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Building a Framework for Transportation Resiliency and Evaluating the Resiliency Benefits of Light Rail Transit in Denver, Colorado

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Building a Framework for Transportation Resiliency and Evaluating the Resiliency Benefits of Light Rail Transit in Denver, Colorado

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ABSTRACT

You might spend nearly your whole life coming across only white swans. Yet, all it takes is a single black swan to prove that not all swans are white. Economist and noted author Nassim Taleb introduced this idea of a "black swan theory" as a metaphor for unexpected events that can qualify as extreme outliers. Due to their rarity, society tends to turn a blind eye toward these outliers. Such inattention and, in turn, the relative unpreparedness perhaps explains the disproportionate impact that so-called black swan events have had on society. If the black swan event represents an economic recession or extreme fuel prices, then the cities and regions that fail to plan for such events that will be economically and socially vulnerable to such shocks.

This report presents a three-part research program examining transportation resiliency and the ability for a transportation system to maintain or return to a previous level of service after a disruptive, black swan type event. With transportation as the second highest household expenditure, it is vital to understand the disproportionate impact that a drastic increase in gas price might have on a major city and region. We seek to increase our understanding of resiliency, vulnerability, and transportation affordability issues by asking what would happen if the cost of driving suddenly doubled or tripled. Who is better off and why? How much difference does being near downtown or jobs make? What matters in terms of transit infrastructure? How much of a role do current travel behaviors play?

The first part of the report examines a regional impact of a drastic fuel price increase. Using a multinomial logistic regression mode choice model developed with major travel surveys conducted for the Denver Metropolitan region in 1997 and 2008 – a time period over which gas prices more than tripled – we derive resiliency scenarios of driving cost increases of 1.5X, 2X, and 3X. Modal shifts are based on the supposition that travel behavior will adapt with increased fuel costs to be more like households with a similar percentage of household income being dedicated to transportation. We focus on work trips – which are most likely to be non-discretionary – and estimate the annual cost to commute as a percentage of the median household income. We then assess the influence that transit infrastructure, active transportation, the built environment, land uses, and socio-economic status play in resiliency, vulnerability, and transportation affordability. While high income represents one path to resilience, our results suggest that higher resilience can also be found in locations with proximity to high levels of employment, with more compact and connected street networks, or with better transit infrastructure. Current transit usage does not seem to make as big of a difference as living in the vicinity of better transit infrastructure. In other words, there is a significant option value to transit in the resiliency scenarios. Transportation choice creates network redundancy and facilitates adaptability under extreme conditions; on the other hand, more suburban locations with fewer transportation options are far more vulnerable than their more urban counterparts.

The second part of the report focuses on city-scale resiliency by accounting for active transportation infrastructure in a detailed manner not feasible at the regional scale. The research applies a "level of traffic stress" methodology that accounts for both the presence and quality of bicycling, walking, and transit modal options as well as the presence of barrier roads and highways. Modeling a drastic fuel price shock via a multinomial logistic regression mode choice model for Denver, Colorado, we measure the resiliency value of these multi-modal transportation infrastructures – even if few people are using those facilities today. Results at the city scale suggest three paths to resiliency: higher income, proximity to downtown, and the availability of transportation options. There is a cumulative effect in these results as well; for instance, low-income, suburban areas tend to spend more of their household budget on transportation than urban, higher income areas, thus increasing their vulnerability. Through this analysis, we also investigate how this resiliency scenario affects geographically and demographically diverse areas

in Denver, as well as how investments in more environmentally sustainable modes of transportation can support more resilient communities.

The third part of this report develops a Transportation Economic Resilience (TER) rating system to help researchers, planners, and policy makers better understand resiliency and vulnerability across different geographical areas. Based on the additional percentage of household expenditures consumed by transportation, the TER scoring system is applied at the traffic analysis zone (TAZ) level of geography across the Denver Metropolitan region. Using the TER scores, we map zones that are resilient or vulnerable to fuel price shocks. TER scores range from zero to 100; when fuel price doubles, the average TER score is 80.6, which is equivalent to a 1.94% increase in the percent of household income dedicated to transportation. Home to work distance, income, and transit share are the most significant variables that contribute to TER score differences at the regional scale.

The results of this report illustrate that transportation choice helps create network redundancy and facilitates adaptability under extreme conditions. While alternative fuels and improvements to the fuel economy of vehicles would help reduce the long-term impacts, the most vulnerable households are already spending more than 30% of their income solely on transportation costs and would be the least likely to benefit from such technological improvements. The most resilient households will live in cities and regions that plan for and invest in diversifying and expanding transportation choice. Those living in cities and regions that continue to promote the automobile as the only viable mode of transportation might be not currently view themselves as at risk, but they will be the most vulnerable should a “black swan” event occur.

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PART 1: RESILIENCY AT THE REGIONAL SCALE[1]

1. INTRODUCTION

Someone can spend nearly a lifetime seeing only white swans, but all it takes is one black swan to disprove the hypothesis that all swans are white (Gladwell, 2002; Taleb, 2001, 2007). Economist and author Nassim Taleb introduced the "black swan theory" in reference to unexpected events that fall into the category of being extreme outliers. Despite their rarity, Taleb describes the tremendous importance that such difficult-to-predict events have had in history. Part of the reason for the disproportionate impact of such black swan events has to do with the blind eye that society collectively turns toward them. Just because black swans are rare and you have not seen one does not mean they do not exist or that you should not be prepared in case they do exist. Failing to be prepared is often what feeds the magnitude of the effects of black swan events. If the black swan event refers to an economic recession or extreme gas prices, then cities and regions more prepared for such scenarios will likely be more resilient than those that bank on the business-as-usual approach to transportation. People living in the latter cities will be economically and socially vulnerable to such shocks.

It is easy to say that somebody driving 60 miles each way to work without any other mode options available would be far worse off than somebody that works within walking distance of their house. However, driving to work today does not necessarily mean that you would still drive tomorrow if fuel prices rose or a recession hit. It is also not very difficult to show that cities with high transit mode shares spend between one-third and two-thirds less wealth on transportation as compared with those heavily reliant on cars (Newman et al., 2009; Newman and Kenworthy, 1999). Yet, a neighborhood that has invested heavily in transit, walking, and biking infrastructures – even if experiencing minimal ridership today – would likely be able to withstand a shock to the system such as rising gas prices far better than an auto-dependent neighborhood that has not made the same investments. So what would happen if the cost of driving suddenly doubled or tripled? Many people could cut back their driving for some trip purposes, but most people would still have to go to work the next morning. What would be the economic and transportation affordability ramifications of such drastic gas price events? Who is better off and why? How much difference does being near downtown make? What matters in terms of transit infrastructure? How much of a role do current travel behaviors play? Are neighborhoods already walking biking, or using transit significantly better off? What about the built environment? Does living in a dense, connected area with mixed use really help?

This research seeks to answer these resiliency questions with a scenario planning investigation of the Denver Metropolitan region. Much of the early resiliency research was qualitative and looked at resiliency primarily through the lens of natural disasters such as hurricanes, earthquakes, or tsunamis (Bruneau et al., 2003; Chang and Nojima, 2001; Foster, 1995; Pelling, 2003), or terrorist attacks (Battelle, 2007). More recently, the concept of resiliency has become more quantitative and expanded to transportation (Berdica, 2002; Cova and Conger, 2004; Heaslip et al., 2010; Husdal, 2004; Murray-Tuite, 2006; Serulle et al., 2011). While overall resilience has been relatively well characterized as a result of the many different disciplines working on the issue, transportation resilience is less well defined. For instance, overall resilience represents the ability to perform under shock effects (shock absorption), to avoid the shock altogether (shock avoidance), or the ability to recover quickly from a shock (shock counteraction) (Briguglio et al., 2005). Transportation resilience has to do with the ability of the transportation system to maintain a desired level of service, or the time it takes to return to that level of

[1]This portion of the report has been peer-reviewed and is scheduled for publication: Marshall, W, and Henao, A. The Shock Heard 'Round the Suburbs: Assessing Vulnerability, Resilience, and Transportation Affordability of Higher Fuel Price Scenarios for the Denver Metropolitan Region. *Transportation Research Record*.

service given a shock to the system; transportation vulnerability refers to the inability to resist or adapt to such a system shock (Heaslip et al., 2009; Heaslip et al., 2010). The transportation research that has looked beyond resilience related to natural disasters and terrorist attacks is rare (Briguglio et al., 2005; Bronson and Marshall, 2014).

We will begin to fill this gap in the literature by deriving resiliency scenarios from the activity-based regional transportation model developed by the Denver Regional Council of Governments (DRCOG, which is the Metropolitan Planning Organization for the Denver region) that is based upon decades of data as well as a 12,000-household travel survey conducted in 1997 and 2008 (a time period over which gas prices tripled). We focus on work trips – as those are the trips most likely to be non-discretionary – and test a baseline condition followed by a range of resiliency scenarios where the cost of driving is increased by 1.5X, 2X, and 3X. Despite our fuel price scenarios falling outside the realm of what is considered typical, the model compares transportation costs as a percentage of overall household income. Modal shifts are thus based on the supposition that travel behavior will adapt with increased fuel costs to be more like households with a similar percentage of household income being dedicated to transportation. We consider the following travel modes: drive alone, carpool, drive to transit, walk to transit, walking, and biking. We then estimate the annual cost to commute and the percent of the median household at the Census block group level being dedicated to the work commute for the baseline condition and the three resiliency scenarios. Recalculating these percentages using the overall regional median income allows us to control for the influence of income. We map the results and assess the influence that differences in transit infrastructure, active transportation, the built environment, land uses, and socio-economic status play in resiliency, vulnerability, and transportation affordability. The next section reviews the most relevant literature on transportation resiliency, vulnerability, and affordability, which is followed by a detailed description of the data gathered and the methodologies used to answer the research questions.

2. LITERATURE REVIEW

The topic of resiliency has been explored through many different lenses, including water, power, and communication systems via natural disasters such as hurricanes, earthquakes, and tsunamis; or terrorist attacks (Bruneau et al., 2003; Chang and Nojima, 2001; Foster, 1993, 1995; Pelling, 2003). As of late, resiliency research has expanded to transportation infrastructure (Berdica, 2002; Cova and Conger, 2004; Heaslip et al., 2009; Heaslip et al., 2010; Husdal, 2004, 2005; Serulle et al., 2011). When applied to transportation infrastructure, better resiliency not only reduces the likelihood of system failure, but it also lessens the consequences of failures that do occur, thereby improving recovery (Freckleton et al., 2012). For transportation system users, transportation resiliency has more to do with "the ability for the system to maintain its demonstrated level of service or to restore itself to that level of service in a specified timeframe" (Heaslip et al., 2010). The existing literature on transportation resiliency tends to be qualitative (Godschalk, 2002), and the researchers that attempt to address the complexities of this topic quantitatively have done so through the use of complicated methodologies such as fuzzy inference models (Heaslip et al., 2009). However, planners and policymakers require straightforward metrics to help foster a better understanding of the issues at hand and the potential negative impacts. Taking a broader view of these issues, the book *Resilient Cities: Responding to Peak Oil and Climate Change* states that "[t]he agenda for future resilient cities is to have sustainable options available so that a city can indeed reduce its driving…" (Newman et al., 2009). In other words, Newman et al. suggest that in order to achieve a more resilient transportation system, cities need to reduce VMT (vehicle miles traveled). Our hypothesis is that resiliency can also be seen when cities have the ability to reduce VMT, even if not doing so in the present. Shedding light on the capacity to do so is where this study aims to make its contribution.

A related strand of academic literature has focused on the elasticity of travel behavior with respect to driving and modal shifts (Currie and Phung, 2007; Haire and Machemehl, 2007; Lane, 2010; Lin and Prince, 2013; Maley and Weinberger, 2009). Most of these studies have shown the price elasticity of demand for gasoline to be small (Ferdous et al., 2010; Nicol, 2003; Puller and Greening, 1999; Small and Van Dender, 2007). For example, Hughes et al. (2008) estimate that the short-run price elasticity of gasoline purchased was between -0.034 and -0.077 while the estimated short-run income elasticities ranged from 0.21 to 0.75. The American Public Transportation Association similarly summarized several of the transit-focused studies with average elasticity values of 0.254 for commuter rail, 0.188 for heavy rail, 0.266 for light rail, 0.139 for buses, and 0.181 for all modes (APTA, 2012). Rather than providing another elasticity analysis, our study examines the potential impact of a drastic fuel price shock. We then look to understand the varying economic response across a metropolitan region in terms of household affordability.

Several researchers, as well as the Center for Neighborhood Technology (CNT) with their wonderful Housing + Transportation Index, have investigated affordability in terms of household-level fuel expenditures (CNT, 2010; Cooper, 2005; Gicheva et al., 2007). Most of the existing work assumes fuel price inelasticity and adjusts household expenditures as a function of current behavior. However, history also suggests that households adjust their consumption expenditures, car usage, and travel behaviors in response to large increases in fuel prices (Anas, 2007; Dargay and Gately, 1997; Ferdous et al., 2010; Yang and Timmermans, 2011). Today's society has also seen many low-income households relocate to the suburban fringe in an effort to find more affordable housing. Unfortunately, the trade-off in housing savings often comes with increased transportation costs. Poor access to transportation options combined with budgetary limitations means that such households will likely be the most vulnerable if a crisis arises (Fitzgerald, 2012). Collectively, these households represent the weakest point in a region's capacity to mitigate such a resiliency event; in such a way, a catastrophic event not only threatens the usefulness of physical infrastructure and the built environment, but it also impacts social systems (Lipman, 2006). Peter Newman, for instance, recalls some of the broader impacts of the 1973 oil crisis saying:

> "Social disarray began to be displayed as people stole fuel, and across society there were myths about giant caverns of oil being stored by greedy oil companies and environmentalists were being accused of causing the deadline. What stays with me from this time was how suddenly a city can flip into a state of fear. It seemed to paralyze the city and lead to behavior you would never expect in normal times" (Newman et al., 2009).

