, 2014). While increasing physical activity is sometimes considered a potential benefit of transportation systems, the health risks of built environments that discourage active transportation behaviors are rarely conceptualized as a health impact of transportation systems (Dannenberg et al., 2014). This work supports substantive consideration of multiple transportation health risks and offers a substantially more rigorous approach than is offered by current tools and approaches.

As interest in the health impacts of transportation has grown, so has the development of decision-support tools seeking to bridge the gap between transportation and public health agencies. However, these emerging tools often provide data at low spatial resolution and provide little insight into the relationships between transportation systems, exposures to transportation health risks, and health impacts. Without sufficient spatial resolution or linkages between exposure and health outcomes, such tools fail to adequately inform transportation decision-makers how their decisions may impact public health. Lacking tools to estimate the health impacts of specific transportation decisions, a number of transportation agencies have recently included health metrics into established decision-making processes as an approach to make progress towards public health goals. At the state level, a number of state departments of transportation have including health-related metrics in structured decision-making processes, such as the inclusion of bicycle and pedestrian mode share as a recommended evaluation metric in Caltrans' Smart Mobility framework (USDOT, 2014). Local-level efforts have also focused on including health metrics in structured decision-making, such as awarding points to transportation projects that address identified health disparities in prioritizing project funds in Nashville, TN (USDOT, 2012). A critical gap in these existing frameworks is the lack of modeling tools to translate transportation-related exposures to population health impacts. Improved modeling of transportation health impacts helps clarify the pathway from exposure to health impacts and could be a valuable tool in integrating health considerations into routine transportation decision-making.

The modeling framework employed in this dissertation is well-suited to integrate with recent innovations in transportation demand modeling. Traditional four-step travel demand models first generate trips at the household level, distribute these trips across space, assign modes to these trips, and finally assign these trips onto the transportation network. Four-step models can be used to support health impact assessments of transportation air quality impacts (Mansfield et al., 2014). However, the usefulness of four-step models is limited when considering other transportation health risks: four-step models divide an urban area into “transportation analysis zones” (TAZs). Four-step models trips estimate between, but not within, TAZs; thus, active trips with short distances (i.e., occurring entirely within a TAZ) are not modeled. Four-step transportation demand models are increasingly being replaced with activity-based transportation demand models, which offer much finer geographic resolution and provide detailed estimations of travel behaviors at the individual level (TRB, 2015). A necessary step when building an activity-based travel demand model is the generation of a synthetic population for which the model will estimate travel behaviors. An emerging literature explores the development of synthetic populations in urban areas for this purpose (Zhu & Ferreira, 2014). Critically, the microsimulation framework used in this research could easily use the same synthetic population as activity-based transportation demand models. Detailed predictions of individual-level travel behaviors (including trip modes, distances, and locations in an urban area) could easily be used to characterize individual-level exposure in the model used in this dissertation. Thus, this work provides a framework that could support the integration of detailed population-level health impacts into routine travel demand modeling activities as activity-based travel demand models gain prominence in the field.

Even without complete integration with transportation demand models, the model developed in this dissertation could support the integration of health considerations into a range of decisions about the built environment. The model is modular and scalable, enabling its application in many routine transportation decision-making practices. Metropolitan planning organizations could use the model developed in this dissertation to support a variety of planning efforts. Integrated land use and transportation planning efforts could be compared based a range of health metrics. The model could also be used to include health outcomes when transportation agencies make funding decisions under budget constraints (e.g., project prioritization). The model could be downscaled further to compare health outcomes between alternatives at the project or corridor scale, offering transportation agencies a means to quantify public health outcomes as a part of the National Environmental Policy Act (NEPA) process. In addition, the model could be used to consider transportation health risks alongside other health risks that vary across space in urban areas. While developed specifically for transportation health risks, the modeling framework is modular and can be modified to include additional intermediate disease pathways and additional exposures. In sum, the modular and scalable design of the model developed here presents an opportunity to integrate health considerations into transportation decision-making in a much more rigorous manner than is currently practiced and to provide robust decision-support as the fields of transportation and public health continue to converge.

5.3. Limitations

While providing a more rigorous approach to estimating the population health impacts of transportation systems, the model developed in this dissertation has substantial data requirements. Notably, dynamic models require detailed age-specific functions characterizing baseline death rates, disease prevalence, and disease incidence. Because mortality is a rare event for younger age groups, state-level data were needed to develop baseline death rate functions. Additionally, incidence data are not readily available for many diseases in the US; thus, disease incidence was estimated using the World Health Organization's *DisMod II* tool. However, baseline model calibration revealed reasonable model performance despite estimations in underlying epidemiological data. Finally, epidemiological evidence linking chronic exposure to $PM_{2.5}$ to morbidity is limited. Thus, the model developed in this dissertation does not consider morbidity related to air pollution exposure. Practically, the model used in this work is very computationally intensive due in large part to the size of the transition matrices within the Markov model. While executable on a typical desktop workstation, the computational demands present practical limitations to performing uncertainty analysis using techniques such as Monte Carlo simulation.

In addition to limitations of the health impacts model itself, estimation of individual-level exposures to transportation health risks presents challenges. The most recent estimates of $PM_{2.5}$ concentrations across the region were for 2011, while other exposures were estimated for 2013. Additionally, it is assumed that $PM_{2.5}$ concentrations are constant over time; however, $PM_{2.5}$ concentrations will change in the future as the vehicle fleet changes and travel behaviors shift. While the model is capable of incorporating exposures that vary over time, limitations in available estimates of $PM_{2.5}$ concentration precluded the inclusion of time-varying $PM_{2.5}$. While the line-source dispersion model used to estimate $PM_{2.5}$ concentrations included most road segments in the study region, traffic levels on many smaller roadways are not routinely collected as part of the Federal Highway Administration's National Highway Performance Program. Contributions to ambient $PM_{2.5}$ from these roadway segments were not included in estimated $PM_{2.5}$ concentrations used in this study. Finally, chemical pathways leading to secondary formation of $PM_{2.5}$ were not modeled in the work used to characterize $PM_{2.5}$. Secondary formation of other pollutants in ambient, such as ozone, are also not considered. However, secondary formation of air pollutants likely occurs after some atmospheric mixing and is thus likely to vary less over space and, in turn, vary less in relation to neighborhood-scale built environment variables. Despite these limitations, use of an advanced line-source dispersion model to provide high-resolution estimates of $PM_{2.5}$ across the study region offered a much more detailed characterization of exposure to air pollution than used in previous studies. Further, the modeling framework developed in this work could easily incorporate new exposure information as advancements in high-resolution air quality modeling continue.

Additionally, the model used in this dissertation does not consider increased inhalation rates during active transportation. Active commuters may be exposed to more air pollution while walking or biking alongside roadways and may inhale greater amounts of pollutants in ambient air due to increased respiration rates while being active. Individuals may also be more active during times of the year when photochemistry is more active. However, using annual average pollutant concentrations masks potential seasonal effects on total inhalation doses of airborne pollutants. Further, the modeling framework used here does not predict where active transportation behaviors will occur—while walking trips may occur in the same block group as an individuals' home, biking trips and walk trips from public transit may occur in other block groups. Annual average $PM_{2.5}$ concentrations are also used in this work to characterize exposure while acute exposure for active commuters may vary significantly within and between days. Additionally, it is unclear how increased acute exposure to air pollution may modify risks estimated in long term cohort studies (Pope et al., 2002). However, Woodcock et al. assume an increase in air pollution exposure for users of the London bike share systems and do not find substantial additional health impacts (2014). Thus, the magnitude of underestimation in health risks for active commuters due to this limitation is likely minor.

Estimations of transportation physical activity are largely based on individual commute modes, while walking and biking trips may be taken by individuals who typically drive to work. While built environment variables—population density and percentage of rental units—are considered and have significant effects on transportation physical activity, the magnitude of these effects is small relative to the magnitude of the commute mode to work variable (Figure 3.3). Thus, the transportation physical activity predictions used in this work may under-predict walking and biking trips for individuals who live in walkable environments but commute to work using a private vehicle. Additionally, fixed-route and demand-responsive (paratransit) services are both considered public transit and riders who access transit via park-and-ride lots are combined with users who walk or bike to access transit. Thus, additional factors that may influence walking and biking associated with public transit use, but are not reported at the Census block group geography in the American Community Survey, may lead to over-predictions of active travel related to transit usage in areas with paratransit service only (e.g., rural areas) and for transit users who use park-and-ride lots to access public transit. Finally, downscaling national level data to estimate transportation physical activity in the study region may result in some upwards or downwards bias due to unobserved variables. Despite these limitations, the regression models used to predict transportation physical activity model performed well when validated in the study region.

The modeling framework used in this dissertation also does not consider area-level built environment factors or the safety-in-numbers phenomenon in estimating fatal crash risk. Epidemiological evidence used in this work conceptualizes fatal crash risk on the individual level, which limits the ability of the model to consider area-based risk modification. Because this framework also does not consider the specific locations of walking and biking trips, the ability to consider the role of specific built environment variables in modifying fatal crash risk is constrained. Additionally, the model developed here considers only mortality from motor vehicle, pedestrian, and bicycle trips in part due to methodological difficulties in characterizing temporary states (e.g., non-fatal crash injuries) within the Markov chain modeling environment. Despite these limitation, this work still finds the lowest total fatal crash risk in the most walkable neighborhoods—neighborhoods that would be most likely to have built environments that support active transportation and have a higher number of commuters. Incorporating risk reductions from area-level factors and the safety-in-numbers phenomenon would likely strengthen the revealed association between neighborhood walkability and fatal crash risk.

Finally, the model developed in this dissertation is applied in only one case study region. The relationship between the built environment and air quality is influenced by exogenous policy variables, such as regulatory regimes for automobile emissions. Additionally, fatal crash risks may be modified by vehicle-level safety standards, cultural norms regarding driving, and other factors. Transportation physical activity levels may also vary relative to built environment characteristics in different ways in different cultural contexts. Thus, the magnitude of risk tradeoffs between air pollution, transportation physical activity, and fatal crashes may differ in cities in less developed countries and in emerging mega-cities with weak environmental regulation (e.g., Asian mega-cities). However, while the conclusions regarding risk tradeoffs discussed here are not widely generalizable, the modeling framework developed in this dissertation could be applied in other contexts to explore risk tradeoffs within different regulatory and cultural contexts.

5.4. Future Research

The model developed in this dissertation assesses transportation health impacts at an individual level, which can then be aggregated into different sub-groups to explore many research questions. The impacts of transportation health risks between different neighborhoods and for different types of commuters is explored in Chapter 4. Future work could explore differences in transportation risks and health impacts between groups with differing socioeconomic status. Prior work provides evidence that individuals with lower socioeconomic status are more likely to be exposed to higher levels of air pollution, but limited work has explored the contribution of transportation systems to these disparities in risk across urban areas (e.g., Houston et al., 2014). Findings regarding transportation physical activity and socioeconomic status are mixed (Pearce et al., 2011). Thus, the model developed in this dissertation could be used to explore potentially disproportionate impacts of the transportation system on vulnerable populations.

Improved characterization of individual-level exposures will further clarify complex risk tradeoffs presented by transportation systems in urban areas. Active commuters may be exposed to significantly higher levels of air pollution while walking or biking along streets with more vehicular traffic (De Nazelle, Rodriguez, & Cawford-Brown, 2009). Walkers and cyclists may also face highly variable risks for fatal crashes as modified by built environment factors and the safety-in-numbers theory (Jacobsen, 2003; Gladhill & Monsere, 2012). More detailed understanding of how acute exposure in such microenvironments may modify risks for active commuters, as well as more detailed information regarding the location and timing of walking and biking trips, could provide a more nuanced consideration of individual-level risk within the modeling framework developed in this dissertation. Integration of this modeling framework with emerging transportation demand models, such as activity-based models, could support such efforts.

Application of the model developed here in a variety of contexts could bolster the generalizability of findings regarding tradeoffs among transportation health risks. Specifically, application of the model in urban areas with more developed public transportation systems (e.g., San Francisco, CA) and/or comparatively poor air quality (e.g., Los Angeles, CA) would provide additional evidence regarding the relationships between built environment variables and transportation health risks. Further, if time-series health, exposure, and built environment data are available in a region that undergoes a natural experiment the model developed here could be applied and estimates could be validated relative to observed data. For example, this model could be applied in a region to estimate changes in population health outcomes after expansion of transit system and these estimate could be compared to observed data. Such a natural experiment could provide a real-world validation of the modeling framework developed in this work, bolstering the rigor of the model substantially.

Similar to common methodological approaches in developing air quality models, the modeling framework developed in this dissertation could support research into the most substantial drivers of transportation health impacts. Rate constants could be derived from transition probabilities in the model in order to clarify the impact of each model parameter on population-level health impacts. A rank order model sensitivity to model parameters could then be developed, identifying key model sensitivities. Such research could inform targeted policy approaches to reduce transportation health impacts.

The model developed here offers a modular, scalable, and flexible framework for providing rigorous estimates of transportation system health impacts over time. As demonstrated in Chapter 4, this model can provide a detailed understanding of baseline transportation health risks across a study region. Critically, the flexibility of the modeling framework developed in this work could be easily adapted to provide decision-support for a wide variety of transportation and built environment decisions. For example, the model could be used to assess health impacts of alternatives at the project or planning scale. However, a tiered approach to estimating the health impacts of transportation systems may be advisable in translating the model developed here into practice. Careful consideration of when certain model components would be activated based on a risk screening approach could provide a unified framework for assessing transportation health risks across a wide range of scales and decision complexity. Pragmatically, transportation practitioners generally have substantially different skillsets than required to accurately apply the model developed in this dissertation in practice. As the fields of public health and transportation continue to merge, focus should be placed on building a shared set of core skills between public health and transportation practitioners to facilitate the application of robust transportation heath impact models such as the model developed here.

5.5. Conclusions

This dissertation develops a novel microsimulation framework to estimate the health impacts of competing transportation health risks present in urban environments. This model combines demonstrated advantages of dynamic microsimulation models (Chapter 2) with novel approaches for characterizing individual-level exposure to transportation health risks at high spatial resolution (Chapter 3). When applied in the Raleigh-Durham-Chapel Hill region, this model shows that the health benefits of increased transportation physical activity and reduced risk for fatal motor vehicle crashes outweigh concomitant health risks in walkable neighborhoods (air pollution and fatal crash risk for pedestrians and cyclists) (Chapter 4). Critically, the modeling framework developed is modular and scalable to enable consideration of transportation health risks in a range of routine transportation decision-making contexts. Further, this modeling framework is very well-positioned to be integrated into emerging transportation demand models, including activity-based models. While transportation agencies have expressed strong interest in integrating health considerations into transportation decision-making, existing tools and methods do not adequately assess the impacts of transportation decisions to this end. The modeling framework developed here uses an advanced, dynamic microsimulation health impacts model that could interface with existing transportation and public health data sources and provide transportation and public health researchers and practitioners with detailed and highly spatially refined estimates of transportation system heath impacts. As demonstrated by the application of this framework in the study region, the health benefits of transportation physical activity and reduced VMT in walkable neighborhoods—health pathways rarely considered in routine transportation decision-making processes—outweigh health risks in these same neighborhoods. To substantively consider the health implications of transportation decisions, a flexible, multi-risk decision-support tool is critically needed. The framework developed in this work provides such a tool.

APPENDIX A: SUPPLEMENTARY MATERIAL FOR CHAPTER 2, HEALTH IMPACTS OF INCREASED PHYSICAL ACTIVITY FROM CHANGES IN TRANSPORTATION INFRASTRUCTURE: QUANTITATIVE ESTIMATES FOR THREE COMMUNITIES

A.1 Additional Case Study Information

Descriptive information for each case study location is summarized in Table A.1. Summary information for meetings held in each community are presented in Table A.2 (scoping meetings) and Table A.3 (post-analysis meetings). Age- and sex-specific population distributions for each community are provided in Figure A.4.

A.1.1 Greenville MPO Bicycle and Pedestrian Master Plan, Winterville, NC

In 2011, the Greenville MPO completed a Bicycle and Pedestrian Master Plan for the Greenville Metropolitan Area, which includes Winterville. We consider the impact of building out the pedestrian network as specified in the plan compared to a no-build scenario (Figure A.1).