Even if such drastic consequences fail to materialize, there are likely to be unwelcomed behavior changes. A 1975 study investigating travel behavior changes in the U.S. versus those in Europe during the oil embargo revealed that Europeans significantly increased their transit use while Americans were much more likely to stay home and forego essential travel (Pisarski and Terra, 1975).

Providing a diversity of transportation choices helps facilitate resiliency to potentially threatening events. If only one mode choice were viable during a resiliency scenario, the network would be overloaded and weakened as users would scramble for that one option; however, if more than one option were available, the network would in theory be less compromised (Freckleton et al., 2012). We will test whether this is an effective strategy for lowering transportation costs and building a system resilient to the "black swan" event of a drastic gas price increase. Unlike much of the existing literature, we are less interested in what mode people are choosing today and more interested in what mode people have the ability to choose in extreme event circumstances. The intent is to study trends in the data to reveal how certain neighborhoods demonstrate different levels of resiliency as a function of varying environmental and demographic circumstances. This work also presents us with a unique understanding of the option value of multi-modal infrastructures.

3. DATA

This paper focuses on the additional transportation expenditures for commuting in the Denver Metropolitan area from a baseline condition to resiliency scenarios where the cost of driving is increased by 1.5X, 2X, and 3X. Work tours were selected from the Denver Regional Council of Governments (DRCOG) regional activity-based travel model, as they represent travel that people would likely still need to make even under an extreme gas price increase. The goal is to evaluate mode shift with respect to commute expenditures in order to understand what factors influence transportation affordability. This comparison includes transit infrastructure, active transportation, the built environment, land uses, and socio-economic status. In order to assess these factors, additional data were collected from several sources and processed spatially in GIS in reference to the mode shift and affordability results.

3.1 Travel Behavior Data

To assess mode shift, commute tours were extracted from the DRCOG travel model and analyzed via a multinomial logistic regression mode choice model. This regional activity-based mode choice model was built based on historical data and in-depth 12,000-household travel surveys conducted in the Denver region in 1997 and 2008 (DRCOG, 2010). The DRCOG region includes the city and county of Denver as well as the surrounding area within an approximately 40-mile radius. In order to facilitate the analysis and modeling efforts of this study, the data were further processed using a series of queries in Microsoft SQL Server and PostGIS in order to:

1. Select tours with a home-based origin
2. Select tours with work destinations
3. Group tours with the same home TAZ origin and the same work TAZ destination
4. Select tours with a total of 10 or more originating at the same home TAZ

The final sample for analysis includes 1,154,673 home-work tours comprising 654,762 home TAZ to work TAZ combinations. The information in the database includes:

- Home TAZ ID
- Work TAZ ID
- Home to Work Average Distance
- Individual Median Income per Home TAZ
- Number of Tours
- Number of Drive Alone Tours (DA)
- Number of 2-person Shared Ride Tours (SR2)
- Number of 3+ people Shared Ride Tours (SR3)
- Number of Drive to Transit Tours (DT)
- Number of Walk to Transit Tours (WT)
- Number of Walk Tours (W)
- Number of Bike Tours (B)
- Drive Alone Cost (DA)

The travel behavior data were supplemented with data from the 2008 American Community Survey (ACS), which represents the same year that the latest DRCOG travel data were collected. The ACS data included means of transportation to work, travel time to work, and the number of vehicles available at the Census block group level of geography. The region totaled 2,032 block groups.

3.2 Transit Infrastructure

Transit-related GIS layers were collected from the Regional Transportation District (RTD), which is the primary provider of transit service in the Denver area. These GIS layers included:

- Light rail stations
- Light rail lines
- Bus stops
- Bus routes
- Park-and-ride stations

Using the Google Maps API, trip distances were calculated from the centroid of each of the 2,032 Census block groups to the nearest bus stop and park-and-ride station (Wang and Xu, 2011). The nearest bus stop and park-and-ride station was determined via a GIS spatial join, and the resulting distances represent a network distance as opposed to an "as the crow flies" Euclidean distance. We also calculated the density of bus stops (per square mile) for each block group.

Several of the existing light rail lines were built along limited-access highway corridors where households that lie in what seems like close proximity to the light rail station area are blocked by a highway or poorly connected street network. To remedy this problem, we created a trip distance matrix using the Google Maps API that calculated the network distance from each block group centroid to each light rail station (Wang and Xu, 2011). This allowed us to find the light rail station that was actually closest in terms of travel distance to each block group centroid. The recently opened West line was excluded since it was not in operation in 2008.

3.3 Built Environment & Land Use Data

To better understand the variance in transportation affordability, we also needed to identify the diversity of built environments in the region. The existing research suggests that measures of street network density and street connectivity are highly correlated with mode choice to work (Ewing and Cervero, 2001, 2010; Marshall and Garrick, 2010a, 2011). Intersection density is a metric representative of street network density and is calculated by dividing the total number of intersections – including dead ends – by the area (in square miles) (Knight and Marshall, 2014; Marshall and Garrick, 2012). The link to node ratio characterizes street connectivity and is calculated by dividing the total number of street links by the total number of intersections (Handy et al., 2003; Knight and Marshall, 2014; Marshall and Garrick, 2012; Marshall et al., 2014). In both cases, higher numbers indicate higher levels of street network density and street connectivity, respectively.

To calculate these built environment variables – for both the home locations (origins) and work locations (destinations) – intersections were extracted from a regional GIS street layer and tallied using a buffer distance of 20' to ensure the intersections falling on the edge of the zone were included. The result was then divided by the zone area (in square miles) to find intersection density. To count the number of street links required splitting the street polylines using the intersection point layer. Using a buffer distance of negative 20' (so that street links with only an endpoint touching the edge of the zone are not included), the number of street links were tallied and divided by the total number of intersections in the same zone to create the link to node ratio. The process was conducted for all block groups. Given the existing literature on these metrics, higher values are representative of a built environment more conducive to walking, bicycling, and transit (Ewing and Cervero, 2001, 2010; Marshall and Garrick, 2010a, 2011).

Land use data were gathered in terms of population and employment density at the block group level. Population data were collected from the ACS while employment data were derived from DRCOG. To estimate the approximate degree of mixed land uses, we divided the number of employees in each block group by the associated population. A value close to one represents an even split of employees and residents, while values much lower or higher than one represent zones weighted more heavily toward jobs or housing, respectively.

The Google Maps API was also used to calculate the distance from the centroid of each block group to three of the major employment centers in the region: the central business district in downtown Denver; the Denver Technological Center (DTC), which is located in south Denver and Greenwood Village along I-25, I-225, and a light rail corridor; and downtown Boulder, which is located approximately 30 miles northwest of downtown Denver.

3.4 Socio-demographic and Socioeconomic Data

The ACS also provided data on income, education, race, and ethnicity. The median income of each block group was collected. We calculated the median income for the region, which was used to calculate commute expenditures that control for income. For level of education, we aggregated the data into an education index score. Scores ranged from zero to four in terms of the highest level of education received, with: less than a high school diploma = 0; high school degree = 1; bachelor’s degree = 2; master’s or professional degree = 3; and doctorate degree = 4. Thus, a score of 2.0 indicates that the average adult level of education for the specified area is a bachelor's degree.

ACS data include the number of housing units built by decade, which we averaged to estimate a year of development for each block group, in a manner similar to a previous study that estimated the year of development for various street networks (Marshall and Garrick, 2010b). Table 3.1 includes the descriptive statistics for the variables used in this study.

Table 3.1 Descriptive Statistics (selected variables)

Variable	Mean	SD	Min	Max
Percent of Household Income Spent on Commuting (N=2,032)				
Baseline Condition	2.18	0.92	0.36	8.96
1.5X Cost of Driving	3.23	1.39	0.48	13.44
2X Cost of Driving	4.27	1.85	0.60	17.93
3X Cost of Driving	6.34	2.79	0.84	26.89
Baseline Condition (control for income)	1.98	0.86	0.44	7.71
1.5X Cost of Driving (control for income)	2.93	1.31	0.56	11.57
2X Cost of Driving (control for income)	3.88	1.76	0.68	15.42
3X Cost of Driving (control for income)	5.78	2.66	0.91	23.13
Transit Infrastructure (N=2,032)				
Network Distance from Light Rail (miles)	10.21	10.23	0.13	63.98
Network Distance from Park-and-Ride (miles)	3.89	7.38	0.02	102.94
Network Distance from Bus Stop (miles)	1.80	4.57	0	56.97
Bus Stop Density (bus stops / sq. mi.)	20.92	25.36	0	331.43
Current Travel Behavior (N=2,021)				
Current Transit to Work Mode Share (%)	4.85	5.70	0	45.08
Current Walking to Work Mode Share (%)	2.53	5.17	0	57.95
Current Bicycling to Work Mode Share (%)	1.23	3.13	0	32.03
Travel Time to Work (min)	29.26	6.15	9.63	57.28
Land Uses (N=2,032)				
Network Distance from Denver Central Business District (miles)	15.94	10.41	0.50	72.38
Network Distance from Denver Tech Center (miles)	19.17	12.43	0.59	83.63
Network Distance from downtown Boulder (miles)	31.06	12.69	0.49	81.12
Ratio of Employees to Population	3.06	2.05	1.00	8.00
Built Environment (N=2,032)				
Intersection Density (intersections /sq. mi.)	177.37	98.95	0	723.51
Link to Node Ratio	1.45	0.20	0	3.00
Population Density (population / sq. mi.)	3.46	1.67	1.00	7.00
Employment Density (employees / sq. mi.)	3.65	1.65	1.00	8.00
Year Built of Housing Stock	1975.20	17.90	1939	2005
Income & Education				
Median Household Income *(N=2,032)*	69,005	35,415	0	250,001
Education Score *(N=1,962)*	1.51	0.44	0.28	2.96
Race / Ethnicity (N=2,022)				
Percent White Residents	82.22	15.54	6.60	100.00
Percent Non-White Residents	17.78	15.54	0	93.40
Percent African American Residents	4.90	9.92	0	71.54
Percent Residents of Hispanic Origin	21.00	21.35	0	99.20
Percent Asian Residents	3.43	4.86	0	43.14
Percent Native American Residents	0.83	2.12	0	22.72

4. METHODS

4.1 Statistical Methodology

The data analysis process began by first calculating the baseline percentage share of the seven commute mode types in the model – drive alone, shared ride 2, shared ride 3+, drive to transit, walk to transit, walking, and biking – using the processed data. We then investigated the statistical relationship between mode choice and a drastic increase in driving costs via the existing multinomial logistic regression model developed for the DRCOG regional travel model. With respect to the mode choice outputs, we are less interested in absolute numbers and more interested in mode shift trends. Thus, the existing mode choice model chosen was a good fit, despite the testing of resilience scenarios beyond the normal range. Furthermore, this mode choice model incorporates longitudinal data based on regional trends from both the 2010 Front Range Travel Counts as well as a similar large-scale travel survey undertaken in 1997. Gas prices more than tripled during this time span, which makes this particular model an advantageous choice for our purposes.

The basic structure of a multinomial logistic regression mode choice model is derived from a basic logit model. The following generalized logit equation determines the probability of choosing a specific mode (Martin and McGuckin, 1998):

$$P_i = \frac{e^{u_i}}{\sum_{i=1}^{k} e^{u_i}}$$

where:

P_i = probability of somebody choosing mode i = 1, 2, …, k;

u_i = utility function describing the relative attractiveness of mode i; and

$\sum_{i=1}^{k} e^{u_i}$= sum of the functions for all available mode alternatives

The probability of choosing a particular mode depends on the above utility function relative to the utility functions for all the other mode options. A multinomial logistic regression simultaneously considers a binary logit model for every possible combination of outcomes (Long, 1997). One assumption of this model is that the probabilities related to the mode choices sum to 1:

$$P(\text{drive alone}) + P(\text{carpool}) + P(\text{drive to transit}) + P(\text{walk to transit}) + P(\text{walking}) + P(\text{biking}) = 1$$

For such a probability-based model, the multinomial logistic regression equation is as follows (30):

$$P(y_i = 1|x_i) = \frac{1}{1+\sum_{j=2}^{J} e^{(x_i\beta_j)}} \text{ for m = 1}$$

$$P(y_i = m|x_i) = \frac{x_i\beta_m}{1+\sum_{j=2}^{J} e^{(x_i\beta_j)}} \text{ for m > 1}$$

where:

y = dependent variable,

j = number of categorical outcomes for the various mode choices,

$P(y = m|x)$ = probability of choosing mode m given x,

x_i = independent predictor variable, and

β = estimated coefficient representing the effects of the independent variable.

Additional details and coefficients for the DRCOG multinomial logistic regression mode choice model can be viewed in the associated user's guide (DRCOG, 2011, 2012). The probability of a commuting tour taking each mode was calculated for a baseline cost of driving as well as for resiliency scenarios of 1.5X, 2X, and 3X driving costs. Mode choice percentages were calculated for 2,832 TAZ zones and multiplied by the total number of tours within each TAZ, spatially joined and summed to the block group level of geography, and divided by the total number of tours. The result is a tour-weighted estimate of mode choice for the baseline condition as well as for each of the three resiliency scenarios at the block group level of geography.