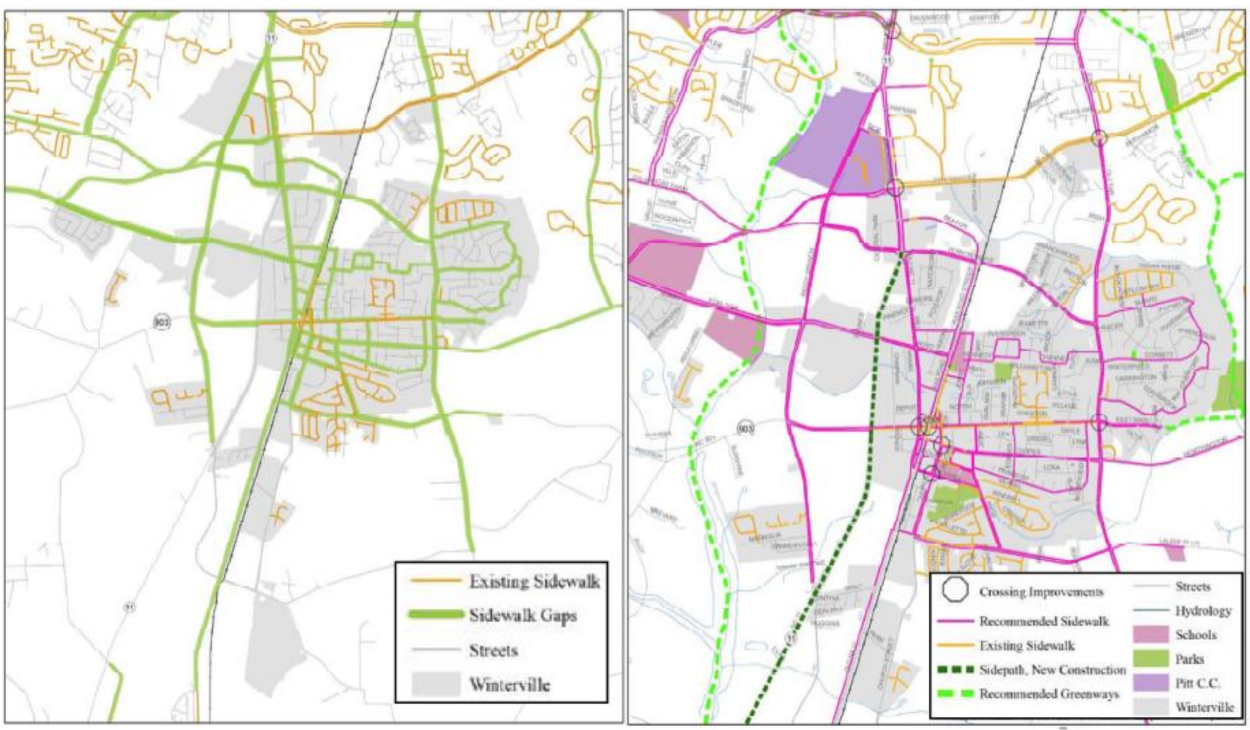


Figure A.1. Winterville existing pedestrian facilities (*left*) and proposed improvements (*right*)

A.1.2 Blue Ridge Road Project, Raleigh, NC

A community visioning and planning effort developed a small area plan for the Blue Ridge Road neighborhood, located in a currently suburban portion of Raleigh, NC. The small area plan includes significant land-use changes, construction of new sidewalks, and streetscape improvements (Figure A.2). We consider the impact of new sidewalks proposed in the plan compared to a no-build scenario.

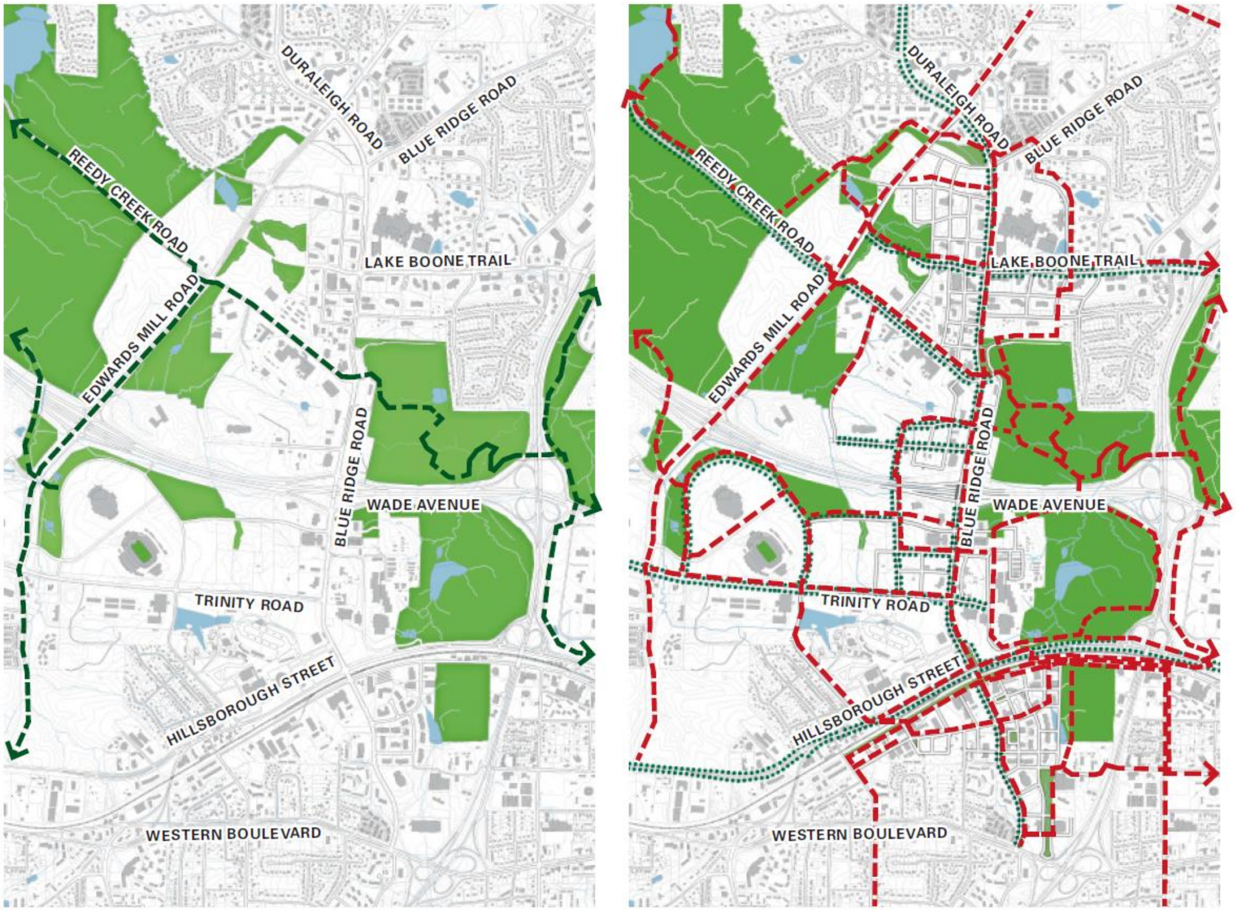


Figure A.2. BRRC existing open space and trails (*left*) and proposed open space, trails, and improved sidewalks (*right*)

Downtown Streetscape Master Plan, Sparta, NC

In 2012, the town of Sparta, NC completed a Downtown Streetscape Strategy, which proposes a number of improvements to the pedestrian environment in downtown. We conducted an HIA on the implementation of the plan and compared the results to the status quo scenario. The project contains streetscape and street crossing improvements along Main Street, which runs through downtown Sparta, as well as complementary improvements to several side streets (Figure 3).

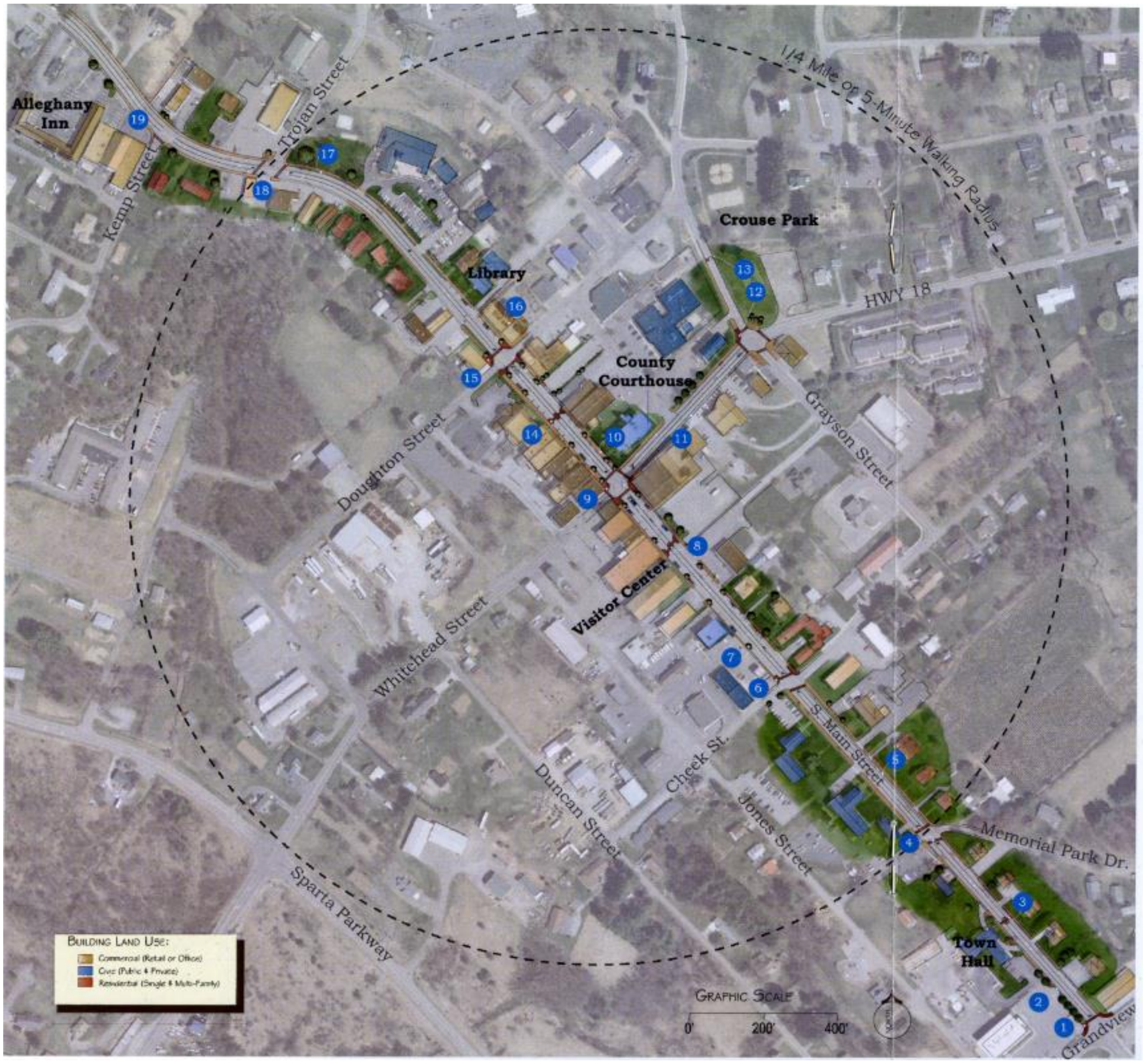


Figure A.3. Sparta proposed downtown streetscape improvements

Community Context

Descriptive statistics for each case study location is summarized in Table A.1. Summary information for meetings held in each community are presented in Table A.2 (scoping meetings) and Table A.3 (post-analysis meetings). Age- and sex-specific population distributions for each community are provided in Figure A.4.

Table A.1. Case Study Location Characteristics

	BRRC	Winterville	Sparta
Metro area population (*persons*)	403,892	9,269	1,770
Study area population (*persons*)	10,929	9,269	1,770
Study area size (*km*^{2})	6.2	11.9	6.2
Population density (*persons/mi*^{2})	1,731	778	285
Development context	Urban	Suburban	Rural
Planning scale	Small-area plan	Comprehensive plan	Corridor plan
Geographic region	Piedmont	Coastal	Mountains
Proposed improvements	New sidewalks	New sidewalks	Streetscape improvements
Length of proposed improvements *(km)*	30.9	82.7	0.6

Table A.2. BRRC focus groups

Meeting Date	Number of Participants	Stakeholder Affiliation
2/28/2012	6	BRRC residents
3/1/2012	9	BRRC HIA advisory council
3/6/2012	7	BRRC resident and property owners
3/8/2012	12	Employees and volunteers of the North Carolina Museum of Art
3/20/2012	6	Local officials, employees, local business owners, and students

Table A.3. Winterville and Sparta meeting participants

	Participant	Role	Organization
Winterville	Alan Lilley	Planning Director	City of Winterville
	Jo Morgan	Health Education Director	Pitt County
	James Rhodes	Planning Director	
	Jennifer Smith	Manager	Vidant Health
	Daryl Vreeland	Transportation Planner	MPO
Sparta	Teresa Buckwalter	Principal	Consultant
	Eric Woolridge	Principal	
	Kevin Dowell	Planner and Codes Enforcement	Town of Sparta
	Bryan Edwards	Town Manager	
	Beth Fornadley	District Health Educator	Appalachian District Health Department
	Jennifer Greene	Director of Allied Health Services	
	Rachel Miller	CTG Health Eating/Active Living Lead	
	Jane Wyatt	Board Member	Chamber of Commerce

Table A.4. Summary of BRRC focus groups and Winterville and Sparta community meeting

	BRRC (top twelve recommended changes from focus groups meetings)	**Winterville**	**Sparta**
Built environment and land use	▪ Make the neighborhood more aesthetically pleasing ▪ Build more things to walk to ▪ Encourage mixed-use development ▪ Encourage greater land-use density	▪ Non-walkable development scales ▪ Car-oriented development ▪ Segregated land uses ▪ Lack of services and employment within city ▪ School siting	▪ Incomplete sidewalk network ▪ Heavy traffic along key routes ▪ Segregated land uses ▪ Rural school siting
Transportation infrastructure	▪ Build sidewalks and crosswalks on major roads ▪ Build bike lanes and bike racks ▪ Build more walking trails ▪ Improve access to walking trails and open space ▪ Improve publicity of existing facilities (e.g., signage, maps, etc.)	▪ Lack of sidewalks ▪ Poor sidewalk connections between developments ▪ Road widening projects undertaken without improvements to sidewalks/bike lanes ▪ Highway and rail that bisects town presents barriers to walking/biking ▪ Poor aesthetic quality of streets	▪ Lack of sidewalks ▪ Width and quality of existing sidewalks (e.g., electric poles in the middle of sidewalks) ▪ Lack of zones to pass cyclists on rural roads ▪ Wide lanes throughout Sparta that encourage high travel speeds ▪ Downtown aesthetics not conducive to walking
Demographics and cultural factors	None	▪ High rates of poverty ▪ High prevalence of risk factors (smoking, alcohol consumption, etc.)	▪ High rates of poverty ▪ Older population ▪ Many residents do not have health insurance ▪ Cultural bias towards the car (rural setting) ▪ Poor nutrition/access to healthy foods ▪ Cultural norms that support tobacco use
Services	▪ Improve the connectivity of public transportation ▪ Build more water fountains and restrooms for walkers and runners	▪ Lack of public transit ▪ Poor access to facilities that offer affordable healthcare	▪ Lack of public transit service ▪ Fragmentation of government services downtown: historically housed in a single building and residents would park once in downtown and walk to other destinations; services now offered in different buildings and residents drive to each
Social and/or economic conditions	▪ Improve educational opportunities	▪ Stigmatization of walking and biking for transportation ▪ Poor awareness the rules of the road by drivers, cyclists, and pedestrians in multi-modal situations	▪ Stigmatization of walking for transportation ▪ Large percentage of the population on fixed incomes ▪ Large number of seasonal workers
Natural environment	None	▪ Noise and air pollution due to North Carolina Highway 11	▪ Extreme elevation changes make cycling (walking not mentioned) difficult; thus, cycling is largely a recreational activity ▪ Lack of programmed open space (e.g., sports fields, playgrounds, etc.)