4.2 Commuting Expenditure Calculations

To calculate the additional annual commuting expenditures due to the increase in driving costs, we assumed the following:

1. The cost for shared ride 2 is equal to 1/2 the cost of driving alone;
2. The cost for shared ride 3+ is equal to 1/3 the cost of driving alone;
3. The cost for walking and biking is negligible; and
4. Transit costs average $1.12 per boarding or $2.24 per tour.

The out-of-pocket transit costs ($1.12 per boarding) were calculated by the dividing the total annual farebox revenue ($110,000,000) by the total number of annual boardings (98,400,000) for the entire RTD system.

Since the model did not specify the length of the driving portion of the drive to transit tour, we calculated that distance based on a 2008 on-board survey of RTD riders in the Denver metro area. The survey, administered by the consultant NuStats, was conducted on local, limited, express, regional, SkyRide, and all light rail routes. Data collected in spring 2008 resulted in a total of 23,865 usable surveys. Riders were surveyed regarding their immediate one-way trip and asked to provide information about their transit access trip, mode of access, origin and destination, and transit route. The survey also included various socio-economic questions, fare payment method, and what alternative mode would have been taken if transit was not available. Samples from all major bus and light rail routes are at the 95% confidence level.

The point level GIS shapefile data representing the distance driven to transit was converted to a raster GIS layer using the Emprical Bayes Kriging (EBK) tool. EBK is an interpolation method that accounts for the known underestimation of the standard errors of prediction that are produced by other kriging methods during semivariogram estimation. EBK automates that process by calculating the necessary semivariogram parameters via repeated simulations using multiple subsets of data (ESRI, 2014; Spöck et al., 2008). The resulting raster layer was converted to a point layer and spatially averaged at the block group level of geography. The resulting number represents the average distance driven to transit, based on license plate data from park-and-rides across the Denver area to the home zone of the vehicle. In the parts of the Denver region beyond the extent of the interpolated raster layer, we used the minimum distance calculated from the centroid to the nearest light rail station, park-and-ride location, or bus stop.

The following equation for daily work tours transportation costs is the total sum of each mode share multiplied by the corresponding mode cost:

$$\begin{array}{c}\text{Daily}\\\text{Commuting}\\\text{Cost}\end{array} = \left(\mathrm{DA_{share}} + \mathrm{SR2_{share}} * \frac{1}{2} + \mathrm{SR3_{share}} * \frac{1}{3}\right) \text{ x } \mathrm{DA_{Cost}} + (\mathrm{DT_{share}} + \mathrm{WT_{share}}) \text{ x } \$2.24 + (\mathrm{DT_{share}}) \text{ x } \mathrm{DT_{Cost}}$$

Driving costs can generally be disaggregated into those that are fixed – such as registration, insurance, and the car itself – and those that are variable – such as gasoline and maintenance. Generally, the fixed costs range between 21 and 37 cents per mile, and the variable costs range between 12 and 18 cents per mile (Litman, 2013). While it would be logical to include the full cost of driving as an input variable in travel forecasting models, doing so tends to result in unrealistically low automobile mode shares; as a result, such models focus on the variable costs of driving as the primary economic influence on mode shares (DRCOG, 2012). So even though the total cost of driving is higher, the current cost of driving alone derived from the DRCOG mode choice model was 15 cents per mile and is representative of the variable driving costs.

Since our study is interested in understanding the difference in money spent on commuting to work under extreme gas price scenarios, we also want to focus on the variable costs of driving instead of the fixed costs. The annual commuting expense was thus calculated by multiplying the above equation by five days a week and 50 weeks a year. Percentages of income spent on commuting for each block group was calculated by dividing the total cost of commuting for all the tours of a particular block group by the median household income for that block group. We control for income in the results by dividing the total cost of commuting by the median household income for the entire region.

5. RESULTS

The results are presented in terms of the percent of household expenditures consumed by travel to work. The intent is to provide a similar set of results for transportation to what is more common to housing. For instance, the typical threshold at which the percentage of income being dedicated to housing becomes unaffordable is 30% (CNT, 2010). With respect to overall transportation costs, the literature suggests an affordability threshold of approximately 15% (CNT, 2010). In other words, a household dedicating more than 15% of their income to transportation is vulnerable to significant disruption with any abrupt variability in transportation costs. The National Household Travel Survey (NHTS) also estimates that approximately one-third of overall travel is work-related (FHWA, 2009). Thus, for the purposes of this analysis, we set 5% as the affordability threshold for which the money spent on the commute to work becomes unaffordable. For example, with the baseline condition, only 32 out of the 2,032 block groups (1.6%) spend more than 5% of household income on transport to work. At 1.5X driving costs, 136 block groups (6.7%) now exceed the 5% threshold. This number jumps to 494 block groups (24.2%) for 2X driving costs and 1,411 block groups (69.4%) for 3X driving costs. When we present the results as percentages of household income spent on commuting, it is important to keep in mind that these figures are conservative as they only represent the variable driving costs and do not include fixed driving costs such as registration, insurance, depreciation, or the car itself. Figure 5.1 depicts these results for the Denver Metropolitan region.

The spatial trends in the data suggest that in the baseline condition, only the exurbs commit what would be considered an unaffordable percentage of household income to commuting. However, housing in these outlying areas may be less of a financial burden than is typical for the inner neighborhoods. As the cost of driving increases, the trends depict vulnerability across the suburbs with shrinking pockets of resilience around Denver and Boulder. How bad goes it get? For the 3X scenario, the percent of income spent just on transportation to work (not including non-work transportation costs) ranges from a block group averaging 0.84% to one averaging 26.89%. The average household in the first block group probably does not even notice the increase in gas price while an average household in the second block group would all of the sudden have little money left over for anything. We will investigate these trends in more depth later in this section.

In order to better assess spatial and infrastructure trends, we also control for income by dividing commuting costs by the overall regional median income (as opposed to the median income for each block group). The overall regional median household income for the Denver metropolitan areas is $38,797. Based on this number, Figure 5.2 depicts the same data as Figure 5.1 but controls for income. Here, we see an even more drastic set of affordability rings around the cities of Denver and Boulder. The inequities are clear in that the suburbs would bear the brunt of the impact.

5.1 Transit Infrastructure

We tested four variables related to transit infrastructure in terms of their relationship with the percent of household income spent on commuting to work: network distance to a light rail station, network distance to a park-and-ride station, network distance to a bus stop, and bus stop density. Table 5.1 depicts the results using the same color coding scheme shown in the legend of Figures 1 and 2. The table includes results that control for income. For instance, with the distance from a light rail station results, we see that those living within two miles of a station do not reach the 5% affordability threshold, even in the 3X driving cost scenario. This range expands to five miles when controlling for income.

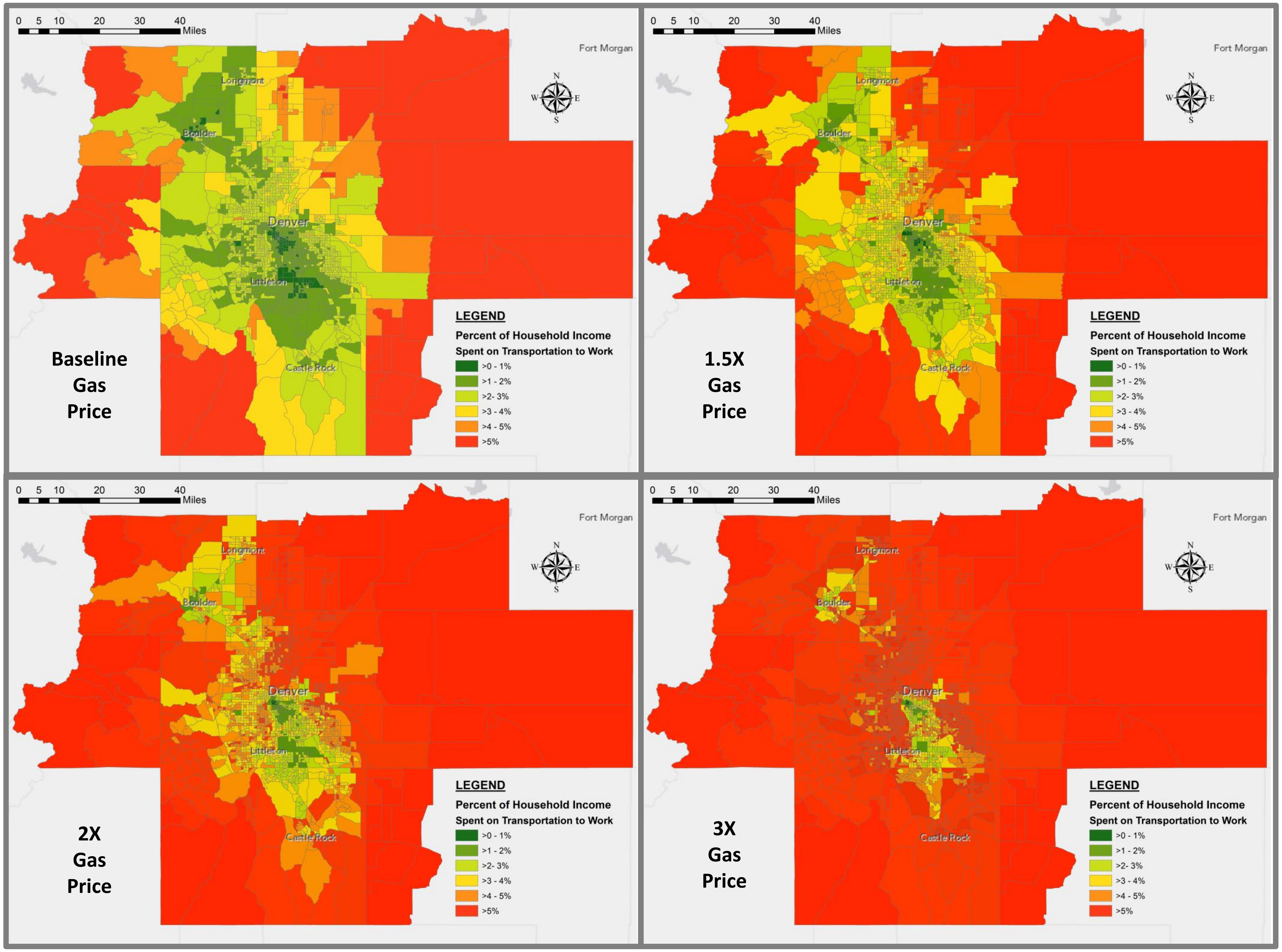

Figure 5.1 Percent of Household Income Spent on Transportation to Work for Four Price Conditions

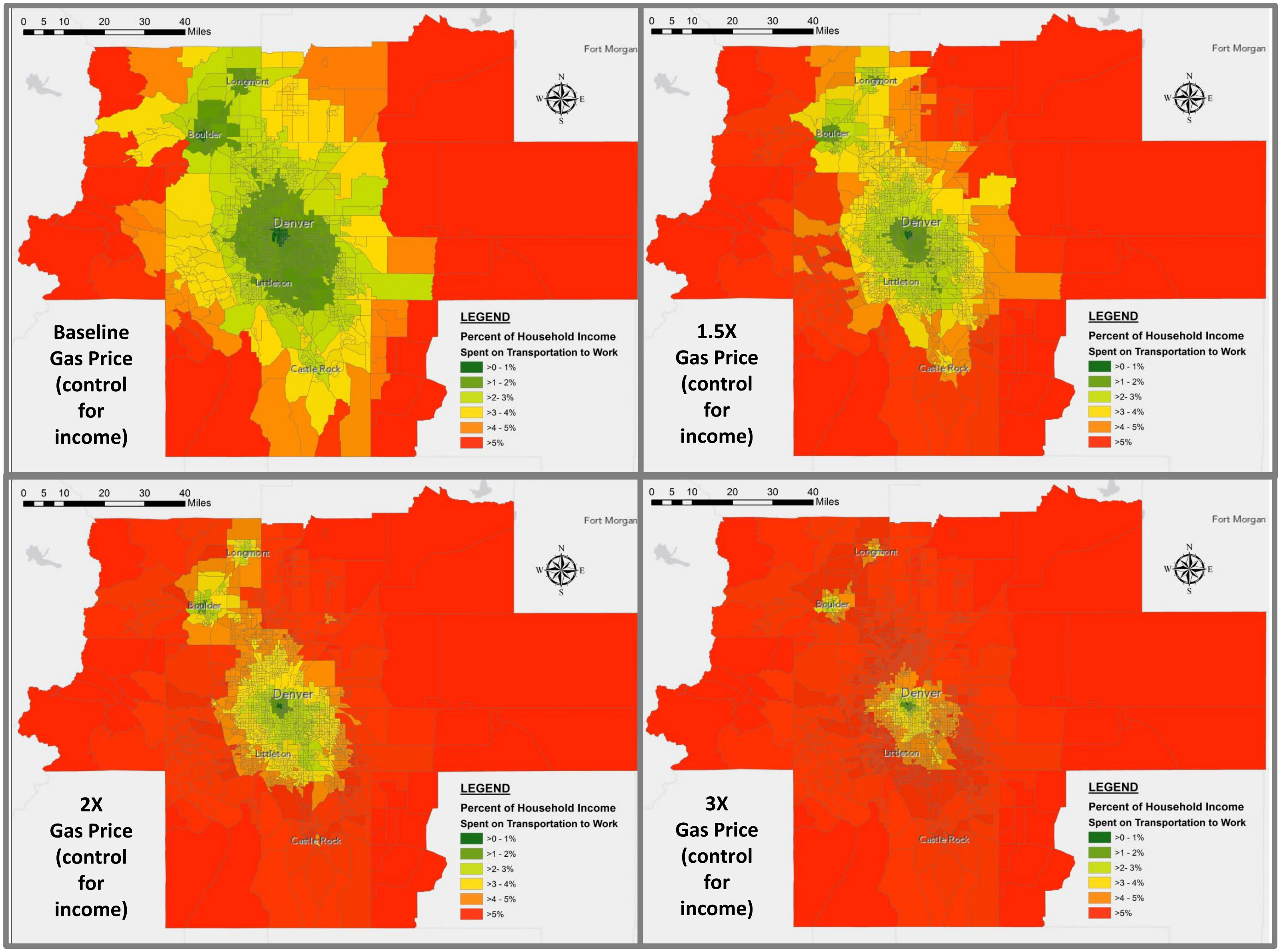

Figure 5.2 Percent of Overall Median Household Income Spent on Transportation to Work for Four Price Conditions

For all the transit infrastructure variables, the evidence suggests a strong distance decay effect. In other words, proximity to transit leads to resilience while those living without viable transit alternatives are the most vulnerable. This result is particularly evident with the bus stop variables. Those living 20 or 30 miles from the nearest bus stop – or essentially in areas without transit – see massive jumps in commute costs, running up to nearly 20% of household income in the 3X scenario. On the other hand, those living in block groups with the highest density of bus stops do not even crack 1% of household expenditures being spent on commuting in the 3X scenario. When we control for income, the results remain similar.

5.2 Current Travel Behaviors

Block groups already seeing higher levels of transit use, walking, and bicycling to work were more resilient than those with higher automobile mode shares. While this result is not surprising, the magnitude of the differences was not as large as we expected. For instance, in Table 5.1, the block groups with the highest current transit mode shares (>30%) still spent 5.8% of household income on commuting in the 3X scenario. At the other end of the spectrum, the block groups starting with <1% transit mode share spent 7.3% of their income on commuting. When compared with the transit infrastructure results, the implication is that current mode shares matter less when it comes to resilience than the ability to change modes if needed. Compared with the transit infrastructure results, however, we see a much larger difference when we control for income. This suggests a larger discrepancy in incomes for current non-automobile mode shares than in the resiliency scenarios.

While we see similar trends for walking and bicycling to work, we also see a greater number of block groups remaining below the affordability threshold in the resiliency scenarios than we found with transit. Current levels of walking and biking seem to be more indicative of the ability to walk or bike in the resiliency scenarios than we saw with transit.

The travel behavior that was most telling to vulnerability was travel time to work. Those traveling more than 30 minutes each way to work pushed quickly toward the affordability threshold in the resiliency scenarios, even when we control for income. Those commuting more than 40 minutes each way averaged close to 11% of income being spent on commuting in the 3X scenario. Interestingly, the transit infrastructure results saw greater disparity in affordability than even travel time to work. So while current mode shares were indicative of differences in resiliency and vulnerability, they do not tell the whole story.

5.3 Land Uses

The land use variables tested include network distance from each block group to three major employment hubs: the Denver CBD, the Denver Tech Center, and downtown Boulder. As shown in Table 5.1, those living in relatively close proximity to any three of these destinations tended to exhibit high resilience. In terms of vulnerability, living farther away from the Denver CBD led to higher commute costs than living far away from either the Denver Tech Center or downtown Boulder. In all cases, the results were similar when we controlled for income.

The other land use variable investigated was a measure of mixed uses calculated by dividing the number of employees in a block group by the population. The trends suggest that low levels of employment in a block group (i.e., a bedroom community) leads to higher vulnerability. This measure, however, was not as telling as those related to transit infrastructure or current mode shares.

Table 5.1 Percent of Household Income Spent on Commuting Based on Transit Infrastructure, Current Travel Behavior, and Land Uses (color coded based on Figures 5.1 & 5.2)

Transit Infrastructure

Dist. from Light Rail	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1 miles	112	1.62%	2.32%	3.02%	4.40%	1.22%	1.75%	2.28%	3.33%
1 - 2 miles	213	1.66%	2.40%	3.14%	4.60%	1.34%	1.94%	2.54%	3.73%
2 - 5 miles	513	1.81%	2.66%	3.50%	5.17%	1.60%	2.36%	3.11%	4.60%
5 - 10 miles	498	2.26%	3.35%	4.43%	6.59%	1.97%	2.93%	3.88%	5.78%
10 - 20 miles	347	2.47%	3.69%	4.90%	7.31%	2.40%	3.57%	4.75%	7.10%
20 - 30 miles	220	2.62%	3.90%	5.18%	7.72%	2.54%	3.78%	5.03%	7.51%
30+ miles	129	3.20%	4.81%	6.40%	9.59%	3.17%	4.75%	6.30%	9.47%

Dist. from Park-and-Ride	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1 miles	182	2.05%	2.99%	3.93%	5.79%	1.60%	2.34%	3.08%	4.56%
1 - 2 miles	528	1.95%	2.87%	3.78%	5.58%	1.64%	2.41%	3.18%	4.71%
2 - 5 miles	1,048	2.05%	3.03%	4.01%	5.95%	1.85%	2.74%	3.62%	5.39%
5 - 10 miles	158	2.65%	3.97%	5.29%	7.92%	2.88%	4.31%	5.74%	8.59%
10 - 20 miles	80	3.44%	5.20%	6.88%	10.31%	3.56%	5.34%	7.12%	10.68%
20 - 30 miles	16	4.82%	7.20%	9.65%	14.46%	4.99%	7.49%	9.98%	14.97%
30+ miles	20	5.60%	8.30%	11.07%	16.59%	5.42%	8.13%	10.83%	16.24%

Dist. from Bus Stop	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1 miles	1,477	2.02%	2.97%	3.91%	5.79%	1.68%	2.47%	3.26%	4.84%
1 - 2 miles	238	2.02%	3.00%	3.98%	5.94%	2.08%	3.10%	4.11%	6.14%
2 - 5 miles	143	2.30%	3.43%	4.57%	6.84%	2.68%	4.00%	5.33%	7.98%
5 - 10 miles	84	3.16%	4.73%	6.30%	9.45%	3.27%	4.90%	6.53%	9.79%
10 - 20 miles	63	3.68%	5.51%	7.35%	11.02%	3.81%	5.72%	7.63%	11.44%
20 - 30 miles	15	4.73%	7.10%	9.47%	14.20%	5.06%	7.60%	10.13%	15.19%
30+ miles	12	6.61%	9.91%	13.21%	19.81%	6.17%	9.26%	12.34%	18.51%

Bus Stop Density	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 5	635	2.58%	3.85%	5.13%	7.67%	2.71%	4.06%	5.40%	8.08%
5 - 10	215	2.02%	2.99%	3.96%	5.90%	1.92%	2.85%	3.79%	5.64%
10 - 20	369	2.10%	3.10%	4.10%	6.08%	1.81%	1.68%	3.55%	5.27%
20 - 50	610	2.02%	2.96%	3.89%	5.75%	1.58%	2.32%	3.05%	4.51%
50 - 100	172	1.85%	2.67%	3.49%	5.11%	1.32%	1.90%	2.49%	3.65%
100 - 200	28	1.48%	2.08%	2.67%	3.84%	0.98%	1.37%	1.77%	2.55%
200+	3	0.47%	0.60%	0.73%	0.98%	0.50%	0.64%	0.79%	1.07%

Current Travel Behavior

Current Transit to Work Mode Share	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1%	577	2.48%	3.69%	4.90%	7.31%	2.39%	3.56%	4.73%	7.07%
1 - 2%	190	2.21%	3.29%	4.37%	6.51%	2.19%	3.26%	4.33%	6.47%
2 - 5%	543	2.10%	3.11%	4.11%	6.11%	1.95%	2.90%	3.84%	5.71%
5 - 10%	420	1.99%	2.92%	3.85%	5.70%	1.70%	2.51%	3.31%	4.91%
10 - 20%	238	2.00%	2.90%	3.81%	5.60%	1.49%	2.18%	2.86%	4.21%
20 - 30%	42	2.03%	2.92%	3.81%	5.57%	1.33%	1.91%	2.50%	3.65%
30+%	11	2.11%	3.03%	3.95%	5.76%	1.35%	1.95%	2.56%	3.74%

Current Walk to Work Mode Share	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1%	1,141	2.21%	3.28%	4.34%	6.46%	2.07%	3.07%	4.07%	6.06%
1 - 2%	217	2.23%	3.31%	4.38%	6.52%	2.14%	3.18%	4.21%	6.27%
2 - 5%	350	2.15%	3.18%	4.20%	6.24%	1.92%	2.84%	3.76%	5.59%
5 - 10%	185	2.24%	3.28%	4.33%	6.40%	1.80%	2.64%	3.49%	5.17%
10 - 20%	91	1.84%	2.65%	3.46%	5.08%	1.40%	2.04%	2.68%	3.92%
20 - 30%	22	2.07%	2.97%	3.87%	5.64%	1.32%	1.91%	2.49%	3.65%
30+%	15	1.35%	1.90%	2.46%	3.55%	0.97%	1.37%	1.77%	2.55%

Current Bike to Work Mode Share	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1%	1,517	2.30%	3.41%	4.52%	6.72%	2.11%	3.13%	4.15%	6.18%
1 - 2%	132	1.89%	2.79%	3.68%	5.46%	1.78%	2.63%	3.47%	5.16%
2 - 5%	223	1.86%	2.73%	3.59%	5.30%	1.64%	2.40%	3.16%	4.68%
5 - 10%	89	1.70%	2.47%	3.23%	4.74%	1.37%	1.99%	2.61%	3.84%
10 - 20%	53	1.64%	2.38%	3.10%	4.55%	1.31%	1.91%	2.50%	3.67%
20 - 30%	7	1.62%	2.31%	2.99%	4.34%	1.14%	1.64%	2.12%	3.09%

Travel Time to Work	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 20 minutes	82	1.65%	2.41%	3.15%	4.64%	1.42%	2.08%	2.74%	4.05%
20 - 30 minutes	1,105	1.93%	2.85%	3.75%	5.56%	1.73%	2.55%	3.37%	5.00%
30 - 40 minutes	727	2.40%	3.56%	4.72%	7.02%	2.17%	3.22%	2.28%	6.37%
40 - 60 minutes	107	3.66%	5.47%	7.28%	10.88%	2.67%	5.49%	7.31%	10.94%

Land Uses

Dist. from CBD	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1 miles	7	0.54%	0.72%	0.90%	1.26%	0.59%	0.80%	1.01%	1.43%
1 - 2 miles	31	1.04%	1.42%	1.79%	2.52%	0.78%	1.06%	1.34%	1.89%
2 - 5 miles	227	1.72%	2.46%	3.20%	4.67%	1.23%	1.76%	2.29%	3.34%
5 - 10 miles	391	2.09%	3.06%	4.02%	5.93%	1.54%	2.26%	2.97%	4.39%
10 - 20 miles	817	2.14%	3.17%	4.20%	6.25%	1.95%	2.90%	3.84%	5.71%
20 - 30 miles	345	2.28%	3.40%	4.52%	6.75%	2.42%	3.60%	4.80%	7.18%
30 - 73 miles	214	3.10%	4.64%	6.18%	9.25%	3.22%	4.81%	6.41%	9.60%

Dist. from Tech Center	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1 miles	4	1.00%	1.45%	1.90%	2.80%	1.31%	1.90%	2.49%	3.67%
1 - 2 miles	11	1.25%	1.82%	2.39%	3.52%	1.43%	2.10%	2.76%	4.08%
2 - 5 miles	77	1.24%	1.96%	2.58%	3.81%	1.47%	2.16%	2.85%	4.22%
5 - 10 miles	439	1.73%	2.54%	3.35%	4.96%	1.60%	2.35%	3.10%	4.59%
10 - 20 miles	712	2.07%	3.03%	4.00%	5.91%	1.75%	2.58%	3.40%	5.05%
20 - 30 miles	428	2.52%	3.75%	4.97%	7.41%	2.25%	3.35%	4.45%	6.64%
30 - 84 miles	361	2.79%	4.16%	5.53%	8.26%	2.71%	4.04%	5.38%	8.04%

Dist. from Boulder	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1 miles	11	1.51%	2.11%	2.71%	3.89%	0.89%	1.26%	1.63%	2.35%
1 - 2 miles	13	1.39%	1.98%	2.58%	3.75%	1.06%	1.53%	2.00%	2.95%
2 - 5 miles	45	1.59%	2.32%	3.04%	4.48%	1.39%	2.04%	2.69%	3.97%
5 - 10 miles	39	1.64%	2.44%	3.25%	4.85%	2.05%	3.06%	4.06%	6.07%
10 - 20 miles	276	2.27%	3.38%	4.49%	6.69%	2.08%	3.10%	4.12%	6.15%
20 - 30 miles	520	2.32%	3.41%	4.49%	6.66%	1.81%	2.66%	3.51%	5.21%
30 - 83 miles	1,128	2.16%	3.19%	4.23%	6.28%	2.08%	3.08%	4.08%	6.08%

Ratio of Employees to Population	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 0.1	337	2.47%	3.67%	4.86%	7.22%	2.05%	3.05%	4.04%	6.01%
0.1 - 0.3	856	2.20%	3.25%	4.30%	6.40%	2.10%	3.12%	4.13%	6.15%
0.3 - 0.5	273	2.14%	3.17%	4.19%	6.22%	1.97%	2.91%	3.85%	5.73%
0.5 - 0.7	163	2.02%	2.98%	3.93%	5.82%	1.79%	2.65%	3.50%	5.19%
0.7 - 0.9	87	2.11%	3.12%	4.12%	6.11%	1.93%	2.85%	3.77%	5.61%
0.9 - 1.1	56	1.99%	2.94%	3.88%	5.75%	1.85%	2.73%	3.61%	5.36%
1.1 - 2.0	107	2.06%	3.01%	3.96%	5.84%	1.68%	2.47%	3.25%	4.81%
2.0+	143	1.88%	2.75%	3.62%	5.34%	1.62%	2.37%	3.13%	4.63%

5.4 Built Environment

Table 5.2 shows the results related to the influence of the built environment on affordability. The color scheme is the same as that used for Table 5.1. Those living in block groups with higher levels of street network density and street connectivity both tended to exhibit higher resilience. For instance, block groups with the highest levels of street connectivity (as measured by the link to node ratio) still spent less than 5% of their income on community in the 3X driving cost scenario. The trends remained the same when we controlled for income.