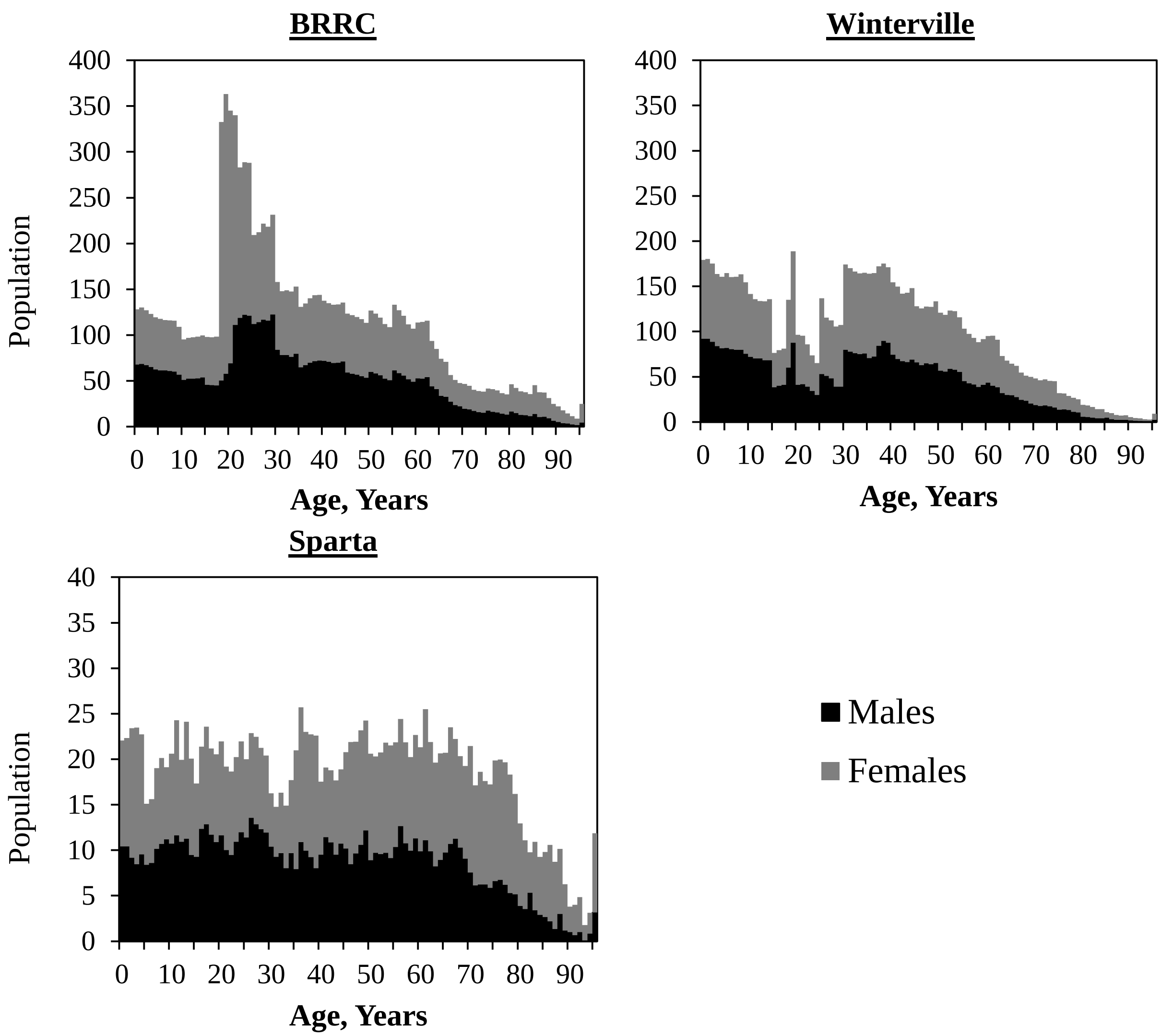


Figure A.4. Case Study Population Distributions

A.2 Baseline Health Information

Additional details are presented below regarding our procedure to estimate continuous disease prevalence and incidence functions for CHD, diabetes, hypertension, and stroke as a function of age in each case study location (Table S4). Detailed vital statistics (baseline death rate, birthrate, and gender ratio) are presented in Table S5.

A.2.1 Disease Prevalence and Incidence Functions

To develop continuous age- and sex-specific prevalence functions for CHD, diabetes, hypertension, and stroke, we use data from the 2009 North Carolina BRFSS survey. The survey asks whether or not a respondent has been diagnosed with these conditions and reports prevalence by age group. In each community, we fit a second-order function to these data assuming that the prevalence reported for each age group represented the actual prevalence of that disease at the population-weighted midpoint of the age group. Using these prevalence estimates, we then derive the age-specific rate at which individuals would have had to develop a disease in order for the observed prevalence to occur. To do so, we define second-order age-specific prevalence functions, $p(x)$, and take the derivative:

$$p(x) = \alpha \cdot x^2 + \beta \cdot x + \gamma$$

$$\frac{dp}{dx} = 2 \cdot \alpha \cdot x + \beta$$

$x =$ age (years)

$\alpha =$ derived parameter for second-order term

$\beta =$ derived parameter for first-order term

$\gamma =$ derived constant

And define $c(x)$:

$$c(x) = \frac{\frac{dp}{dx}}{(1 - p(x))}$$

$c(x) =$ number of cases at age x

And define the incidence function, $i(x)$:

$$i(x) = c(x) + m(x) \cdot (1 - (p(x) \cdot R(x) - 1)^{-1})$$

$i(x) =$ Incidence rate at age x

$m(x) =$ All-cause mortality at age x

$R(x) =$ Relative risk of all-cause mortality associated with the disease for which incidence is being derived at age x

Estimated disease prevalence and incident functions are presented in Table A.4.

Table A.5. Baseline Disease Functions

	Case Study Location	Prevalence as a function of age, *p(x)* Incidence as a function of age, *i(x)*
CHD	BRRC	$p(x) = 9.7 \times 10^{-3} - 9.1 \times 10^{-4}x + 2.5 \times 10^{-5}x^2$ $i(x) = 0.37 - 5.0 \times 10^{-2}x + 2.4 \times 10^{-3}x^2 - 4.3 \times 10^{-5}x^3 + 2.8 \times 10^{-7}x^4$
	Winterville	$p(x) = 6.1 \times 10^{-3} - 2.1 \times 10^{-4}x + 1.2 \times 10^{-5}x^2$ $i(x) = 0.38 - 4.5 \times 10^{-2}x + 2.0 \times 10^{-3}x^2 - 3.5 \times 10^{-5}x^3 + 2.3 \times 10^{-7}x^4$
	Sparta	$p(x) = -2.3 \times 10^{-2} + 5.1 \times 10^{-4}x + 1.9 \times 10^{-5}x^2$ $i(x) = 0.50 - 4.8 \times 10^{-2}x + 2.2 \times 10^{-3}x^2 - 3.8 \times 10^{-5}x^3 + 2.5 \times 10^{-7}x^4$
Diabetes	BRRC	$p(x) = -5.6 \times 10^{-2} + 2.1 \times 10^{-3}x + 1.1 \times 10^{-5}x^2$ $i(x) = 0.76 - 6.5 \times 10^{-2}x + 2.8 \times 10^{-3}x^2 - 5.1 \times 10^{-5}x^3 + 3.3 \times 10^{-7}x^4$
	Winterville	$p(x) = -1.4 \times 10^{-2} - 3.9 \times 10^{-4}x + 4.4 \times 10^{-5}x^2$ $i(x) = 0.94 - 1.1 \times 10^{-1}x + 4.6 \times 10^{-3}x^2 - 8.0 \times 10^{-5}x^3 + 5.1 \times 10^{-7}x^4$
	Sparta	$p(x) = -7.7 \times 10^{-2} + 3.4 \times 10^{-3}x + 1.3 \times 10^{-6}x^2$ $i(x) = 1.02 - 8.1 \times 10^{-2}x + 3.3 \times 10^{-3}x^2 - 5.5 \times 10^{-5}x^3 + 3.4 \times 10^{-7}x^4$
Hypertension	BRRC	$p(x) = -7.6 \times 10^{-2} + 5.0 \times 10^{-3}x + 6.1 \times 10^{-5}x^2$ $i(x) = 2.3 - 2.1 \times 10^{-1}x + 9.6 \times 10^{-3}x^2 - 1.8 \times 10^{-4}x^3 + 1.2 \times 10^{-6}x^4$
	Winterville	$p(x) = -2.1 \times 10^{-1} + 1.1 \times 10^{-2}x - 2.9 \times 10^{-6}x^2$ $i(x) = 2.7 - 2.0 \times 10^{-1}x + 8.9 \times 10^{-3}x^2 - 1.6 \times 10^{-4}x^3 + 1.0 \times 10^{-6}x^4$
	Sparta	$p(x) = -1.6 \times 10^{-1} + 8.9 \times 10^{-3}x + 1.3 \times 10^{-5}x^2$ $i(x) = 1.8 - 1.1 \times 10^{-1}x + 5.1 \times 10^{-3}x^2 - 8.8 \times 10^{-5}x^3 + 5.9 \times 10^{-7}x^4$
Stroke	BRRC	$p(x) = 2.9 \times 10^{-2} - 2.5 \times 10^{-3}x + 5.2 \times 10^{-5}x^2$ $i(x) = 1.3 - 1.5 \times 10^{-1}x + 6.3 \times 10^{-3}x^2 - 1.1 \times 10^{-4}x^3 + 6.6 \times 10^{-7}x^4$
	Winterville	$p(x) = 3.1 \times 10^{-2} - 2.4 \times 10^{-3}x + 4.3 \times 10^{-5}x$ $i(x) = 2.5 - 2.7 \times 10^{-1}x + 1.0 \times 10^{-2}x^2 - 1.6 \times 10^{-4}x^3 + 9.0 \times 10^{-7}x^4$
	Sparta	$p(x) = -1.3 \times 10^{-3} - 1.5 \times 10^{-4}x + 1.5 \times 10^{-5}x$ $i(x) = 0.52 - 5.9 \times 10^{-2}x + 2.6 \times 10^{-3}x^2 - 4.6 \times 10^{-5}x^3 + 3.0 \times 10^{-7}x^4$

Table A.6. Baseline Vital Statistics

		BRRC		Winterville		Sparta	
	Age Group	Male	Female	Male	Female	Male	Female
Death Rate (per 100,000)	0-5	160.01	172.81	226.60	243.86	367.65	75.71
	5-10	6.63	13.79	57.45	20.52	188.39	94.80
	10-15	16.65	7.00	20.69	0	331.13	118.69
	15-20	49.94	19.61	61.51	13.58	286.16	148.61
	20-25	93.44	27.91	152.66	30.10	352.67	186.08
	25-35	80.80	31.83	186.20	77.9	146.41	378.07
	35-45	115.57	89.44	187.38	117.32	787.40	408.71
	45-55	245.93	182.33	744.58	352.75	626.57	641.85
	55-65	727.96	530.22	1,088.58	643.99	985.22	853.66
	65-75	2,079.77	1,508.45	3,381.39	2,321.51	2,503.91	845.07
	75-85	5,955.81	4,021.64	6,068.60	4,555.74	5,507.25	1,486.20
	85+	14,704.68	14,568.07	14,951.77	12,741.31	11,764.71	9,691.63
Birth Rate		0.0146		0.0145		0.00977	
Gender Ratio (M:F)		1.05		1.04		1.25	

A.3 Baseline Transportation Behavior

In Winterville and Sparta, we use data from the 2009 BRFSS survey. In 2009, North Carolina included an additional question regarding walking for transportation. Specifically, the survey asked "In the past week, how much time did you walk or bicycle for transportation, such as to and from work or shopping, or walk to the bus stop?" Respondents replied in one of five categories: No time, Less than 30 minutes, 30 minutes to 1 hour, 1 to 2 hours, or 2 hours or more.[34] In Winterville, we use county-level data (Pitt County) whereas in Sparta we use data aggregated across the Northwest Area Health Education Center (HEC), a ten-country area (Alleghany, Ashe, Davie, Davidson, Forsyth, Stokes, Surry, Watauga, Wilkes, and Yadkin counties). In BRRC, we use data from a survey conducted in 2012 by MacDonald Gibson et al. The survey used the International Physical Activity questionnaire, a previously validated survey instrument.[37] The survey asked two questions from which estimates of weekly walking for transportation were derived: "During the last 7 days, on how many days did you walk for at least 10 minutes at a time to go from place to place?" immediately followed by "How much time did you usually spend on one of those days walking from place to place?" These estimates were then used to develop a distribution of walking for transportation time by placing each in one of 20 transportation physical activity time bins to: one for no walking, a series of twenty-minute bins up to 360 minutes per week (i.e., 0–20 minutes, 20–40 minutes, etc.), and a top bin for greater than 360 minutes per week.[36] Survey characteristics are summarized in Table A.6.

Table A.7. Baseline Transportation Physical Activity Survey Characteristics

Case Study Location	Survey and question wording	Sample size	Responses: Category	n	Percent
BRRC	Survey Based on International Physical Activity Questionnaire *Question wording: "During the last 7 days, on how many days did you walk for at least 10 minutes at a time to go from place to place?* *How much time did you usually spend on one of those days walking from place to place?"*	386	0	157	40.7%
			1–20	28	7.3%
			20–40	30	7.8%
			40–60	32	8.3%
			60–80	17	4.4%
			80–100	21	5.4%
			100–120	18	4.7%
			120–140	8	2.1%
			140–160	7	1.8%
			160–180	6	1.6%
			180–200	1	0.3%
			200–220	13	3.4%
			220–240	3	0.8%
			240–260	2	0.5%
			260–280	7	1.8%
			280–300	4	1.0%
			300–320	4	1.0%
			320–340	0	0.0%
			340–360	4	1.0%
			360+	24	6.2%
Winterville (Pitt County)	2009 NC BRFSS *Question wording: "In the past week, how much time did you walk or bicycle for transportation, such as to and from work or shopping, or walk to the bus stop?"*	323	0	276	84.3%
			1–30	14	3.4%
			30–60	11	2.5%
			60–120	9	2.9%
			120+	13	6.9%
Sparta (Northwest Area HEC)	2009 NC BRFSS *Question wording: "In the past week, how much time did you walk or bicycle for transportation, such as to and from work or shopping, or walk to the bus stop?"*	2,661	0	2,322	85.3%
			1–30	82	3.7%
			30–60	70	3.2%
			60–120	70	2.7%
			120+	117	5.0%

A.4 Economic Valuations

To account for uncertainty inherent in selecting an appropriate discount rate, we consider three discount rates: 7%, 5%, and 3.5%. Benefit-cost ratios for the central estimate of health outcomes for each case study location at each of these three discount rates are plotted in Figure A.2.

Table A.8. Economic valuation assumptions

Health Outcome	Source of Monetary Benefits	Monetary Value (2012 USD)
Avoided premature mortality	Value of a statistical life (VSL)	$9,100,000
CHD	*Yearly treatment costs*	*$8,154*
	Yearly productivity losses	*$4,981*
	Total yearly costs avoided:	$13.135
Diabetes	*Yearly treatment costs*	*$11,508*
	Yearly productivity losses	*$2,763*
	Total yearly costs avoided:	$14.271
Hypertension	*Yearly treatment costs*	*$11,321*
	Yearly productivity losses	*$1,265*
	Total yearly costs avoided:	$12,685
Stroke	*Yearly treatment costs*	*$13,551*
	Yearly productivity losses	*$9,001*
	Total yearly costs avoided:	$22,552

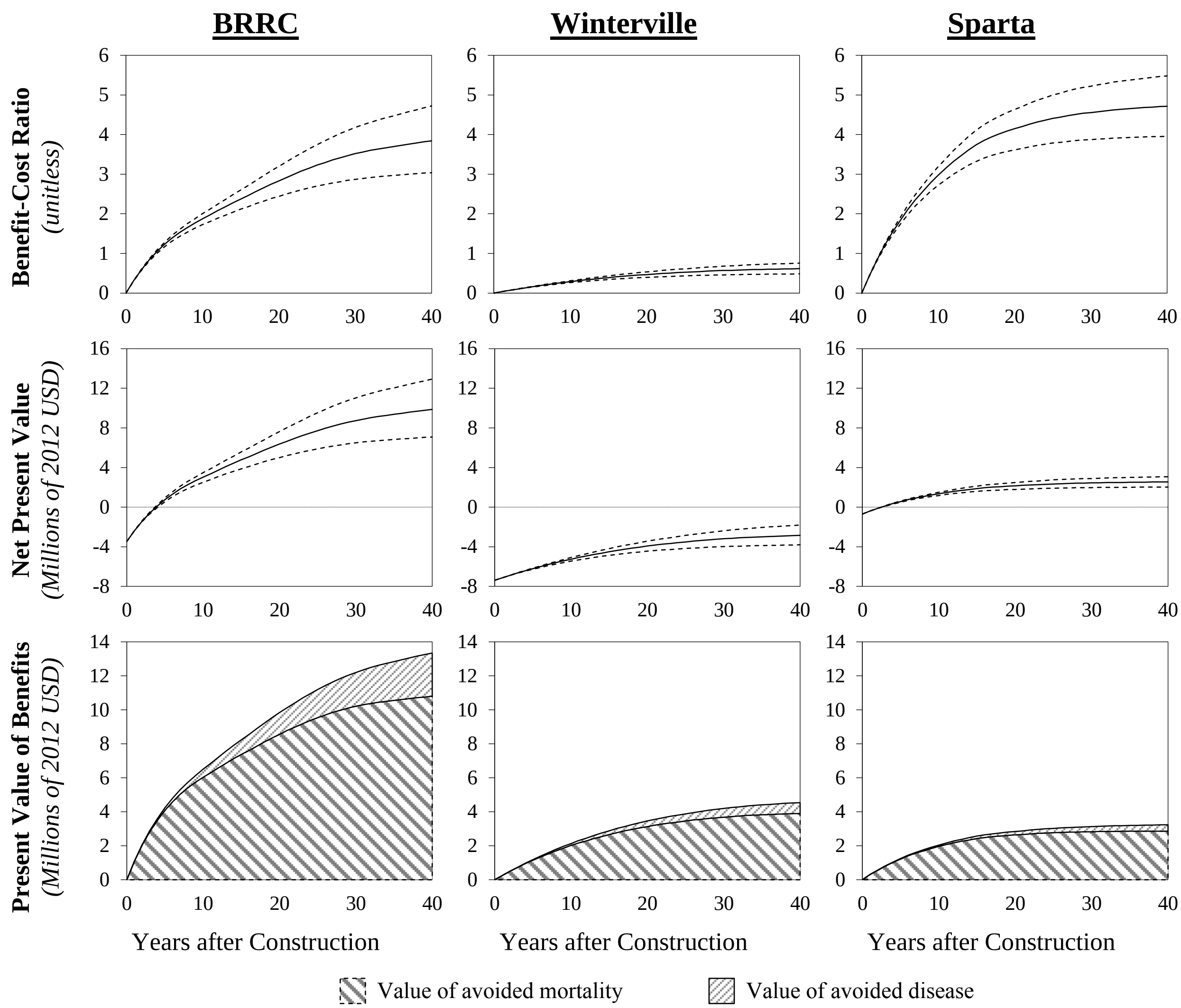
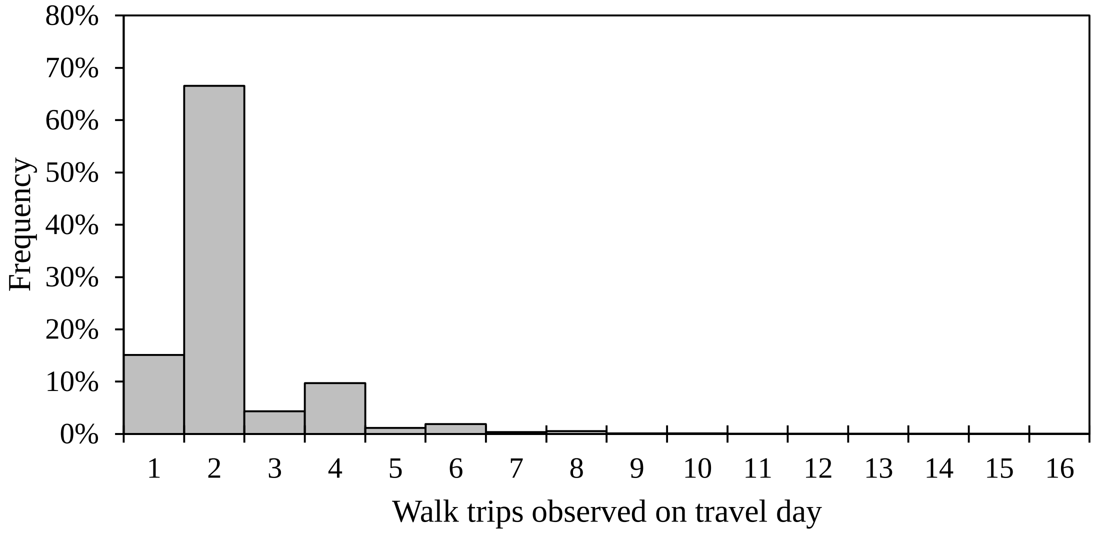


Figure A.5. Economic valuations over time

APPENDIX B: SUPPLEMENTARY MATERIAL FOR CHAPTER 3, ESTIMATING ACTIVE TRANSPORTATION BEHAVIORS TO SUPPORT HEALTH IMPACT ASSESSMENT IN THE UNITED STATES

B.1. Supporting descriptive statistics of the 2009 National Household Travel Survey and 2006 Greater Triangle Travel Survey

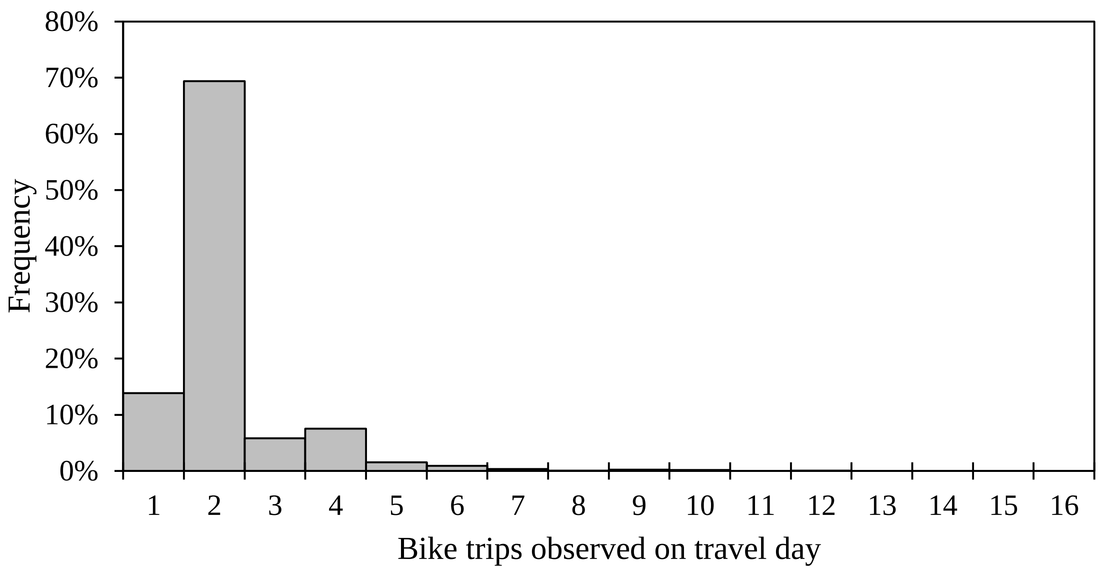
Unweighted descriptive statistics of the final sample used to estimate all regression models (NHTS) validate the transportation physical activity model (Greater Triangle Travel Survey) are summarized in Table B.1 (person file) and Table B.2 (trip file). Distributions of observed daily walk and bike trip counts in the 2009 National Household Travel Survey are presented in Figure B.1.



Percent zero counts, travel day walk trips: 86.0%

Mean: 0.32 (including zeroes); 2.27 (excluding zeroes)

Variance: 0.82 (including zeroes); 1.43 (excluding zeroes)



Percent zero, travel day bike trips: 98.9%

Mean: 0.025 (including zeroes); 2.22 (excluding zeroes)

Variance: 0.069 (including zeroes); 1.17 (excluding zeroes)

Figure B.1. Distribution of non-zero trip observed walk and bike trips counts and descriptive statistics showing little evidence of overdispersion for non-zero counts

Table B.1. Unweighted Descriptive Statistics, Person Data

Variable	2009 NHTS In Labor Force (n = 109,250) Mean	S.D.	2009 NHTS Not In Labor Force (n = 119,743) Mean	S.D.	2006 Triangle Survey In Labor Force (n = 3,246) Mean	S.D.
Number of walk trips	0.31	0.90	0.30	0.92	0.88	3.40
Number of bike trips	0.03	0.26	0.02	0.22	0.14	0.91
Percentage reporting zero walk trips	86.3%		87.4%		78.8%	
Percentage reporting zero bike trips	98.9%		99.3%		95.7%	
Number of trips on travel day	4.34	2.67	3.45	2.91	4.92	2.66
Age	87.0	13.1	64.2	16.7	47.4	13.2
Population density [a]	3.55	4.99	3.46	4.96	1.56	1.63
Percent units rented [a]	23.7%	21.2	25.1%	21.5	34.0%	20.3
Travel time to work [a]	23.2	17.3	-	-	25.9	5.36
Mode to work						
Automobile	95.1%		-	-	94.0%	
Public Transit	2.53%		-	-	2.50%	
Walk	1.81%		-	-	2.56%	
Bike	0.55%		-	-	0.96%	
Male	50.2%		38.9%		42.4%	
Female	49.8%		61.1%		57.6%	
Race/Ethnicity						
Non-Hispanic White	82.5%		83.8%		82.1%	
Non-Hispanic Black	5.29%		5.92%		10.9%	
Hispanic	7.63%		6.73%		3.57%	
Non-Hispanic Asian	2.72%		1.60%		1.85%	
Non-Hispanic Other	1.89%		1.90%		1.60%	
Education						
Less than High School	3.91%		12.0%		2.05%	
High School or GED	23.8%		32.8%		11.1%	
Some college	29.5%		27.3%		13.2%	
Bachelor's/Associate	24.4%		16.7%		43.3%	
Graduate/Professional	18.5%		11.3%		30.5%	
Medical Condition	2.69%		23.1%		2.53%	
Heavy Rail in MSA	18.3%		16.3%		0%	
Proxy Respondent	18.2%		16.1%		4.78%	
Season						
Winter	23.3%		22.6%		68.5%	
Spring	23.1%		24.8%		0%	
Summer	27.9%		27.2%		0%	
Fall	25.6%		25.5%		31.5%	

[a] For the 2006 Triangle household survey, value is taken from mean value of block group containing household

Table B.2. Unweighted Descriptive Statistics, Active Trips (NHTS only)

Working Adults	All active trips (n = 36,569)		Walk trips (n = 33,863)		Bike trips (n = 2,706)	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.
Duration (min)	14.1	12.0	13.4	10.7	22.9	20.7
Trip Purpose						
Work commute	8.93%		7.54%		26.3%	
Shopping	9.44%		9.38%		10.2%	
Social	9.86%		9.91%		9.13%	
Recreational	36.6%		36.2%		40.9%	
Personal/family business	35.2%		36.9%		13.5%	
Trip duration, by purpose						
Work commute	13.3	12.9	11.0	10.2	21.2	17.5
Shopping	9.86	9.56	9.44	9.08	14.7	13.0
Social	10.6	11.2	10.2	10.3	17.1	18.6
Recreational	19.5	13.2	18.6	11.3	29.3	23.9
Personal/family business	10.9	8.7	10.7	8.33	16.8	15.6
Non-working Adults	All active trips (n = 37,311)		Walk trips (n = 35,330)		Bike trips (n = 1,981)	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.
Duration (min)	15.1	12.0	14/7	11.4	21.2	19.4
Trip Purpose						
Work commute	0%		0%		0%	
Shopping	14.8%		14.7%		16.6%	
Social	15.2%		15.2%		16.5%	
Recreational	43.2%		42.7%		50.5%	
Personal/family business	26.9%		27.5%		16.4%	
Trip duration, by purpose						
Shopping	11.8	11.0	11.6	10.8	14.0	12.9
Social	10.3	11.1	9.9	10.4	17.5	18.2
Recreational	19.5	12.5	19.0	11.6	26.1	21.2
Personal/family business	12.4	9.83	12.3	9.52	17.2	15.9

B.2. Supporting information for regression models

B.2.1. Trip count models

The Long and Freese countfit command was used in Stata to select between possible count model forms (Poisson, negative binomial, zero-inflated Poisson, and zero-inflated negative binomial). Convergence problems were encountered when estimating all zero-inflated negative binomial models; thus, only the first three model forms were compared (Figure B.2). In all cases, the zero-inflated Poisson regression model provided the best fit, as shown by various specification tests (Tables B.3 and B.4). Predicted probabilities are plotted versus observed counts in Figure B.3.

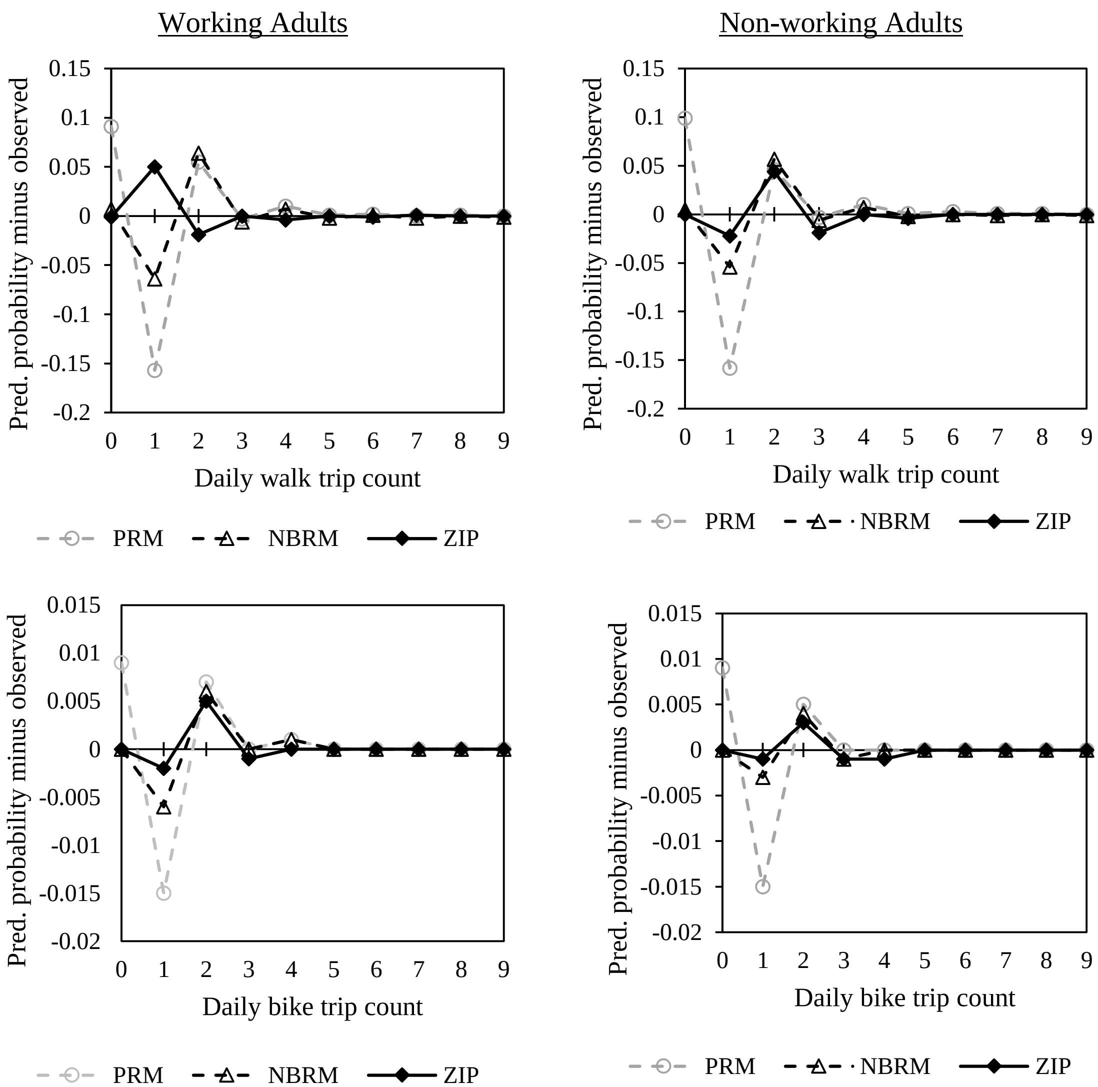


Figure B.2. Comparison of model error (predicted probability minus observed) for each model form (Poisson, negative binomial, and zero-inflated Poisson) for walk and bike trip count models for working adults and non-working adults.