Both population density and employment density were strong indicators of resilience and vulnerability. Differences in employment density, however, were more revealing. Even with the 3X scenario, households living in the highest density block groups spent around 3% of their income on commuting. Alternatively, households in the block groups with little to no employment options spent close to 11% of their income on commuting to work in the 3X scenario. These differences became even greater when controlling for income.

The approximate year of development of each block group (based on the ACS variable "year structure built") showed that older neighborhoods are more resilient than newer neighborhoods. While this result is likely indicative of older neighborhoods with good transit infrastructure and proximity to downtown, it speaks to the economic vulnerability of many new developments.

5.5 Income & Education

Given the focus on affordability, high levels of household income is clearly one path toward resilience in the scenarios we tested. For block groups with median household incomes higher than $200,000, as shown in Table 5.2, the 3X scenario did not even bring their commuting expenditures up to 3.5%. However, we did find that households in the $120,000–$160,000 range, the 3X scenario resulted in more than 5% spent on commuting. The vulnerability of these households was less than those with much lower incomes, but the difference was not as large as expected. This result suggests that low income households are already minimizing their transportation expenses. So while an increase in driving costs is detrimental to low income households, the medium-to-high income households seem more likely to have commuting costs that are difficult to moderate. As suggested by the literature, income and education were highly correlated in our study, and both variables had similar results.

5.6 Race/Ethnicity

We also wanted to investigate whether certain races or ethnicities experienced atypical levels of resiliency or vulnerability. Table 5.2 shows results based on the percent of white residents, non-white residents, black, Hispanic, Asian, and Native American. Overall, the results suggest a more equitable distribution of vulnerability than expected. For example, the percentage of white residents or black residents in a block group did little to impact the relative level of resiliency.

However, block groups with a relatively high percentage of residents of Hispanic origin and those with more Native Americans both resulted in increased vulnerability. In both cases, the results flipped when controlling for income. Despite these trends, there seems to be more work to do on this front with respect to increasing the resiliency of, for instance, lower income Hispanic neighborhoods.

Table 5.2 Percent of Household Income Spent on Commuting based on Built Environment, Income, Education, and Race/Ethnicity (color coded based on Figures 5.1 & 5.2)

Built Environment

Intersection Density	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 144	719	2.52%	3.75%	4.98%	7.42%	2.49%	3.72%	4.94%	7.38%
144 - 225	648	2.00%	2.95%	3.89%	5.77%	1.75%	2.58%	3.41%	5.06%
225 - 324	553	2.02%	2.97%	3.91%	5.78%	1.66%	2.45%	3.23%	4.78%
324 - 625	112	1.89%	2.77%	3.65%	5.39%	1.60%	2.34%	3.09%	4.57%

Link to Node Ratio	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1	9	2.24%	3.30%	4.36%	6.47%	1.93%	2.85%	3.77%	5.60%
1 - 1.2	149	2.13%	3.18%	4.23%	6.32%	2.52%	3.76%	5.00%	7.47%
1.2 - 1.4	706	2.26%	3.36%	4.46%	6.65%	2.21%	3.28%	4.36%	6.50%
1.4 - 1.6	813	2.23%	3.28%	4.30%	6.42%	1.85%	2.72%	3.60%	5.35%
1.6 - 1.8	272	2.02%	2.97%	3.91%	5.79%	1.66%	2.44%	3.22%	4.77%
1.8 - 2.0	83	1.69%	2.45%	3.22%	4.73%	1.46%	2.13%	2.80%	4.12%

Population Density	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1,000	298	3.03%	4.53%	6.04%	9.04%	3.23%	4.83%	6.44%	9.64%
1,000 - 3,000	312	2.11%	3.13%	4.15%	6.19%	2.08%	3.09%	4.10%	6.12%
3,000 - 5,000	456	1.94%	2.86%	3.79%	5.62%	1.81%	2.67%	3.54%	5.26%
5,000 - 7,000	455	2.02%	2.98%	3.93%	5.83%	1.74%	2.57%	3.40%	5.05%
7,000 - 9,000	244	2.16%	3.17%	4.18%	6.18%	1.69%	2.48%	3.28%	4.85%
9,000 - 12,000	162	2.16%	3.16%	4.14%	6.10%	1.54%	2.26%	2.97%	4.38%
12,000+	105	1.88%	2.70%	3.52%	5.13%	1.29%	1.85%	2.41%	3.52%

Employment Density	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 100	171	3.66%	5.49%	7.32%	10.97%	3.87%	5.81%	7.75%	11.62%
100 - 500	365	2.33%	3.46%	4.60%	6.86%	2.42%	3.34%	4.44%	6.63%
500 - 1,000	489	2.02%	2.99%	3.96%	5.89%	1.91%	2.84%	3.76%	5.60%
1,000 - 2,000	414	2.06%	3.04%	4.01%	5.95%	1.75%	2.58%	3.41%	5.06%
2,000 - 4,000	324	2.00%	2.93%	3.86%	5.70%	1.62%	2.38%	3.14%	4.64%
4,000 - 8,000	174	1.96%	2.95%	3.74%	5.49%	1.45%	2.11%	2.76%	4.07%
8,000 - 10,000	37	1.71%	2.45%	3.20%	4.67%	1.32%	1.91%	2.49%	3.65%
12,000+	58	1.24%	1.73%	2.22%	3.19%	1.03%	1.45%	1.87%	2.70%

Year Built of Housing Stock	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
1930s	123	1.54%	2.21%	2.87%	4.19%	1.28%	1.84%	2.40%	3.51%
1940s	62	1.91%	2.76%	3.62%	5.31%	1.40%	2.03%	2.66%	3.91%
1950s	275	2.17%	3.17%	4.17%	6.16%	1.56%	2.28%	3.01%	4.44%
1960s	260	2.14%	3.14%	4.14%	6.12%	1.70%	2.51%	3.31%	4.90%
1970s	441	2.20%	3.25%	4.31%	6.40%	2.00%	2.96%	3.93%	5.84%
1980s	343	2.25%	3.35%	4.44%	6.61%	2.18%	3.24%	4.29%	6.40%
1990s	275	2.32%	3.45%	4.59%	6.86%	2.46%	3.67%	4.87%	7.28%
2000s	183	2.45%	3.66%	4.86%	7.27%	2.47%	3.69%	4.90%	7.33%

Income / Education

Median Household Income	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 20k	47	2.41%	3.48%	4.55%	6.69%	1.54%	2.24%	2.94%	4.36%
20k - 40k	369	2.24%	3.27%	4.30%	6.33%	1.52%	2.22%	2.93%	4.31%
40k - 80k	961	2.29%	3.38%	4.47%	6.64%	1.95%	2.89%	3.82%	5.68%
80k - 120k	480	2.12%	3.16%	4.19%	6.27%	2.32%	3.46%	4.59%	6.86%
120k - 160k	135	1.69%	2.52%	3.35%	5.01%	2.32%	3.46%	4.60%	6.88%
160k - 200k	29	1.54%	2.30%	3.06%	4.58%	2.33%	3.48%	4.62%	6.91%
200k+	11	1.18%	1.75%	2.33%	3.47%	2.05%	3.05%	4.05%	6.05%

Education Score	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 1	282	2.68%	3.93%	5.18%	7.66%	1.70%	2.49%	3.29%	4.86%
1 - 2	1,468	2.23%	3.30%	4.36%	6.49%	2.06%	3.06%	4.05%	6.03%
2 - 4	272	1.42%	2.10%	2.78%	4.13%	1.82%	2.70%	3.57%	5.31%

Race / Ethnicity

% White	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 20%	4	2.47%	3.62%	4.75%	7.00%	1.71%	2.51%	3.30%	4.89%
20 - 30%	15	2.09%	3.06%	4.02%	5.93%	1.47%	2.15%	2.82%	4.17%
30 - 50%	81	2.47%	3.63%	4.77%	7.05%	1.68%	2.46%	3.25%	4.80%
50 - 70%	269	2.30%	3.38%	4.45%	6.59%	1.68%	2.48%	3.65%	4.84%
70 - 90%	860	2.15%	3.17%	4.20%	6.23%	1.86%	2.76%	4.43%	5.42%
90+%	793	2.14%	3.18%	4.22%	6.29%	2.24%	3.34%	4.43%	6.60%

% Non-White	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 5%	397	2.20%	3.27%	4.34%	6.48%	2.40%	3.57%	4.74%	7.07%
5 - 10%	396	2.09%	3.09%	4.09%	6.09%	2.09%	3.10%	4.11%	6.13%
10 - 20%	550	2.09%	3.09%	4.08%	6.07%	1.89%	2.80%	3.71%	5.13%
20 - 30%	310	2.26%	3.33%	4.40%	6.52%	1.81%	2.68%	3.54%	5.25%
30 - 50%	269	2.30%	3.38%	4.45%	6.59%	1.68%	2.48%	3.27%	4.84%
50+%	100	2.42%	3.54%	4.66%	6.88%	1.65%	2.42%	3.19%	4.71%

% Black	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 5%	1,550	2.20%	3.26%	4.31%	6.41%	2.06%	3.06%	4.06%	6.04%
5 - 10%	163	2.10%	3.09%	4.08%	6.05%	1.79%	2.63%	3.48%	5.16%
10 - 20%	151	2.04%	3.00%	3.95%	5.83%	1.65%	2.43%	3.20%	4.74%
20 - 30%	85	2.20%	3.22%	4.24%	6.27%	1.63%	2.40%	3.16%	4.67%
30 - 50%	53	2.30%	3.39%	4.47%	6.62%	1.74%	2.56%	3.28%	5.01%
50+%	20	2.00%	2.93%	3.84%	5.65%	1.46%	2.13%	2.80%	4.13%

% Hispanic Origin	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 5%	481	1.89%	2.80%	3.71%	5.53%	2.17%	3.22%	4.27%	6.37%
5 - 10%	387	2.06%	3.06%	4.06%	6.04%	2.15%	3.19%	4.22%	6.30%
10 - 20%	417	2.13%	3.16%	4.18%	6.22%	1.98%	2.93%	3.89%	5.78%
20 - 30%	235	2.36%	3.49%	4.61%	6.86%	1.96%	2.90%	3.84%	5.72%
30 - 50%	239	2.44%	3.59%	4.73%	7.00%	1.76%	2.60%	3.43%	5.08%
50+%	262	2.58%	3.78%	4.97%	7.35%	1.60%	2.35%	3.09%	4.56%

% Asian	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 5%	1,544	2.23%	3.29%	4.36%	6.47%	2.01%	2.97%	3.93%	5.85%
5 - 10%	299	2.04%	3.02%	3.99%	5.93%	1.91%	2.83%	3.75%	5.58%
10 - 20%	147	1.99%	2.94%	3.90%	5.79%	1.90%	2.81%	3.72%	5.54%
20+%	32	2.09%	3.06%	4.02%	5.94%	1.67%	2.46%	3.24%	4.81%

% Native American	n	Baseline Condition	1.5X Scenario	2X Scenario	3X Scenario	Median Income Baseline	Median Income 1.5X	Median Income 2X	Median Income 3X
0 - 5%	1,939	2.18%	3.21%	4.25%	6.31%	1.99%	2.95%	3.91%	5.81%
5 - 10%	61	2.34%	3.44%	4.52%	6.69%	1.69%	2.49%	3.28%	4.86%
10+%	22	2.43%	3.56%	4.69%	6.93%	1.66%	2.44%	3.22%	4.76%

6. CONCLUSIONS

With transportation as the second highest household expenditure in a typical U.S. budget, it is vital to understand the disproportionate impact that a "black swan" gas price event might have on a major city and region. We tested a baseline condition and resiliency scenarios of driving cost increases of 1.5X, 2X, and 3X via a multinomial logistic regression mode choice model from the DRCOG regional activity-based travel model for the Denver Metropolitan area. The mode choice model was developed based on extensive data collected by DRCOG during travel surveys conducted in 1997 and 2008, a time period over which gas prices more than tripled. While high income represents one path to resilience, our results suggest that higher resilience can also be found in locations with:

- Proximity to high employment areas,
- More compact and connected street networks, and/or
- Better transit infrastructure.