Table B.3. Walk trip count modes specification tests, from Long and Freese countfit command

Model 1: Walk trips, working adults

PRM		BIC =145,099	AIC=144,421	Prefer	Over	Evidence
	Compared to NBRM	BIC=122,208	dif=22,891	NBRM	PRM	Very strong
		AIC=121,521	dif=22,901	NBRM	PRM	
		LRX2=22,903	prob=0	NBRM	PRM	*p=0.000*
	Compared to ZIP	BIC=112,221	dif=32,878	ZIP	PRM	Very strong
		AIC=110,837	dif=33,585	ZIP	PRM	
		Vuong= 97.433	prob=0	ZIP	PRM	*p=0.000*
NBRM		BIC =122,208	AIC=121,521	Prefer	Over	Evidence
	Compared to ZIP	BIC=112,221	dif=9,987	ZIP	NBRM	Very strong
		AIC=110,837	dif=10,684	ZIP	NBRM	

Model 2: Walk trips, non-working adults

PRM		BIC =152,134	AIC=151,434	Prefer	Over	Evidence
	Compared to NBRM	BIC=121,613	dif=30,621	NBRM	PRM	Very strong
		AIC=120,904	dif=30,531	NBRM	PRM	
		LRX2=30,533	prob=0	NBRM	PRM	*p=0.000*
	Compared to ZIP	BIC=113,667	dif=38,467	ZIP	PRM	Very strong
		AIC=112,287	dif=39,147	ZIP	PRM	
		Vuong= 93.347	prob=0	ZIP	PRM	*p=0.000*
NBRM		BIC =121,613	AIC=120,902	Prefer	Over	Evidence
	Compared to ZIP	BIC=113,667	dif=7,946	ZIP	NBRM	Very strong
		AIC=112,287	dif=8,617	ZIP	NBRM	

Table B.4. Bike trip count modes specification tests, from Long and Freese countfit command

Model 1: Bike trips, working adults

PRM		BIC =19,560	AIC=19,284	Prefer	Over	Evidence
	Compared to NBRM	BIC=15,571	dif=3,989	NBRM	PRM	Very strong
		AIC=15,285	dif=3,999	NBRM	PRM	
		LRX2=4,001	prob=0	NBRM	PRM	*p=0.000*
	Compared to ZIP	BIC=13,283	dif=6,278	ZIP	PRM	Very strong
		AIC=12,710	dif=6,574	ZIP	PRM	
		Vuong= 25.693	prob=0	ZIP	PRM	*p=0.000*
NBRM		BIC =15,571	AIC=15,285	Prefer	Over	Evidence
	Compared to ZIP	BIC=13,283	dif=2,289	ZIP	NBRM	Very strong
		AIC=12,710	dif=2,575	ZIP	NBRM	

Model 2: Bike trips, non-working adults

PRM		BIC =19,046	AIC=18,816	Prefer	Over	Evidence
	Compared to NBRM	BIC=11,977	dif=7,069	NBRM	PRM	Very strong
		AIC=11,737	dif=7,079	NBRM	PRM	
		LRX2=7,081	prob=0	NBRM	PRM	*p=0.000*
	Compared to ZIP	BIC=11,353	dif=7,692	ZIP	PRM	Very strong
		AIC=10,884	dif=7,932	ZIP	PRM	
		Vuong= 23.2	prob=0	ZIP	PRM	*p=0.000*
NBRM		BIC =121,613	AIC=120,902	Prefer	Over	Evidence
	Compared to ZIP	BIC=11,353	dif=623	ZIP	NBRM	Very strong
		AIC=10,884	dif=853	ZIP	NBRM	

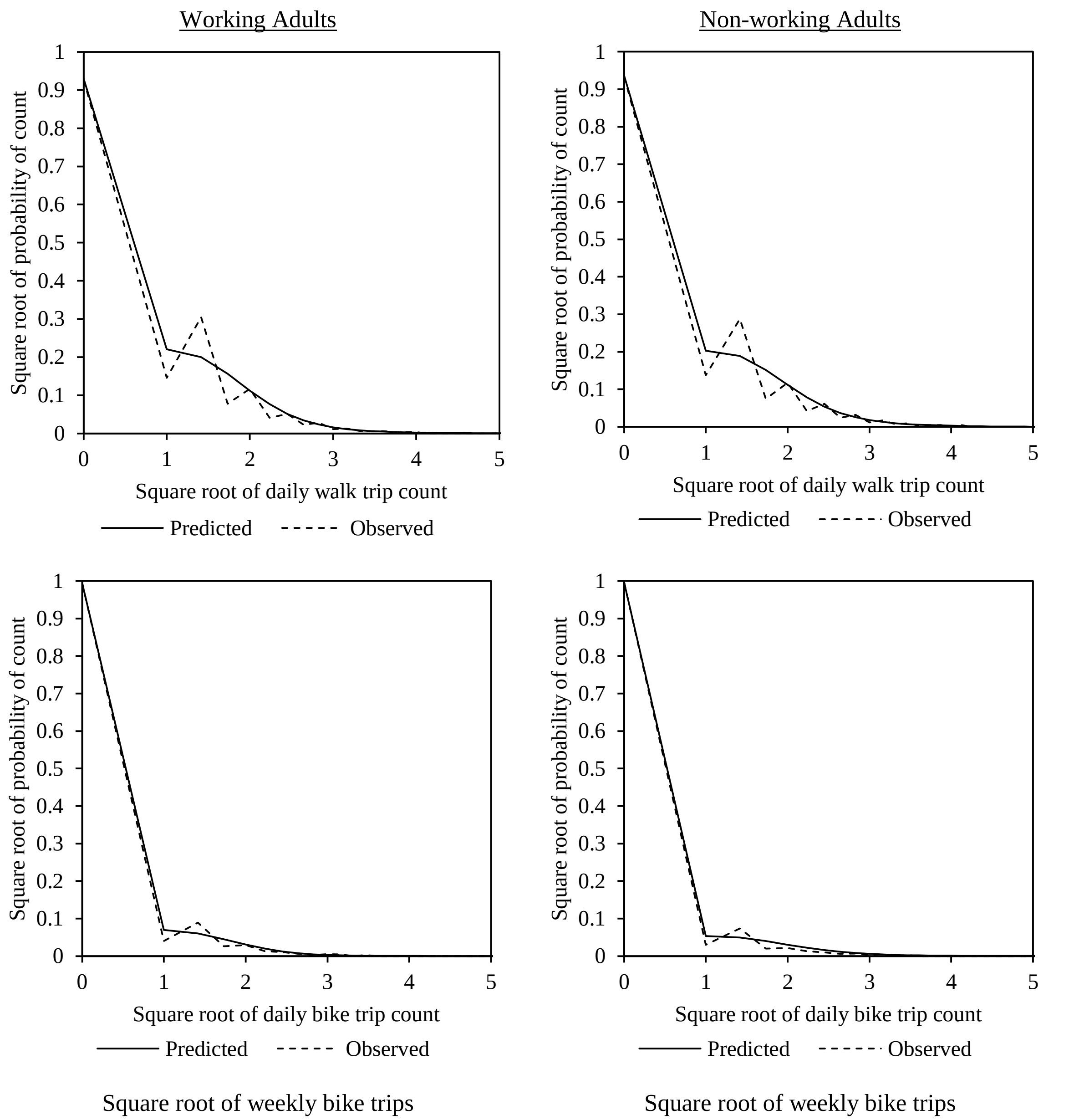


Figure B.3. Predicted probabilities of weekly walk and bike trips. Solid black lines illustrate predicted probabilities and observed trip counts are represented by the dashed black line.

B.2.2. Marginal Effects

Average marginal effects for working adults each model (count models, trip purpose probability models, and trip duration models) are presented in Table B.5 and Figures B.4, B.5, and B.6. These figures were generated using the margins command in Stata.

Table B.5. Average marginal effects, daily walk and bike trip count models

			Mode to Work *(ref: private vehicle)*			Population density	Percent rental units
			Public transit	Walk	Bike		
Daily walk trips	Both Sexes	Non-Hispanic White	0.49***	1.6***	0.30***	0.006***	0.002***
		Non-Hispanic Black	0.42***	1.4***	0.24***	0.005***	0.002***
		Hispanic	0.47***	1.5***	0.28***	0.006***	0.002***
		Non-Hispanic Asian	0.42***	1.4***	0.23***	0.005***	0.002***
		Non-Hispanic Other	0.47***	1.5***	0.28***	0.006***	0.002***
Daily bike trips	Male	Non-Hispanic White	0.06**	0.004	1.4***	0.001	-
		Non-Hispanic Black	0.02**	0.001	0.95***	0.0005	-
		Hispanic	0.04	0.003	1.5***	0.001	-
		Non-Hispanic Asian	0.01*	0.001	0.93***	0.0004*	-
		Non-Hispanic Other	0.05	0.004	1.4***	0.001	-
	Female	Non-Hispanic White	0.02	0.001	0.92***	0.0005	-
		Non-Hispanic Black	0.04*	0.003	1.5***	0.001*	-
		Hispanic	0.01*	0.001	0.85***	0.0004*	-
		Non-Hispanic Asian	0.03	0.002	1.2***	0.001	-
		Non-Hispanic Other	0.01	0.001	0.72***	0.0003	-

***p<0.01 **p<0.05 *p<0.10

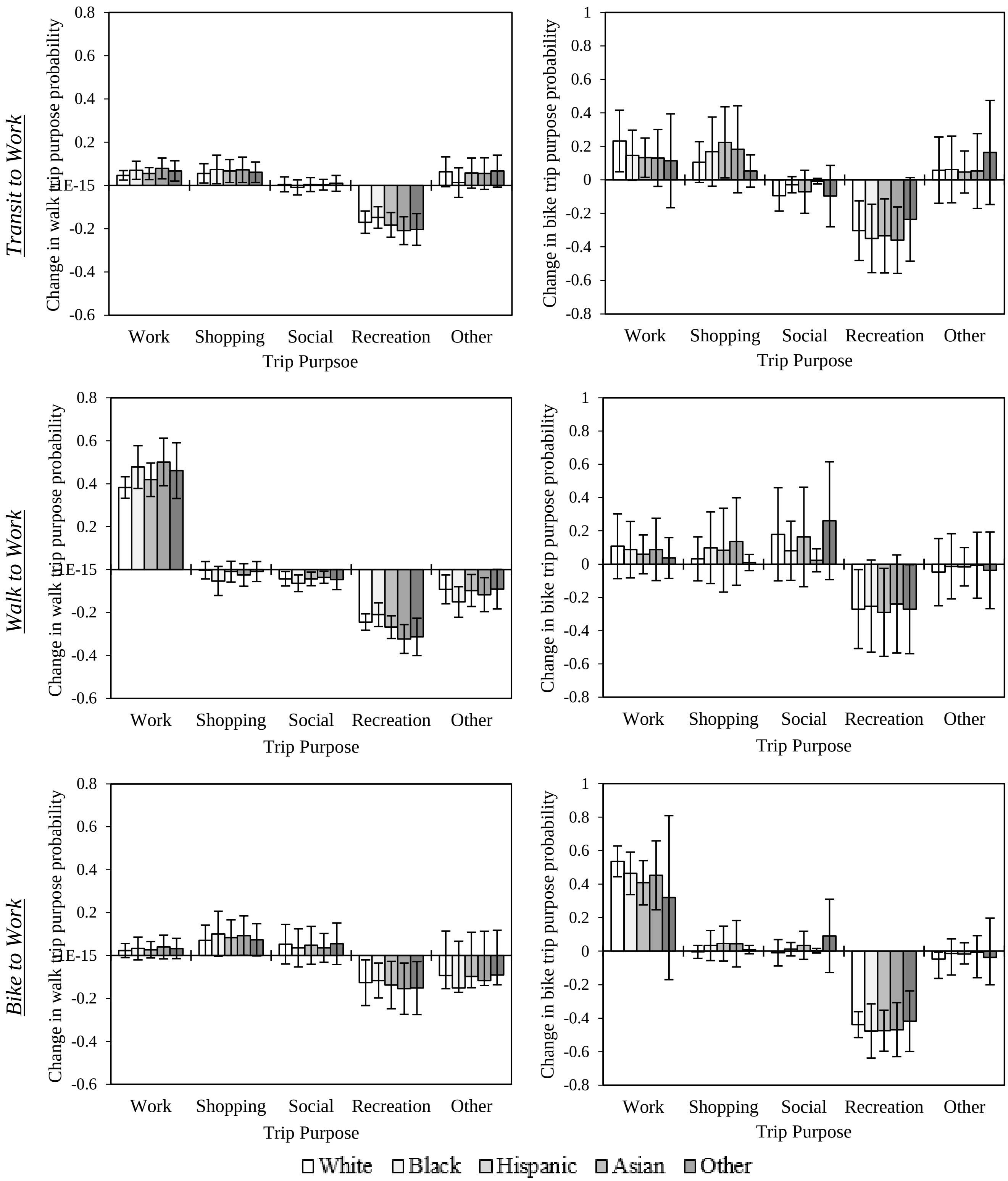


Figure B.4. Average marginal effects of commute mode to work on the probability that a given trip is for one of five purposes (listed across the bottom axis) by race/ethnicity relative to the reference group (private automobile to work)

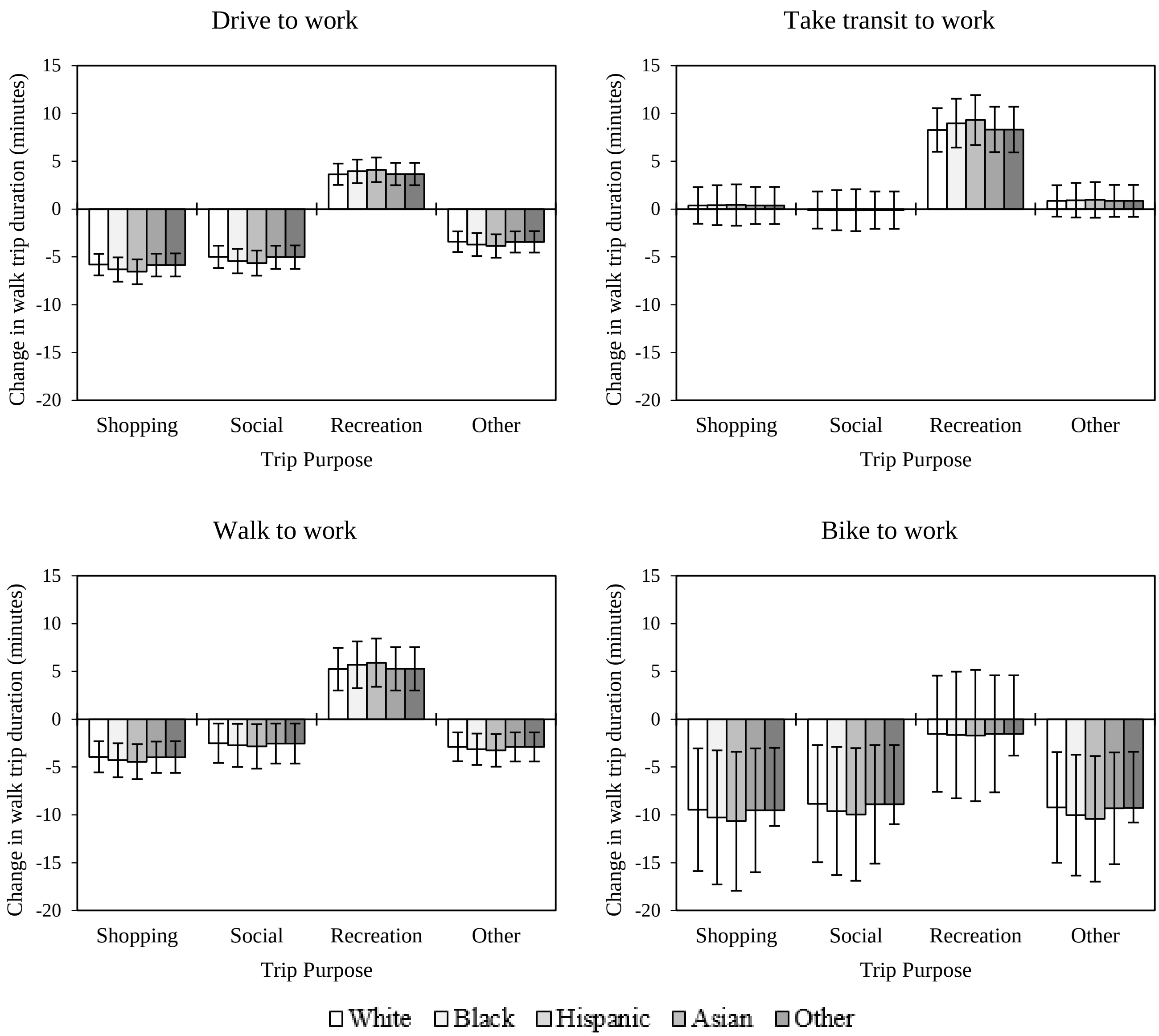


Figure B.5. Average marginal effects of trip purpose on walk trip duration for four trip purposes (listed across the bottom axis) relative to work trip duration, by commute mode to work and race/ethnicities