Current transit usage does not seem to make as big of a difference as living in the vicinity of better transit infrastructure. In other words, there is a significant option value to transit in the resiliency scenarios. This result suggests that cities and regions should consider investing in such infrastructure, even in situations with low projected ridership. Those living in a city or region that has made such transit investments would be far better off in a "black swan" event.

On the other side of the resiliency equation is vulnerability. Our results found that more suburban locations with fewer transportation options were far more vulnerable than their more urban counterparts. The differences were drastic with some block groups still dedicating less than 1% of their household income to commuting in the 3X driving cost scenario while other block groups expended almost 27% of their income on commuting under the same scenario. The economic ramifications of anywhere near that much income being consumed by simply getting to work could be devastating to these areas with few transportation choices beyond the automobile.

While this paper focuses on non-discretionary travel, the impact of such drastic gas price increases would also extend to non-work travel, vehicle choice, residential and work location choice, and land use patterns. Such a broader range of topics and the long-term impacts of the scenarios presented should be considered for future research. Including frequency of service and the number of different routes would also be interesting factors to study with respect to resiliency. Nevertheless, prediction is always a tough business (Silver, 2012). For instance, the results of this study are limited by the fact that we modeled travel behaviors based on gas prices extrapolated beyond the range of existing data. However, we crafted our methodology specifically to minimize this limitation as much as possible. First, our multinomial logistic regression mode choice model was developed using travel surveys conducted in 1997 and 2008, a time period when gas prices more than tripled. Also, we theorize that travel behaviors for households needing to dedicate a higher percentage of their income to transportation will shift to be more like the current travel behavior of households that dedicate a similar percentage of income to transportation, all else being held constant. Moreover, we are more interested in the relative trends found in the results, as compared with the precision of the numbers themselves. From that perspective, the results suggest that the Denver region has much work to do if such price shocks came to be, but also that other cities and regions should be conducting similar scenario planning analyses of their own.

The long-term impacts of high gas prices might ease with alternative fuels and improvements to the fuel economy of vehicles; however, the most vulnerable households would be least likely to reap those benefits. The existing literature suggests that many working families with incomes in the range of \$20,000 to \$50,000 spend more than 30% of their income solely on transportation costs (CNT, 2010; Lipman, 2006). The disproportionate impact to low and moderate income households is often part of the tradeoff with housing costs. Families that spend less of their total housing budget on housing often spend more on transportation costs. These are also the suburban families that are most vulnerable to a drastic price increase in the cost of driving.

Transportation choice creates network redundancy and facilitates adaptability under extreme conditions. The most resilient cities and regions will be those that plan for and invest in diversifying and expanding transportation choice. On the other hand, cities and regions that continue to promote a single mode of transportation like the automobile might be okay for the time being, but they will be the most vulnerable should a “black swan” event occur.

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PART 2: RESILIENCY AT THE CITY SCALE[2]

8. INTRODUCTION

Transportation is critical to sustaining the economic and social vitality of communities. As these systems become more complex and integrated regionally, nationally, and internationally, their sustained safety and operation becomes increasingly essential to the social, economic, and environmental activities of a community (Hanson and Giuliano, 2004). Given this intrinsic relationship, the continued operation of these transportation systems is critical to societal well-being (Freckleton et al., 2012).

One aspect of transportation that is vulnerable to both abrupt variability as well as long-term change – thus causing significant disruption to individuals, households, and the overall community – is the cost of gas. Gas prices have been increasing over the last decade and are projected to continue to increase (Lipman, 2006). According to data from the US Energy Information Administration, from 2002 – 2012, gas prices have increased more than 10% annually, compounded (US Energy Information Administration, 2013). At this rate, gas prices would be more than $8.00/gallon in 2020. Moreover, gas prices are also subject to extreme volatility and have the potential to increase dramatically in a short time period. Such abrupt fluctuations are difficult to guard against, as the events that might cause them are unpredictable and often half a world away.

This research seeks to understand how the availability of bicycling, walking, and transit modal options contribute to resiliency as caused by an abrupt doubling of gas price. Our hypothesis is that the availability of these more environmentally friendly modes – even if few are using them today – contribute significantly to the resiliency of a community. Although this approach is similar to the Center for Housing Policy affordability work that measures combined housing and transportation costs (Lipman, 2006), we make one important distinction: we do not assume that people pursue the same transportation mode as they did in the before case. In other words, two neighborhoods could be very similar in many respects, but if one possesses good active transportation infrastructure and/or decent transit service, that neighborhood could conceivably be less vulnerable to an abrupt gas price increase. Understanding the latent resiliency value of multi-modal transportation options is where our study hopes to make a contribution.

When a crisis arises, the households that are already vulnerable because of their poor access to transportation and other vital resources will be most deprived (Fitzgerald, 2012). Such vulnerable households are often those that have significant housing and transportation cost burdens. Because of the constraints and budgetary limitations to these households, they have the least access to coping resources if a crisis arises. Collectively, these households represent the weakest point in a city's capacity to mitigate such an event; in such a way, a catastrophic event not only threatens the usefulness of physical infrastructure and the built environment, but it also impacts social systems (Lipman, 2006).

Policies to overcome these risks have often focused on lowering gas prices (Haas et al., 2008); however, gasoline and motor oil average only 21% of total transportation expenditures (Bureau of Labor Statistics, 2013). It is not uncommon in the literature to model the economic impact of increased fuel prices via scenario planning; for example, a recent study suggested that the cost of fuel in Bangladesh could increase from 1.4% of GDP to 14.9% in such an increased fuel price scenario (Alam et al., 2013). To truly

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overcome the economical and societal implications of increased fuel costs, the goal must be to build resilient cities that offer a network of sustainable systems and communities (Newman et al., 2009). Broadly, resiliency is a system's capacity to manage unexpected events without catastrophic failure (Heaslip et al., 2009). A city without these resiliency measures is vulnerable to a threat that arises (Godschalk, 2002).

Much of the early resiliency research was qualitative and looked at resiliency primarily through the lens of natural disasters such as hurricanes, earthquakes, or tsunamis (Bruneau et al., 2003; Chang and Nojima, 2001; Foster, 1995; Pelling, 2003) or terrorist attacks (Battelle, 2007). More recently, the concept of resiliency has become more quantitative and expanded to transportation (Berdica, 2002; Cova and Conger, 2004; Heaslip et al., 2010; Husdal, 2004; Murray-Tuite, 2006; Serulle et al., 2011). While overall resilience has been relatively well characterized as a result of the many different disciplines working on the issue, transportation resilience is less well defined. For instance, overall resilience represents the ability to perform under shock effects (shock-absorption), to avoid the shock altogether (vulnerability), or to have the ability to recover quickly from a shock (shock-counteraction) (Briguglio et al., 2005); transportation resilience has to do with the ability of the transportation system to maintain a desired level of service or the time it takes to return to that level of service given a shock to the system (Heaslip et al., 2009; Heaslip et al., 2010). The transportation research that has looked beyond resilience related to natural disasters and terrorist attacks has most often been economic (Briguglio et al., 2005; Echeverry et al., 2004; Zheng et al., 2011) and focused on issues such as gas prices (Dodson and Sipe, 2006), but there has also been a strand more focused on environmental issues such as climate change (Brenkert and Malone, 2005). Today's society has seen many low-income households relocate away from downtown in an effort to find more affordable housing. Without options beyond the automobile, these are the very same households that are likely to experience the greatest negative impact of rising gas prices.

In the book, Resilient Cities: Responding to Peak Oil and Climate Change, Peter Newman et al. state that "[t]he agenda for future resilient cities is to have sustainable options available so that a city can indeed reduce its driving or VMT" (vehicle miles travelled). Newman et al. propose seven elements to achieve more resilient transportation systems that have reductions in VMT; bicycling, walking, and transit – as alternatives to driving – are central to each of these elements (Newman et al., 2009). VMT is linked to negative effects of traffic safety, environmental health, public health, energy consumption, and other social costs of automobile use (Ewing and Cervero, 2010); reducing VMT is thereby fundamental to building resiliency. However, the capacity to reduce VMT – even if a community is not doing so today – is equally important.

Decision makers need metrics and tools to assess transportation system resiliency; however, predicting and measuring transportation under disruptive events is extremely complex. Nouri and Malmasi conducted an environmental impact assessment of urban development in Tehran using an ecological vulnerability model (Nouri and Malmasi, 2004). The use of multiple metrics is another approach that has long been used with sustainability and is being used for resiliency as well (Rassafi and Vaziri, 2005). For example, Godschalk and Murray-Tuite identify 10 critical components of transportation resiliency: redundancy, diversity, efficiency, autonomous components, strength, collaboration, adaptability, mobility, safety, and the ability to recover quickly (Godschalk, 2002; Murray-Tuite, 2006). Many of these elements are qualitative in nature; however, the work of Heaslip et al. attempts to quantify many of these resiliency measures by using a fuzzy inference approach (Heaslip et al., 2009).

In the Heaslip et al. study, there are various attributes that support resiliency; one attribute that is central to this study is personal mode choice (Heaslip et al., 2009). Transportation mode choice, for the individual and community, is the opportunity to use multiple means of transportation. The provision of multiple transportation options helps facilitate resiliency by relieving the transportation system stress that tends to occur in many situations when only one modal option is available (Freckleton et al., 2012). Thus, creating a built environment with transportation alternatives and land uses that support them can be an important and effective strategy for building resiliency into a system (Haas et al., 2008).

For the sake of this research, modeling such transportation options represents an opportunity to better understand the impact of various resiliency scenarios. This modeling process, conducted in the fall of 2013, reveals how certain communities and neighborhoods demonstrate different mode shift capabilities based on varying environmental and demographic circumstances. This research also presents a unique understanding of the option value of environmentally friendly transportation infrastructures.

9. MATERIALS & METHODS

The analysis in this paper focuses on the mode share for work trips in the city and county of Denver following a drastic gas price increase. Work trips were selected as they represent travel that people would likely still need to make after a gas price event. To assess this hypothetical mode shift, actual trips made in the region are analyzed under a series of gas price scenarios using a multinomial logistic regression mode choice model. These trips were extracted from the Denver Regional Council of Governments (DRCOG) Focus travel model, a regional activity model. This model was based on an in-depth travel behavior survey of 12,000 households in the Denver region, called Front Range Travel Counts (DRCOG, 2013).

The database output from the DRCOG Focus travel model was provided to us in the information platform Microsoft SQL Server. Several queries with specific characteristics were executed, such as "Tour Type: Home based" and "Tour Purpose: Work" to determine the number of total work trips from each origin traffic analysis zone (TAZ) to all work destination TAZ's. The total trips were broken down by the following four modes: automobile, pedestrian, bicycle, and transit. The trips' databases were then aggregated from the TAZ to the census tract level for the home origin. For the work destination, they were aggregated from the TAZ to the neighborhood level (within the city and county of Denver) or city (in the case that a trip's work destination was located outside the city and county of Denver). There were a total of 143 home origins, which comprise the total number of census tracts in the city and county of Denver as configured in the 2010 U.S. Census; of these origins, the top four work commute destinations were extracted. Four destinations were selected, as this number offers a sizable portion of the total trips taken in the census tract with respect to the overall distribution while still offering a viable number of total regional trips to analyze. Trips to the top four destinations were investigated for each of the 143 census tracts, for a total of 572. Data for each of the four transportation modes were collected for each of these 572 trips; this equals 2,288 different combinations.

In order to understand the bike, pedestrian, auto, and transit mode choices for each combination, the Google Maps Engine Lite tool was consulted to determine the suggested route for each mode between these origins and destinations. The geographic coordinates of each census tract centroid was determined and entered into Google Maps as the starting location. For the neighborhood destinations, the geographic coordinates of the centroid were also used. However, if the destination was outside of Denver neighborhoods and the destination was a city, Google Maps was consulted to provide the best location for the city's geographic coordinates (as the centroid of a city boundary does not often represent a city center). From these results, the top trip route option was selected for each mode and several variables were recorded as follows:

- For the auto mode:
    - Travel time (minutes)
    - Trip length (miles)
    - Whether the trip required limited access highway travel
- For the bicycle and pedestrian modes:
    - Travel time (minutes)
    - Trip length
    - Level of traffic stress for the trip
- For the transit mode:
    - Travel time (minutes)
    - Level of traffic stress for the trip

The data collected via Google Maps are intended to provide a sense of the lowest cost route by each mode; actual route choice between origins and destinations may vary from Google's suggestion but such differences should not be detrimental to our results. In the following section, the traffic stress methodology is described in greater detail, including the relevant variables of interest.

9.1 Traffic Stress Methodology

In order to more realistically assess the alternative mode options for each trip, accounting for the fact that not everyone will bike, walk, or use transit – even in situations where those modes offer the lowest dollar cost options – we adapted and refined the bicycle level of traffic stress approach developed by Mekuria et al. (Mekuria et al., 2012). This methodology classifies streets based on their bicycle level of traffic stress (LTS) that they exhibit to the user, and we applied our own adaptation of this methodology to the pedestrian and transit modes as well. A Geographic Information System (GIS) was used to assign traffic stress levels to Denver streets by the bike and walk mode, while Google Maps was used to determine transit traffic stress. By estimating the bike/pedestrian/transit LTS options, we were able to more realistically assess the ability of different population groups across Denver to shift to these modes from the driving mode. The following sections describe the methodologies used to determine these modal LTS levels.