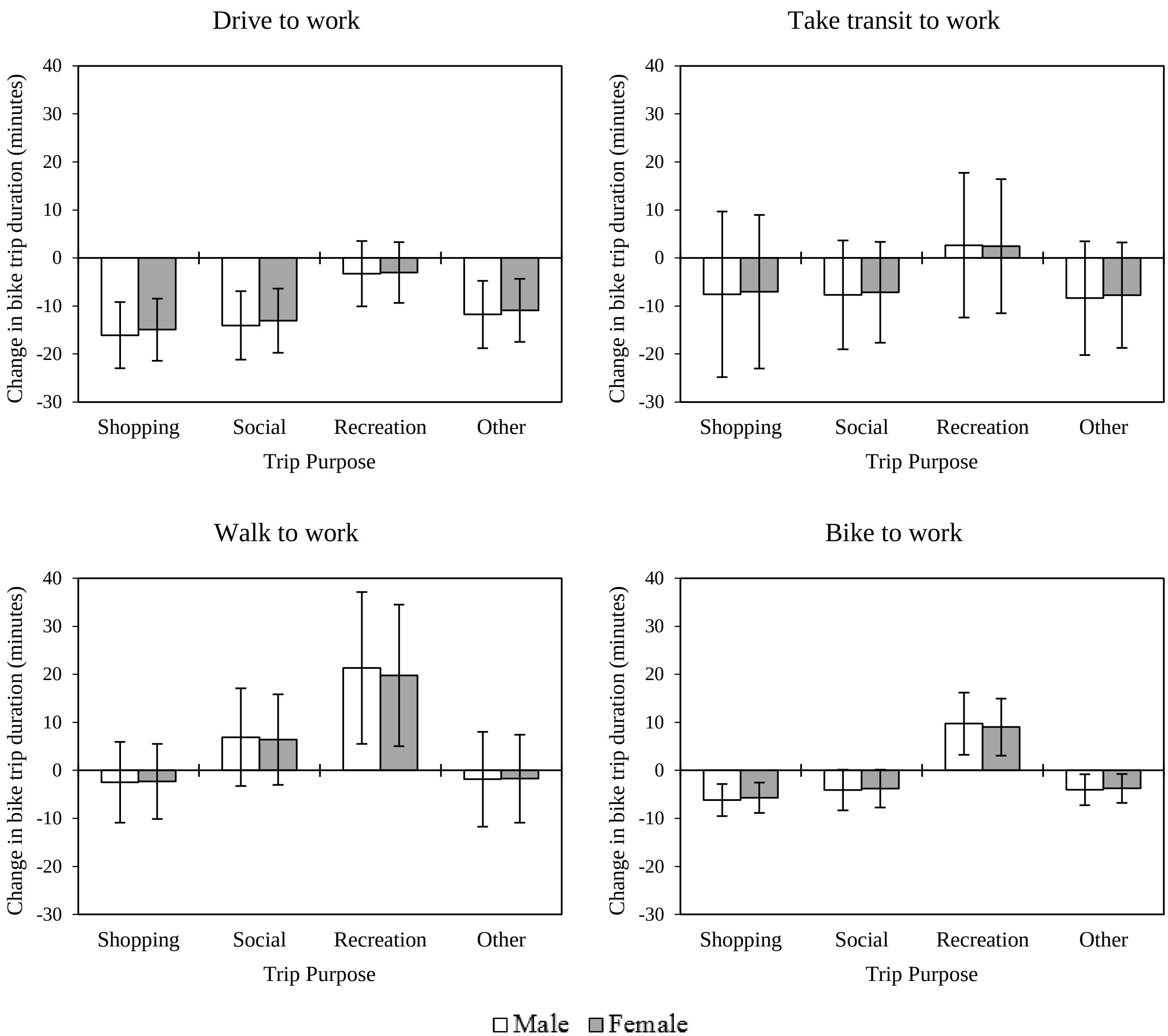


Figure B.6. Average marginal effects of trip purpose on bike trip duration for four trip purposes (listed across the bottom axis) relative to work trip duration, by commute mode to work and sex

B.3 Supporting demographic information

Five-year average death rates for men and women, grouped into 13 age categories, are presented for each county in the study region in Table B.6.

Table B.6. Baseline five-year (2009-2013) average death rates per 100,000 persons, by age, sex, and county

		Age Group												
County	Sex	<1	1-4	5-9	10-14	15-19	20-24	35-34	35-44	45-54	55-64	65-74	75-84	85+
Chatham	Male	354.5	14.4	0.0	0.0	76.5	140.1	131.8	174.4	470.3	1,031.8	1,733.1	4,289.9	13,368.2
	Female	456.2	0.0	9.9	0.0	0.0	59.1	75.4	96.1	206.3	534.2	1,072.3	3,649.4	12,441.1
Durham	Male	496.7	33.7	18.4	12.4	73.5	91.4	128.6	219.0	481.4	1,107.5	2,379.3	5,499.7	14,403.9
	Female	426.2	26.2	15.7	18.6	26.6	32.0	38.7	123.2	307.0	636.1	1,521.4	4,099.7	12,570.4
Franklin	Male	423.7	42.5	18.9	27.5	90.0	184.1	168.0	276.8	545.9	1,168.8	2,860.8	6,321.0	13,481.2
	Female	423.5	44.1	9.7	9.8	20.0	81.0	62.9	143.0	427.2	740.8	1,633.9	3,973.8	12,403.4
Granville	Male	533.0	18.1	10.6	10.6	100.9	152.7	164.5	225.5	556.6	1,092.5	2,513.4	6,048.7	14,508.5
	Female	269.3	88.6	11.5	11.3	21.9	43.0	33.3	155.3	334.6	794.2	1,702.6	4,741.0	12,582.4
Harnett	Male	574.7	30.0	21.3	48.2	115.3	183.9	169.5	274.3	609.1	1,385.1	2,859.2	6,580.1	15,711.1
	Female	437.1	6.2	13.4	9.1	64.3	37.9	60.7	129.0	351.6	722.5	1,762.1	4,626.9	14,329.7
Johnston	Male	416.5	26.5	14.3	11.4	88.4	171.1	144.1	228.4	493.0	1,260.5	2,855.3	6,427.9	17,881.1
	Female	409.8	51.7	6.1	3.2	34.4	83.5	68.2	120.8	370.4	696.9	1,741.7	4,523.0	15,120.2
Nash	Male	615.7	39.8	0.0	35.8	112.1	193.0	210.0	293.6	619.1	1,426.1	2,756.7	7,005.8	16,910.1
	Female	479.0	10.1	6.6	6.1	49.1	30.9	108.0	200.7	416.2	781.5	1,753.1	4,374.1	14,524.7
Orange	Male	386.1	17.2	5.0	19.0	37.6	51.1	92.0	112.2	359.8	744.4	1,692.7	5,150.4	16,231.0
	Female	209.5	17.5	10.4	14.4	27.1	14.8	71.8	90.7	228.9	482.8	1,184.5	3,842.7	13,697.5
Person	Male	557.9	96.5	15.2	0.0	45.5	132.4	187.8	264.9	631.5	1,172.2	2,853.2	6,489.5	17,165.2
	Female	358.2	24.4	17.0	15.5	32.5	42.6	108.0	144.2	448.9	692.5	1,668.9	4,604.0	14,827.5
Wake	Male	448.7	25.8	16.6	12.5	46.2	98.9	86.5	126.3	309.0	770.9	1,744.4	5,247.7	15,217.2
	Female	406.0	24.1	9.5	9.0	18.9	29.8	39.6	79.4	195.3	490.8	1,259.9	3,867.5	13,311.6

B.4. Step-by-step example of calculating health impact estimates

A step-by-step explanation of estimating transportation physical activity, assigning these estimates to a population distribution in a block group, and using these estimates to develop health impact estimates for an example block group is provided below. Block Group 2, Census Tract 107.03 in Orange County, North Carolina had 2,142 residents in 2013. This block group has a relatively high share of active commuters, with 70% of commuters traveling to work by car or working at home, 21% taking public transit to work, and 9% biking to work. The population is composed of 69% non-Hispanic White individuals, 9% non-Hispanic Black individuals, 12% Hispanic individuals, 3% non-Hispanic Asian individuals, and 7% non-Hispanic other individuals. This block group also has a high share of residential units that are rented (62.4%) and a higher than average population density (4,700 persons per square mile).

B.4.1. Step 1: Estimating daily walk and bike trip counts for workers and non-workers

Regression coefficients from the zero-inflated Poisson models are used to estimate daily walking and biking trips for a typical weekday and a typical weekend, once for workers and once for non-workers. Coefficients for explanatory variables are provided in Table 1 (walk trips) and Table 2 (bike trips). Coefficients for model controls are not presented in text but included in the application below. These models are estimated for all possible combinations of individual-level variables within each block group. Area-level variables (e.g., population density) vary between block groups; thus, all possible combinations of individual-level variables share the same area-level variables within a block group. This generates eight sets of estimates for $E(t_{m,i})$ in Equation 5:

1. Typical weekday walk trips for working adults, $E(t_{m=walk,i})|weekday,\ working$
2. Typical weekend walk trips for working adults, $E(t_{m=walk,i})|weekend,\ working$
3. Typical weekday walk trips for non-working adults, $E(t_{m=walk,i})|weekday, non\ working$
4. Typical weekend walk trips for non-working adults, $E(t_{m=walk,i})|weekend,\ nonworking$
5. Typical weekday bike trips for working adults, $E(t_{m=bike,i})|weekday,\ working$
6. Typical weekend bike trips for working adults, $E(t_{m=bike,i})|weekdend,\ working$

7. Typical weekday bike trips for non-working adults, $E(t_{m=bike,i})|weekday, nonworking$
8. Typical weekend bike trips for non-working adults, $E(t_{m=bike,i})|weekend,\ nonworking$

Each of these sets of estimates contains unique values for each possible combination of age (ranging from 18-95), sex (male or female), race (non-Hispanic White, non-Hispanic Black, Hispanic, non-Hispanic Asian, or non-Hispanic other), and, for working adults, mode to work (drive, transit, walk, or bike). These estimates are stored in a matrix $\mathbf{TPA_{count}}$ containing 3,900 cells (78 possible ages, two possible sexes, five possible races, and five possible modes to work, including non-working as a fifth mode). For our example block group, estimates of typical weekday daily walk trips for a working, non-Hispanic Black adult are provided below, by commute to work (Figure B.6):

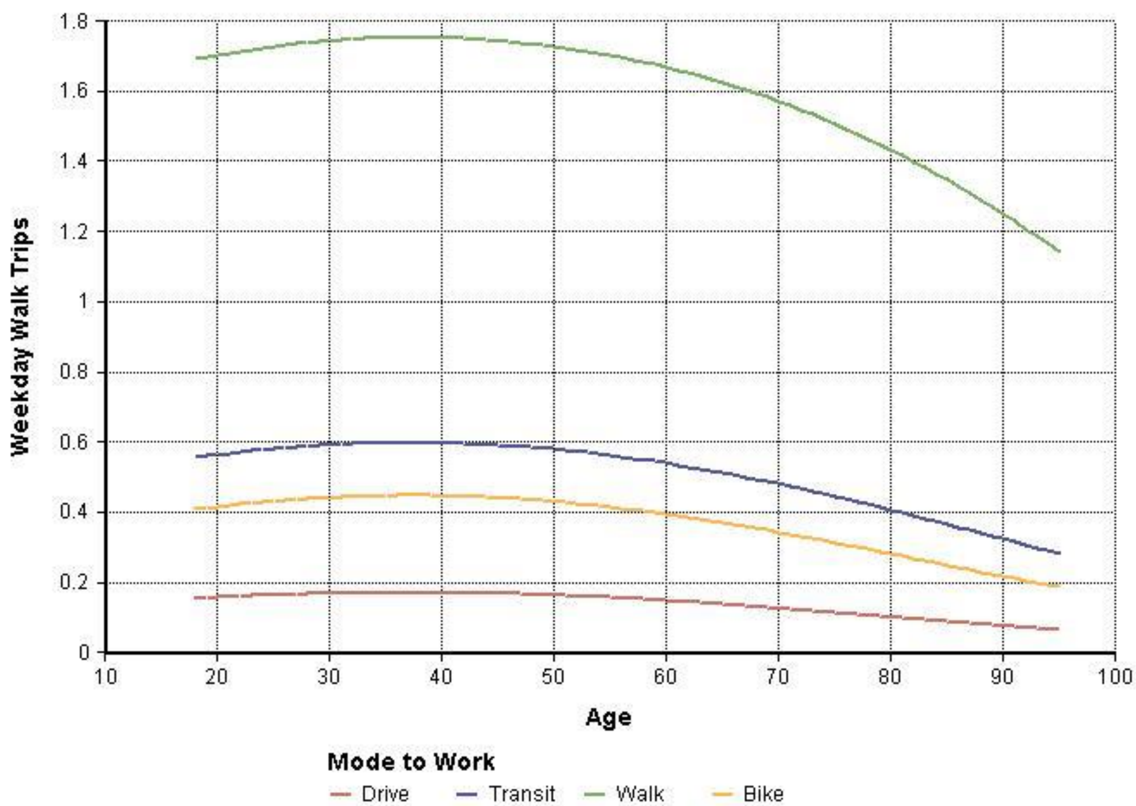


Figure B.7. Predictions of typical weekday walk trips for a non-Hispanic Black working adult living in the example block group

B.4.2. Step 2: Estimating walk and bike trip purpose probabilities for workers and non-workers

Regression coefficients from the multinomial logistic regression models are then used to estimate the probability that a given walk or bike trip for a specific individual is for one of the five purposes outlined in the text. Regression coefficients for these models appear in Table 3 (walk trips) and Table 4 (bike trips). Using the same dimensions as above, these models are used to estimate $Pr(p_{m,i})$ in Equation 5 for the same eight groups:

1. Weekday walk trips made by working adults, $Pr(p_{m=walk,i})|weekday,\ working$
2. Weekend walk trips made by working adults, $Pr(p_{m=walk,i})|weekend,\ working$
3. Weekday walk trips made by non-working adults, $Pr(p_{m=walk,i})|weekday,\ nonworking$
4. Weekend walk trips made by non-working adults, $Pr(p_{m=walk,i})|weekend,\ nonworking$
5. Weekday bike trips made by working adults, $Pr(p_{m=bike,i})|weekday,\ working$
6. Weekend bike trips made by working adults, $Pr(p_{m=bike,i})|weekend,\ working$
7. Weekday bike trips made by non-working adults, $Pr(p_{m=bike,i})|weekday,\ nonworking$
8. Weekend bike trips made by non-working adults, $Pr(p_{m=bike,i})|weekend,\ nonworking$

As before, each of these sets of estimates contains unique values for each possible combination of age (ranging from 18-95), sex (male or female), race (non-Hispanic White, non-Hispanic Black, Hispanic, non-Hispanic Asian, or non-Hispanic other), and, for working adults, mode to work (drive, transit, walk, or bike). Additionally, unique estimates for each trip purpose are included for each set. These estimates are stored in a matrix $\mathbf{TPA_{prob}}$ containing 19,500 cells (five possible purposes, 78 possible ages, two possible sexes, five possible races, and five possible modes to work, including non-working as a fifth mode).

For our example block, estimates of walk trip purpose probabilities for a non-Hispanic Black adult who takes transit to work across age are provided below (Figure B.7):

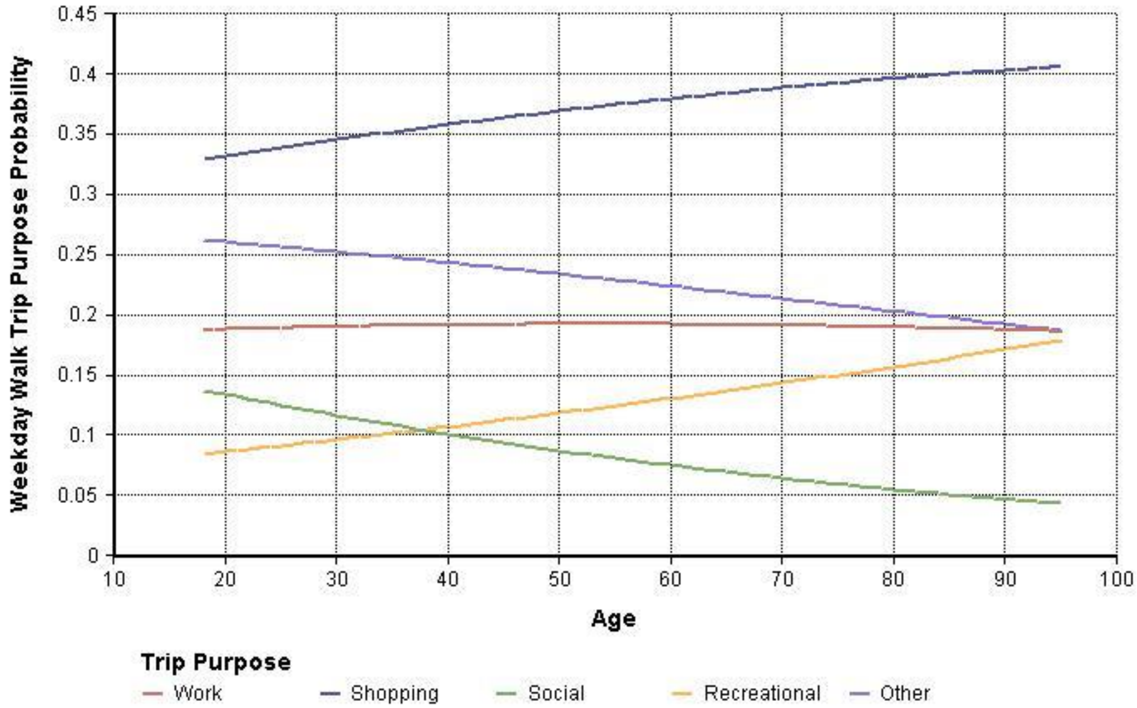


Figure B.8. Predictions of weekday walk trip purpose probabilities for a non-Hispanic Black working adult who takes transit in work living in the example block group

B.4.3. Step 3: Estimating walk and bike trip durations for workers and non-workers

Finally, regression coefficients from the GEE models are then used to estimate the duration of walk and bike trips made by an individual for a specific purpose Regression coefficients for these models appear in Table 5 (walk trips) and Table 6 (bike trips). Using the same dimensions as above, these models are used to estimate $d_{p,m,i}$

1. Weekday walk trips durations for working adults, $\boldsymbol{d_{p,m,i}}|weekday,\ working$
2. Weekend walk trips durations for working adults, $\boldsymbol{d_{p,m,i}}|weekend,\ working$
3. Weekday walk trips durations for non-working adults, $\boldsymbol{d_{p,m,i}}|weekday,\ nonworking$
4. Weekend walk trips durations for non-working adults, $\boldsymbol{d_{p,m,i}}|weekend,\ nonworking$
5. Weekday bike trips durations for working adults, $\boldsymbol{d_{p,m,i}}|weekday,\ working$
6. Weekend bike trips durations for working adults, $\boldsymbol{d_{p,m,i}}|weekend,\ working$
7. Weekday bike trips durations for non-working adults, $\boldsymbol{d_{p,m,i}}|weekday,\ nonworking$
8. Weekend bike trips durations for non-working adults, $\boldsymbol{d_{p,m,i}}|weekend,\ nonworking$

As above, each of these sets of estimates contains unique values for each possible combination of trip purpose, age (ranging from 18-95), sex (male or female), race (non-Hispanic White, non-Hispanic Black, Hispanic, non-Hispanic Asian, or non-Hispanic other), and, for working adults, mode to work (drive, transit, walk, or bike). These estimates are stored in a matrix $\mathbf{TPA_{dur}}$ containing 19,500 cells (five possible purposes, 78 possible ages, two possible sexes, five possible races, and five possible modes to work, including non-working as a fifth mode).

For our example block, estimates of walk trip duration for a non-Hispanic Black adult who takes transit to work across age are provided below (Figure B.8):

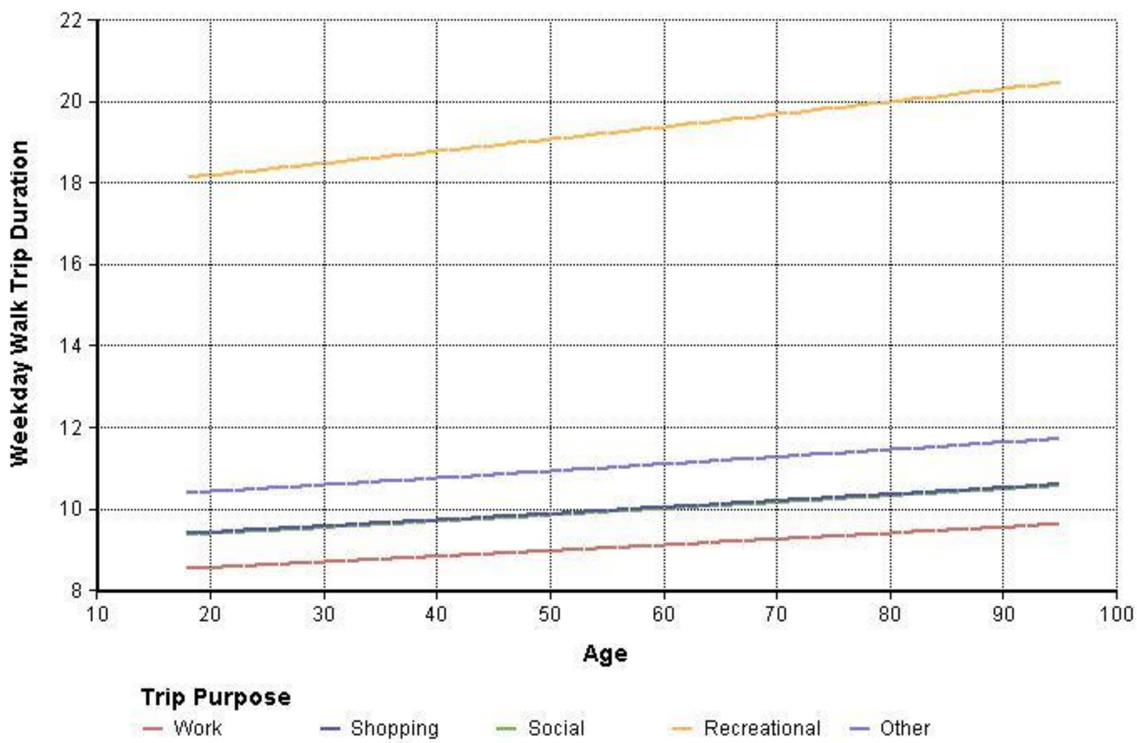


Figure B.9. Predictions of weekday walk trip durations by purpose for a non-Hispanic Black working adult who takes transit in work living in the example block group

B.4.4. Step 4: Combing model estimates

Estimates stored in $\mathbf{TPA_{count}}$, $\mathbf{TPA_{prob}}$, and $\mathbf{TPA_{dur}}$, are then combined using Equation 1. For the application included in the main text, durations from recreational trips are not included when calculating Equation 1 (i.e., the summation does not included the fourth purpose, recreational, when summing the product of trip probability and trip duration). This yields the matrix **TPA** mentioned in-text. The dimensions of this matrix expand as transportation physical activity is estimated for additional block groups.

For our example block, estimates of weekly walk time for a non-Hispanic Black adult across age are provided below (Figure B.9):

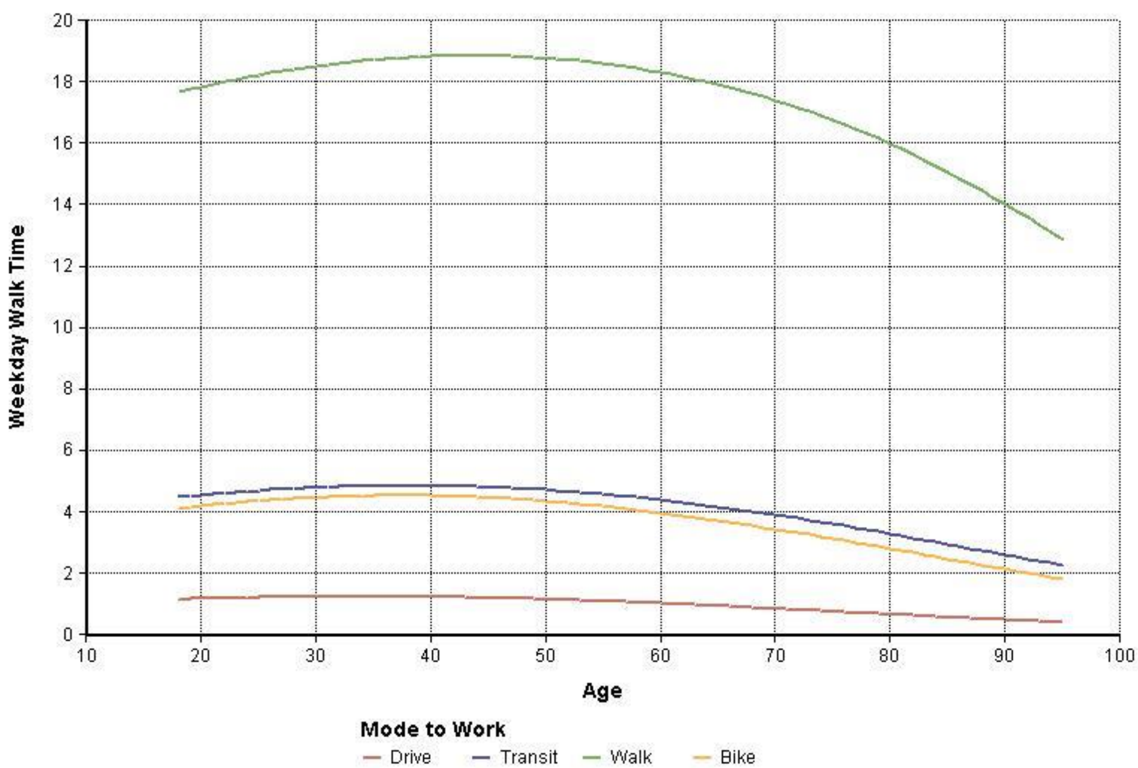


Figure B.10. Predictions of weekday walking time by commute mode to for a non-Hispanic Black working adult who takes transit in work living in the example block group

B.4.5.Step 5: Developing a representative population distribution

Transportation physical activity estimates contained in **TPA** must be applied to a population that is distributed across the same dimensions as the matrix (age, sex, race, mode to work, and block group-level variables). In each block group, cross-tabulations of age and sex are taken from the American Community Survey and used to develop a joint distribution of age and sex in each block group. These data are then multiplied by the distribution of race and commute mode to work, including a category for non-workers, in the block group. Finally, **NPD** is multiplied by the total block group population. This generates a representative population in each block group that has the same dimensions as our transportation physical activity estimates.

In our example block group, the population, distributed by age and sex (Figure B.10), is multiplied by the block group distribution of race (Figure B.11) and commute mode to work (Figure B.12):

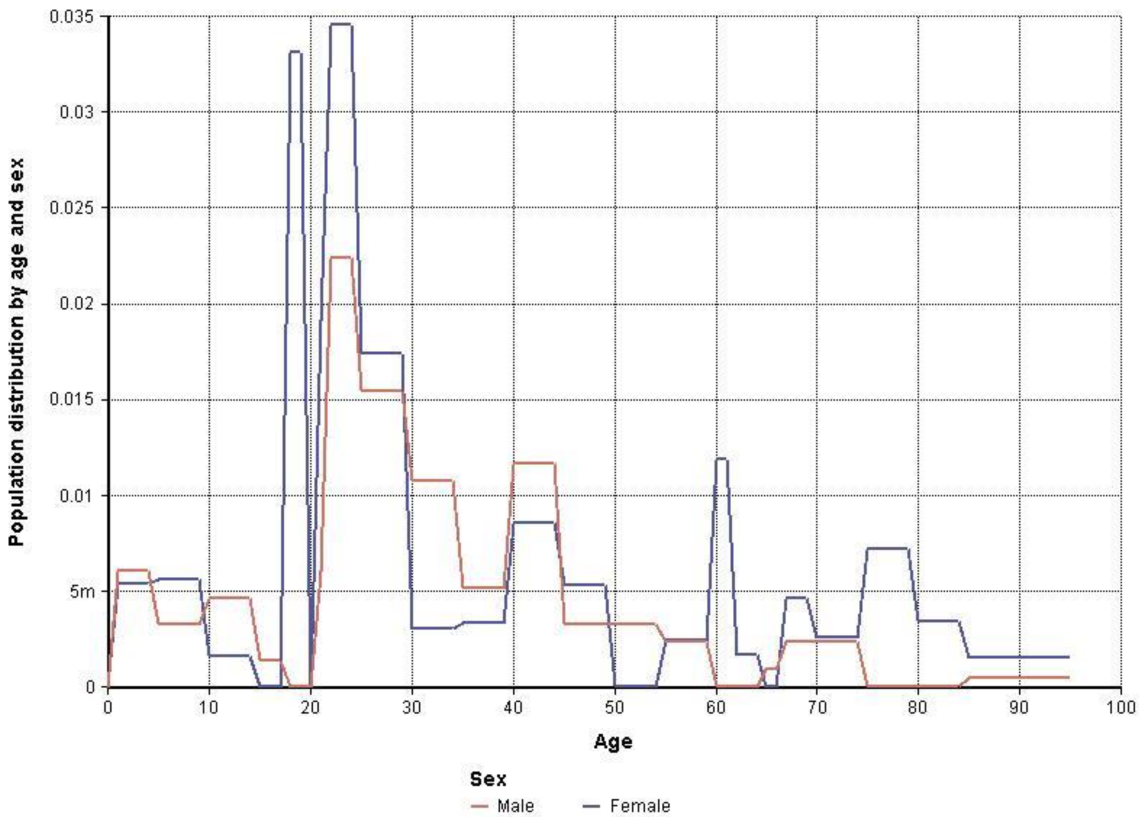


Figure B.11. Distribution of population for males and females in the example block group

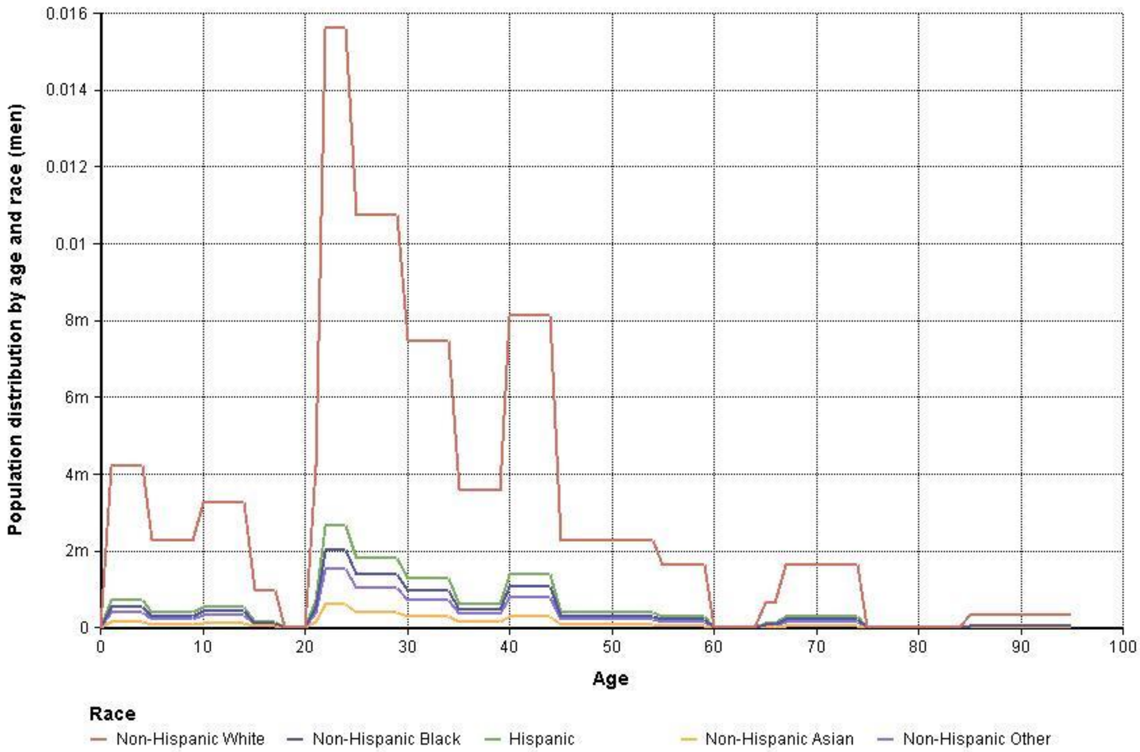


Figure B.12. Distribution of population race for males in the example block group