9.1.1 Bicycle Level of Traffic Stress

The bicycle LTS work of Mekuria et al. assigns four traffic stress levels to street segments and intersections based on characteristics such as operating space, speed, and intersection treatment (Mekuria et al., 2012). In this methodology, we attempted to reasonably measure the stress that different types of bicyclists might experience while relying on variables that were readily available or easily measurable. The methodology we used for the analysis of Denver streets, while based on the work of Mekuria et al., focused on three traffic and street characteristics: speed, number of travel lanes, and the presence of bicycle facilities. The two data sources used in this analysis are:

- A street database for the city and county of Denver available in a GIS format with attribute data for each street segment including the number of lanes, speed limit, and functional classification (local, collector, arterial)
- A street database for the city and county of Denver available in a GIS file with all of the on- and off-road bicycle facilities in Denver, including varying bicycle treatments (bike lanes, cycle tracks, etc.)

Similar to the work by Mekuria et al, four levels of stress were identified in the Denver methodology and assigned to every street in the city. LTS 1 is acceptable for all users and includes paved off-street paths and trails only. Many adults tolerate LTS 2, while LTS 3 is unacceptable to most. Finally, LTS 4 is the highest stress and is tolerated by few individuals (Mekuria et al., 2012). The specific characteristics designating each stress level are summarized in Table 9.1 (with LTS 1 unlisted as it applies only to off-street paths and trails).

Table 9.1 Criteria for Bicycle Level of Traffic Stress (LTS)

Based on posted speed limit and number of travel lanes, adapted from Mekuria et al (LTS 1 is unlisted as it applies to only off-street paths and trails) (Mekuria et al., 2012).

	≤25 mph	**=30 mph**	**≥35 mph**
2-3 lanes	LTS 2	LTS 3	LTS 4
4-5 lanes	LTS 3	LTS 4	LTS 4
6+ lanes	LTS 4	LTS 4	LTS 4

As an addendum to the above criteria, we assessed specific bicycle infrastructure on streets and adjusted traffic stress accordingly. For instance, if a street characterized by LTS 4 had a bike lane, this street was reassigned to LTS 3. Also, if a lower traffic stress street intersected a higher traffic stress street, the approaching lower stress street segment was reassigned the higher stress level. The rationale behind this is that a user will likely experience the stress of the higher LTS street when crossing that street even if the street that they were travelling on was defined by a lower stress level.

After each street in Denver was assigned a traffic stress level, the top four work commute trips for each of the 143 Denver census tract origins were assigned a traffic stress level based on the stress of the streets along the trip route. The LTS of the route was predicated by the highest traffic stress value assigned to any street segment along the way; thus, if a route contained largely LTS 2 streets but crossed one LTS 4 arterial, then that route was assigned the highest stress experienced by the user, or LTS 4. These values were assessed and recorded for all 572 trips for the bike mode.

9.1.2 Pedestrian Level of Traffic Stress

As with the bicycle LTS methodology, the pedestrian approach we developed similarly intends to measure the stress pedestrians experience on a roadway by using data that are measurable and readily available. The pedestrian LTS was based on three primary characteristics: speed, number of travel lanes, and sidewalk width. Since the bicycle LTS methodology measured these first two variables, as well as the presence of bicycle facilities (which are often installed as a countermeasure to improve pedestrian safety [Harkey and Zegeer, 2004]), the pedestrian LTS methodology was built on the bicycle LTS designations. Given this approach and using the GIS data built for the bicycle LTS levels, the pedestrian analysis assigned traffic stress based on the sidewalk width of these bicycle LTS graded streets. The data available on the sidewalk width were acquired from a citywide database in a GIS file that included all the sidewalks in the Denver street network. Table 9.2 describes each pedestrian LTS designation; in the criteria, the larger sidewalk widths contribute to a lower pedestrian level of traffic stress. Since this is based on bike LTS, sidewalk widths of less than 5 feet are not applicable to the bike LTS value of 1 since all bicycle paths (which exclusively represents bike LTS 1) in Denver are greater than this width.

Table 9.2 Criteria for Pedestrian Level of Traffic Stress (LTS)

Ped LTS is based on sidewalk width and bicycle LTS (where an LTS does not apply to sidewalk widths of less than 5' that are within the Bike LTS category since such facilities are not narrower than this width)

	Bike LTS 1	Bike LTS 2	Bike LTS 3	Bike LTS 4
Sidewalk ≥5ft	LTS 1	LTS 1	LTS 1	LTS 3
Sidewalk 4ft	n/a	LTS 1	LTS 2	LTS 3
Sidewalk 3ft	n/a	LTS 2	LTS 3	LTS 4
Sidewalk ≤2ft	n/a	LTS 3	LTS 4	LTS 4

The process of assigning traffic stress to the pedestrian mode option for the top four commute areas was similar to the bicycle mode. Given the trip route suggested by Google Maps, pedestrian LTS was based on the highest stress street experienced, and this was again repeated for all 572 walking trips.

9.1.3 Transit Level of Traffic Stress

Instead of focusing on street and traffic characteristics for the transit LTS methodology, as was done with the bicycle and pedestrian LTS methodology, this approach analyzed the transit options available for each of the four trips using Google Maps. Transit traffic stress was based on two criteria: the number of transfers required to make the trip and whether these transit connections were available by light rail transit or commuter bus. Cognitive research conducted in the United States and Europe has shown an individual preference for light rail over bus (Scherer, 2010); thus, in this methodology, light rail transit favors a lower traffic stress experience, as do fewer transit transfers. Accordingly, transit traffic stress was assigned based on the following assignments:

- LTS 1: Light rail only
- LTS 2: Light rail with one transfer, or bus only (no transfers)
- LTS 3: Light rail with two transfers, or any other transit combination (bus-bus or light rail-bus) with one transfer
- LTS 4: Light rail with three or more transfers, or any other transit combination (bus-bus or light rail-bus) with two transfers

For each trip origin and destination, the number of transfers and transit options were assessed for the first route suggested in the Google Maps results. For the transit function, the Google Map tool defaults to the current date and time that the user is investigating. Thus, a consistent day and time was utilized: the trip was entered to arrive by 8:00 AM on the nearest Wednesday. In the analysis, if walking was determined to be more efficient than taking transit, Google Maps often recommends walking as the first option. In this case, the first instance that transit is recommended was utilized for that particular trip. Finally, if there were no transit options available for a certain trip, then no LTS level was assigned. This procedure was repeated for all 572 transit trips.

9.2 Statistical Methodology

The statistical relationship between mode choice and a drastic shift in gas price, with respect to the level of traffic stress of the various modes, was investigated by using a multinomial logistic regression model. The intent was to provide us with a realistic understanding of who might be able to access certain facilities. Many mode choice investigations fail to differentiate between different types of infrastructures. For instance, the bicycle pavement marking known as the sharrow (or shared-use arrow) that is present on a busy street might not be modeled any differently from a bike lane or a cycle track. In reality, there is a percentage of the population that would ride every day on a cycle track but not in a bike lane; and there is another percentage of the population that would ride in a bike lane but not on a route marked with a sharrow. These distinctions are what we were looking to model. Accordingly, the LTS proxy variables took into account the following: the presence of different types of bicycle, pedestrian, and transit infrastructure; characteristics of the street such as number of lanes and traffic speed; and functional classification of the street. Also considered were travel time and distance between origins and destinations, population density, and socioeconomic status (SES) variables such as household income and the percentage of minorities. Interactions among the selected variables were also tested and analyzed; in particular, interactions between the LTS and SES variables were tested. The variables used in the final models were selected in an effort to maximize model significance using the Akaike Information Criterion (AIC) value. With respect to multi-collinearity, none of the variables used in the final models were highly correlated with one another. For instance, travel time and distance between origins and destinations are highly correlated variables, both of which should not be used as independent variables in the same mode choice model. Travel time turned out to be the more highly significant variable and was used in the final model.

The basic structure of a multinomial logistic regression mode choice model is derived from a basic logit model. The following generalized logit equation determines the probability of choosing a specific mode (Martin and McGuckin, 1998).

$$P_i = \frac{e^{u_i}}{\sum_{i=1}^{k} e^{u_i}}$$

where:

P_i = probability of somebody choosing mode i = 1, 2, . . . , k;

u_i = utility function describing the relative attractiveness of mode i; and

$\sum_{i=1}^{k} e^{u_i}$= sum of the functions for all available mode alternatives

The probability of choosing a particular mode depends on the above utility function relative to the utility functions for all the other mode options. In conventional four-step model transportation planning, the utility function of the logit equation typically contains variables such as in-vehicle travel time, out-of-vehicle travel time, and the cost associated with each mode for a particular type of trip between two specific zones. Our utility functions included travel time and costs but also took into consideration the level of traffic stress for bicycling, walking, and transit, and with respect to driving, whether or not the trip includes a limited access highway. Four mode types were modeled – transit, walking, biking, and driving – and to account for four separate categorical outcomes, a multinomial logistic regression model was used (Ben-Akiva and Morikawa, 2002). A multinomial logistic regression simultaneously considers a binary logit model for every possible combination of outcomes; in this study, the four different outcomes are equivalent to six binary logit models (Long, 1997). One assumption of this model is that the probabilities related to the mode choices sum to 1:

$$P(transit) + P(walking) + P(biking) + P(driving) = 1$$

For such a probability-based model, the multinomial logistic regression equation is:

$$P(y_i = 1|x_i) = \frac{1}{1+\sum_{j=2}^{J} e^{(x_i \beta_j)}} \text{ for m = 1}$$

$$P(y_i = m|x_i) = \frac{x_i \beta_m}{1+\sum_{j=2}^{J} e^{(x_i \beta_j)}} \text{ for m > 1}$$

where:

y = dependent variable,
j = number of categorical outcomes for four mode choices,
$P(y = m|x)$ = probability of choosing mode m given x,
x_i = independent predictor variable, and
β = estimated coefficient representing the effects of the independent variable.

The probability of the four modes (transit, walking, biking, and driving) was calculated for the top four work trip destinations for each Denver census tract origin using the multinomial logistic regression model for a baseline gasoline price of $2.70 and a doubling of that price to $5.40 per gallon. The base gas price was chosen because it was the prevailing gas price estimate for Denver region when the Front Range Travel Survey (a 12,000 household travel survey for the region from which our data were gathered) was being administered (DRCOG, 2013). This gas price was used to determine the average annual cost of gas for each 572 commute trips using an average vehicle efficiency of 20.2 miles per gallon, which was the national average during the same time period (EPA, 2007). We then calculated the average annual percent of the median household income spent on gas for each census tract on commute trips, a value that could be doubled in the model to reflect the resiliency scenario. This informed the cost of driving for these work commute trips.

Table 9.3 provides the descriptive statistics of all the data that were put into the model. This includes the following for each variable: the minimum and maximum values, the mean, standard deviation (SD), and number of observations. The values in Table 9.3 represent the data for each origin via all four modal options. For instance, the average number of minutes walking to work value is based on all origins to all destinations, which does not reflect actual behavior but is needed for the mode choice model. Table 9.4 shows the results of the mode choice model.

Table 9.3 Descriptive Statistics (selected variables)

	Variable	Obs	Mean	SD	Min	Max
Misc.	Population of origin census tract	2,288	4,129.42	1,567.84	314	9,462.00
	Population density of origin census tract	2,288	7,032.95	3,938.61	28.51	24,770.81
	Percent minority in origin census tract	2,288	25.2	17.12	0	79.91
	Median HH income of origin census tract	2,288	52,354.48	24,550.32	9,571.00	153,571.00
Automobile	# of driving miles to work (avg.)	2,288	6.47	4.74	0	27.4
	# of minutes driving to work (avg.)	2,288	13.8	6.61	0	40
	Whether car trip to work includes hwy driving (avg. of 0, 1 variable)	2,288	0.46	0.5	0	1
	Proportion of income spent on annual driving to work (avg.)	2,288	0.01	0.01	0	0.11
Transit	# of minutes for transit trip to work (avg.)	2,224	44.6	23.73	0	123
	# of transfers for transit trip to work (avg.)	2,224	0.55	0.64	0	3
	Whether transit trip to work includes light rail (avg. of 0, 1 variable)	2,224	0.14	0.35	0	1
	Transit LTS score for trip to work (avg.)	2,224	2.48	0.72	0	4
Walk	# of walking miles to work (avg.)	2,288	5.86	13.01	0	304
	# of minutes walking to work (avg.)	2,288	106	71.62	0	469
	Walking LTS score for trip to work (avg.)	2,288	3.6	0.66	0	4
Bike	# of biking miles to work (avg.)	2,288	6.22	4.28	0	26.8
	# of minutes biking to work (avg.)	2,288	35.35	23.3	0	138
	Biking LTS score for trip to work (avg.)	2,288	3.93	0.44	0	4

Table 9.4 Results of the Mode Choice Model

Variable	Transit	Walking	Biking
Intercept	0.6197 ***	1.9941 ***	1.1106 ***
Miscellaneous			
Population of origin Census Tract	0.00008	0.00021	0.00014 ***
Population Density of origin Census Tract	0.000071 ***	0.000095 ***	0.000055 ***
Percent Minority in origin Census Tract	0.00799 ***	0.0155 ***	0.0032 *
Median HH Income of origin Census Tract	2.94E-06 **	3.64E-06 **	7.59E-06 ***
Driving			
# of driving miles to work (avg.)	0.1477 ***	0.7477 ***	0.1907 ***
Proportion of income spent on annual driving to work (avg.)	45.4014 ***	66.357 ***	50.6937 ***
Transit			
Transit LTS score for trip	0.4131 ***	0.0249	0.3663 ***
Whether transit trip to wo	0.7098 ***	0.4461 ***	0.2331 **
Walking			
Walking LTS score for trip to work (avg.)	0.313 ***	0.3473 ***	0.2145 ***
** p<.10, ** p <.05, *** p*			
Observations	2,224		

Results of the mode shares for a given home census tract were weighted based on the relative number of trips. For example, if the top 4 destinations for a home zone have 100 people total and 60 of them were going to destination A with 80% auto mode share, 20 to B with 60% auto mode share, 15 to C with 90% auto mode share, and 5 to D with 40% auto mode share, the home census tract automobile mode share would be 75.5%, as follows:

$$0.755 = \frac{0.8(60) + 0.6(20) + 0.9(15) + 0.4(5)}{100}$$

To determine mode shift at the census tract level after a two-fold increase in gas price, each trip taken in each Denver census tract was averaged and normalized based on the actual number of trips taken for each origin and destination. Data used for this analysis were from the 2010 American Community Survey (ACS), administered by the U.S. Census (ACS, 2013).