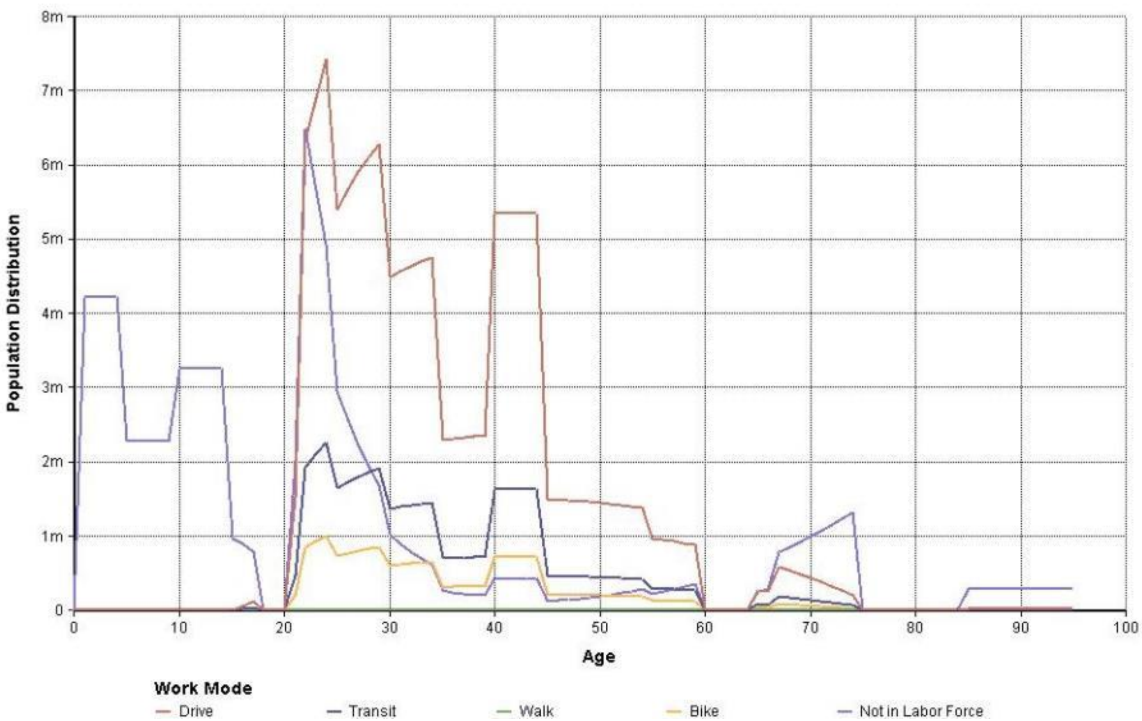


Figure B.13. Distribution of commute mode to work, including non-workers, for a White male in the example block group

Finally, the distribution above is multiplied by the total block group population to obtain the approximate number of persons in each category of age, sex, race, and mode to work.

B.4.6. Step 6: Assigning transportation physical activity estimates to the population and estimating health impacts

The representative population in each cell of the matrix storing the population is assigned the corresponding level estimate transportation physical activity stored in $\mathbf{TPA_i}$. In our example, a 50 year old non-Hispanic Black adult who walks is estimated to walk about 105 minutes per week for transportation. This value, plus estimated transportation biking, is transformed to MET-hours using Equation 6. In turn, Equations 10 and 11 are then used, where $f_{est}(TPA)$ is the distribution of physical activity estimates assigned to the population distribution and $f_{cf}(TPA)$ is the appropriate counterfactual scenario (Table B.7).

Table B.7. Transportation physical activity levels and estimated health impacts relative to the walkable neighborhood counterfactual for Block Group 2, Census Tract 107.03 in Orange County, North Carolina.

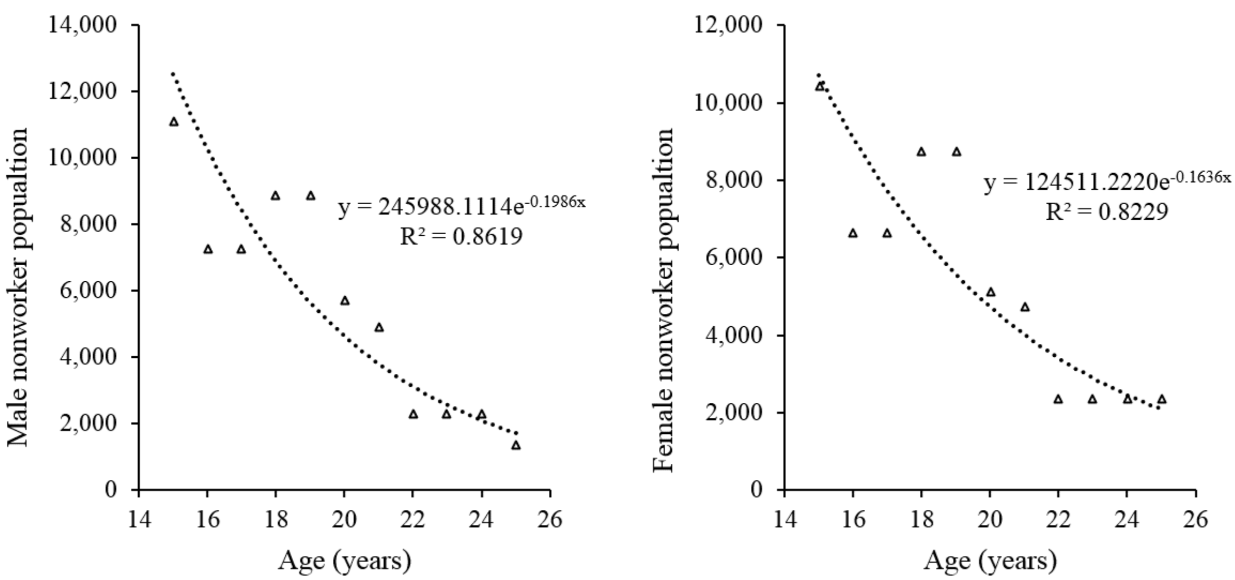
Commute Mode to Work	Population	Estimate transportation physical activity (MET-hrs/week)	Preventable mortality (deaths/100,000 persons) [a]
Population	2,142	3.39	-0.89
Drive to work	856	0.85	1.69
Transit to work	261	2.97	-1.02
Walk to work	0	n/a	n/a
Bike to work	116	26.9	-30.5
Not in labor force	909	2.47	0.50

[a] Negative preventable mortality indicates that observed transportation physical activity exceeds the counterfactual scenario and represent existing health benefits relative to the counterfactual (37.4 minutes walking/week)

APPENDIX C: SUPPLEMENTARY MATERIAL FOR CHAPTER 4, EXPLORING COMPETING TRANSPORTATION HEALTH RISKS AT THE NEIGHBORHOOD SCALE: DEVELOPMENT AND APPLICATION OF A NOVEL DYNAMIC MICROSIMULATION MODEL

C.1. Estimated transition into workforce

To estimate transition into the workforce, the number of men and women in the region who reported not participating in the labor force in the 2013 ACS was plotted against age. Sex-specific curves were then fitted to these data to model the rate at which these populations decreased with age, assuming that as individuals aged they moved into the labor force at the rate *Tw*. Exponential functions were fitted to both data (Figure C.1); thus, *Tw* is equal to the coefficient in the exponentiated portion of the fitted function.



Estimates T_w, men: 0.1986

Estimates T_w, women: 0.1636

Figure C.1. Estimates of transition rates into the labor force for men (left) and women (right).

C.2. Estimated disease incidence functions

Baseline estimates of estimates of $P_{d,a,s}$, $I_{d,a,s}$, and of $RR_{m,d}|d$ were obtained using *DisMod II*.

These estimates are shown below for women (Figure C.2) and men (Figure C.3).

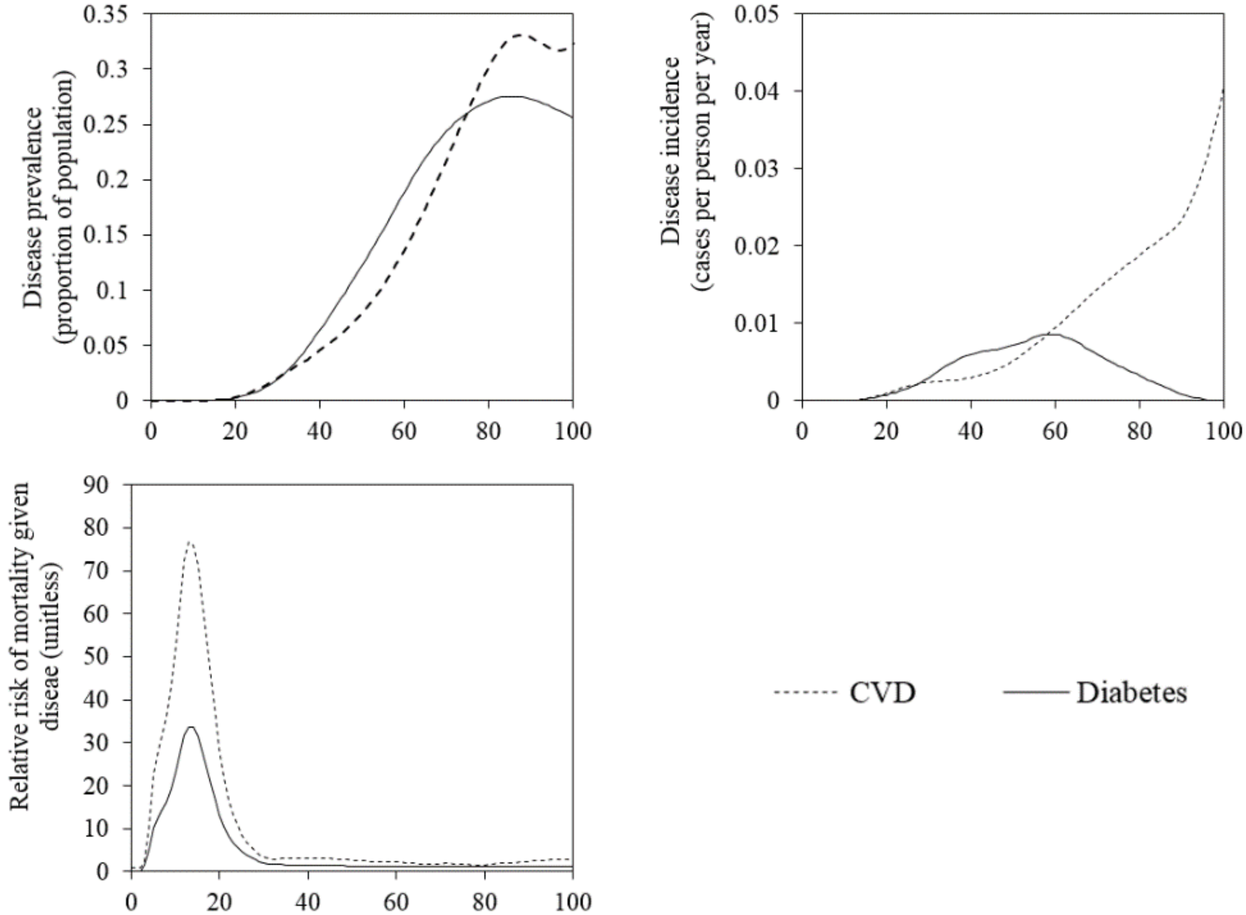


Figure C.2. Estimates of prevalence (top left panel), incidence (top right panel), and $RR_{m,d}|d$ for CVD and diabetes for women, obtained using DisMod II.

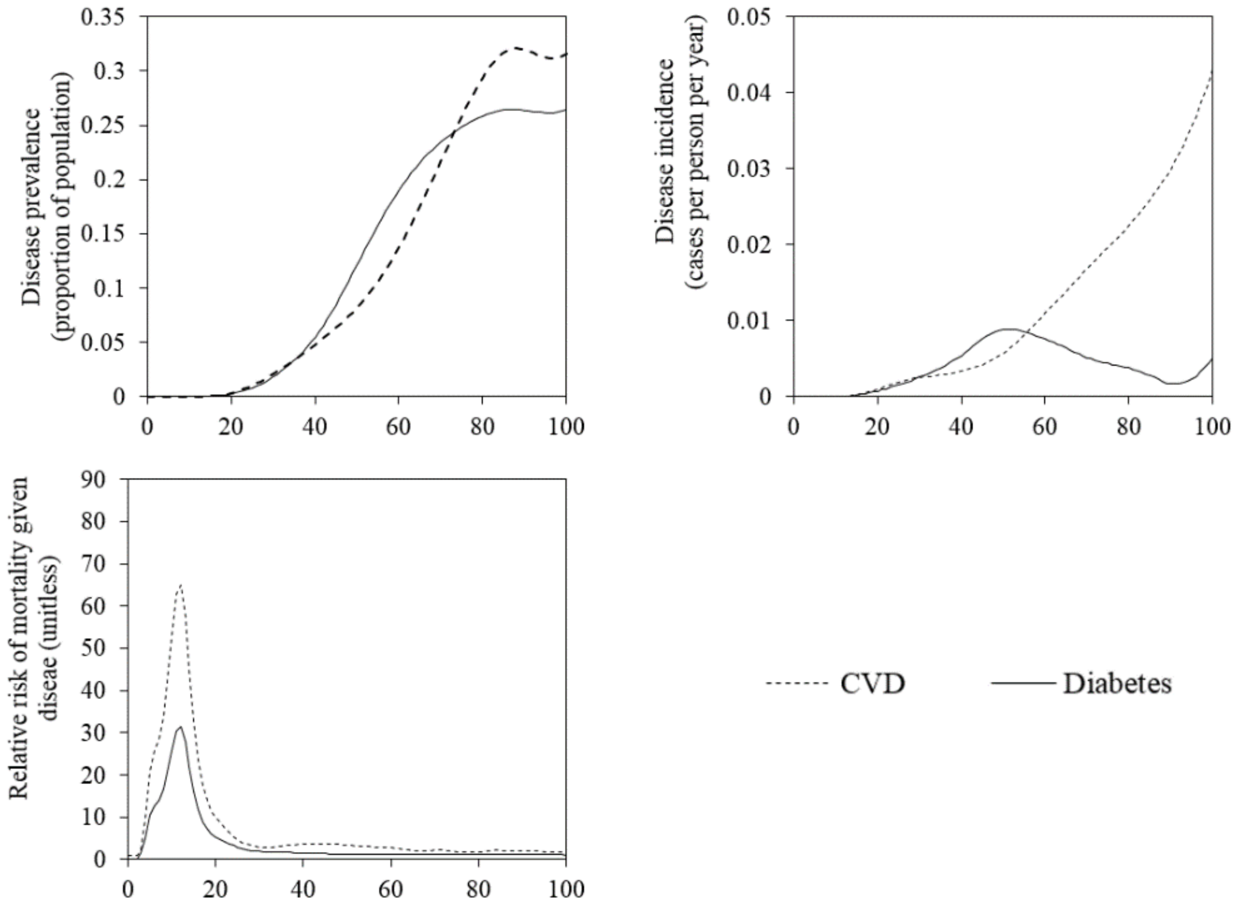


Figure C.3. Estimates of prevalence (top left panel), incidence (top right panel), and $RR_{m,d}|d$ for CVD and diabetes for men, obtained using DisMod II.

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