10. RESULTS & DISCUSSION

10.1 Census Tract Analysis

In reporting the results, we first explore expected trends at the census tract level for the entire city and county of Denver, and then we explore trends and contributing factors further by investigating expected changes at six specific census tracts. We compare mode shifts at the census tract level in Denver in a scenario where the gas price doubles, from a base price of $2.70 per gallon (the baseline scenario) to a two-fold increase of $5.40 (the resiliency scenario).

For each 143 Denver census tracts, after the resiliency scenario, car mode share decreased by varying amounts while bicycle, walking, and transit mode shares increased. These data are best depicted spatially in Figure 10.1, where the changes in car mode shares in each census tract are shown. Figure 10.1 is compared side-by-side to Figure 10.1, where the change in driving mode share is displayed with income held constant. Figures 10.1 and 10.2 also illustrate the major street network, bicycle paths, and light rail facilities in Denver.

Those census tracts that have the highest change in driving mode share, displayed in Figure 10.1 as the darker shaded color, have a greater shift away from driving to transit, biking, and walking. Many of these census tracts appear to be located away from the Central Business District (CBD), particularly scattered throughout the southwestern areas of Denver. On the other hand, those census tracts with the lowest shift in driving mode share appear to be clustered around the CBD and in the northeast areas of Denver. These more urban census tracts already have a lower driving mode share, thus the driving mode shift after the resiliency scenario is less acute. Other socio-economic or demographic factors may also affect the shift as it occurs in different geographic census tracts.

In order to understand what other factors may be impacting these trends, we held income constant for all Denver census tracts and displayed the results in Figure 10.2. The Metro Denver Economic Development Corporation reports that for 2011, the median household income in Denver was $59,230 (Metro Denver, 2013). In Figure 10.2, the darker colors again indicate the higher shift away from driving mode share. There is a significant group of these census tracts with a higher shift away from the driving mode share located south of the CBD. These census tracts are not adjacent to the CBD, but they are surrounded by high ease-of-use transit and bicycling facilities: light rail transit and multiple bicycle paths. Thus, it appears there are factors, in addition to income, that may be impacting mode share, and further analysis is merited to better understand what these elements may be.

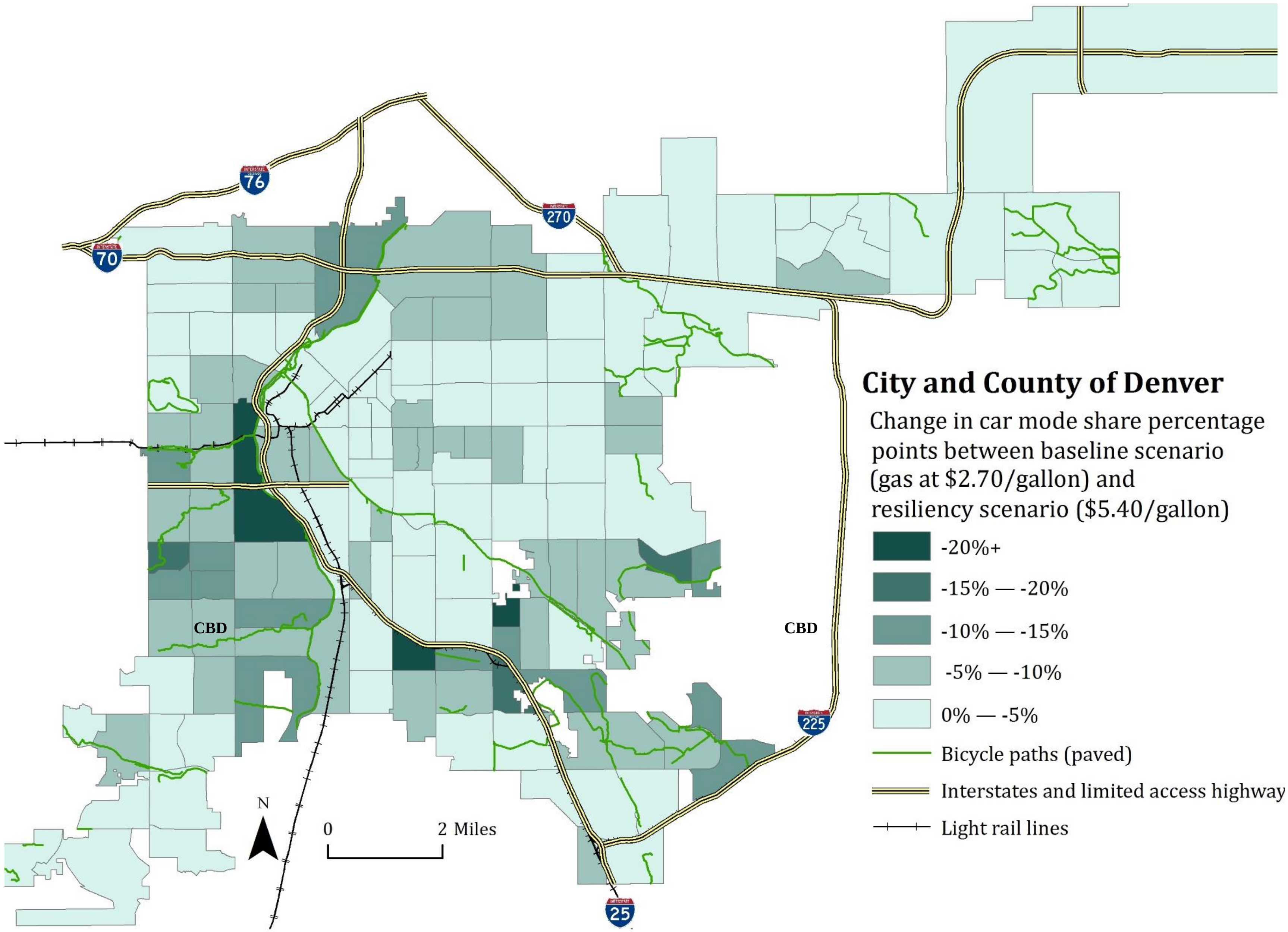

Figure 10.1 Change in Car Mode Share by Census Tract in Denver after the Resiliency Scenario (in relation to the major streets and highways, bicycle paths, and light rail transit network)

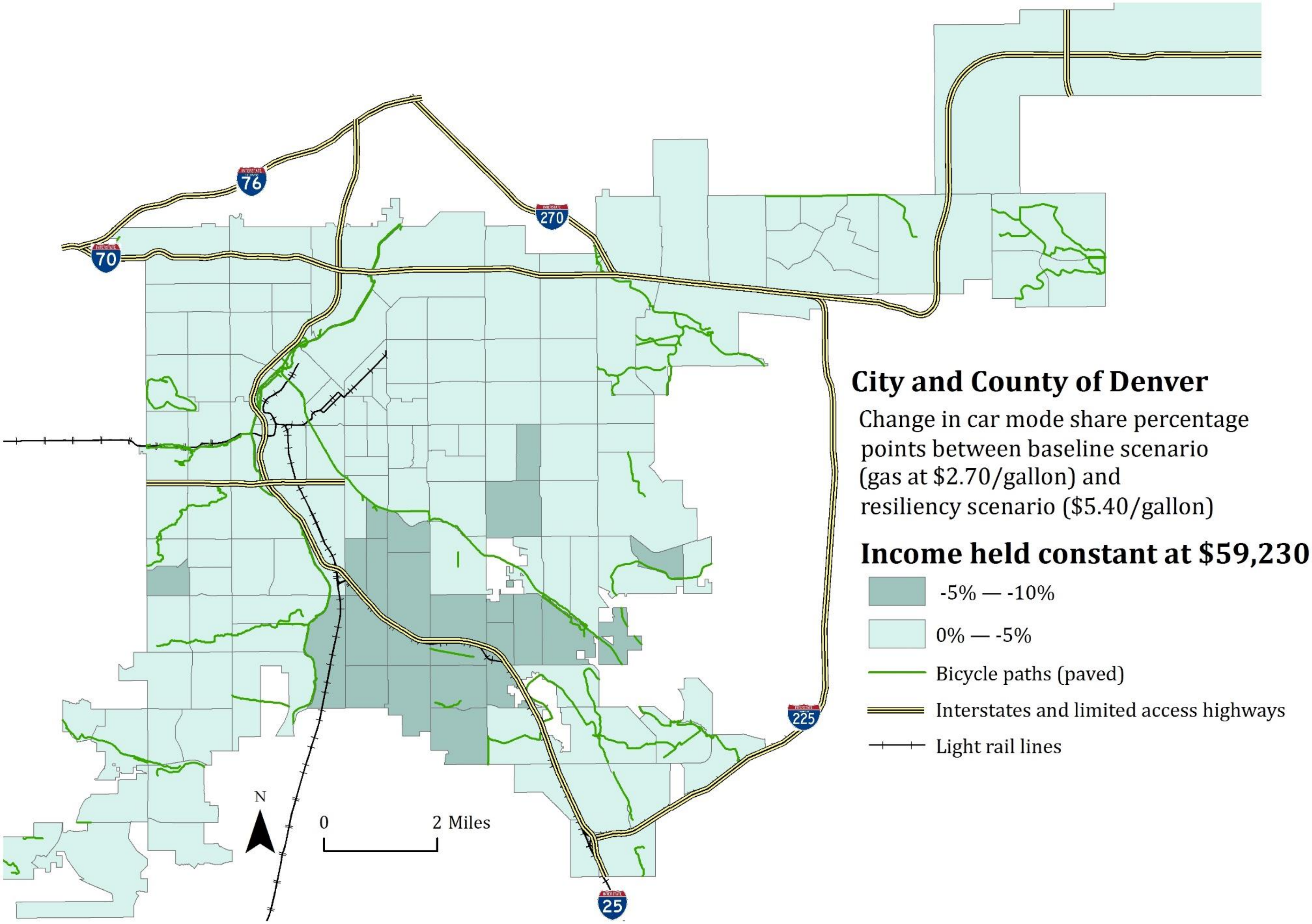

Figure 10.2 Change in Car Mode Share by Census Tract in Denver after the Resiliency Scenario with Income Held Constant at $59,230 (based upon 2011 median household income as reported by the Denver Metro Chamber of Commerce)

10.2 Census Tract Study Areas

10.2.1 Study Area Characteristics

Since it seems that geographic and demographic factors impact transportation choices after the change from the baseline to the resiliency scenario, we take a closer look at mode shift trends in six Denver census tracts. In selecting these census tracts, our variables of interest are proximity to downtown and income. We selected three census tracts that are situated closer to the city center and three that are in more suburban locations. We also chose census tracts that have low, middle, and high median household incomes, selecting two in each income range (based on 2010 ACS household income values) (ACS, 2013). To facilitate the comparison, we also selected census tracts that share the following two top work destinations: the Denver Central Business District (CBD) and the city of Aurora (located to the east of the Denver city limits).

The six census tract origins that were selected for this analysis will be referred to by the neighborhood contained within the census tract, not by the census tract number. Globeville, an urban census tract with lower household income, is located just north of the CBD. College View/S Platte is a lower-income, suburban census tract that is located in the southern part of the Denver city/county limits. City Park West is a middle-income census tract that is located just east of the CBD. Sunnyside is also a middle-income census tract but it is located in the northwestern portion of the Denver limits. Finally, Country Club is a higher-income census tract that is located directly southeast of the CBD, while Stapleton is high-income census tract that is located near the northeast corner of Denver city/county limits.

Work trips from these six census tracts to two destinations (Aurora and the CBD) were analyzed. Aurora and CBD are two of the top four work commute destinations for each origin census tract. Additionally, CBD and Aurora represent an urban and suburban destination, respectively, which is relevant to our analysis of urban and suburban trip origins.

In the analysis of these census tracts, three elements have a significant impact on mode shift in our six census tracts and are further explored: proximity to downtown, income, and availability of multi-modal transportation infrastructure.

10.2.2 Proximity to Downtown

Results from the mode choice model reveal that for the six Denver census tract study areas, the driving mode share is consistently higher for suburban census tracts origins as compared with their urban counterparts. Trips from Stapleton, Sunnyside, and College View/S Platte have higher driving mode share than trips from Country Club, City Park West, and Globeville. Figure 10.3 illustrates these trends for work trips from the six census tract study areas to the CBD. This trend is particularly acute for the higher income census tracts: Stapleton and Country Club. A factor influencing this is that Stapleton is significantly farther from the CBD than Country Club (12 miles versus 2.9). Globeville and College View/S Platte – low-income census tracts – also are quite different in their distance to the CBD (3.4 and 17.8 miles, respectively), but do not display the driving mode share difference that the high-income study areas do.

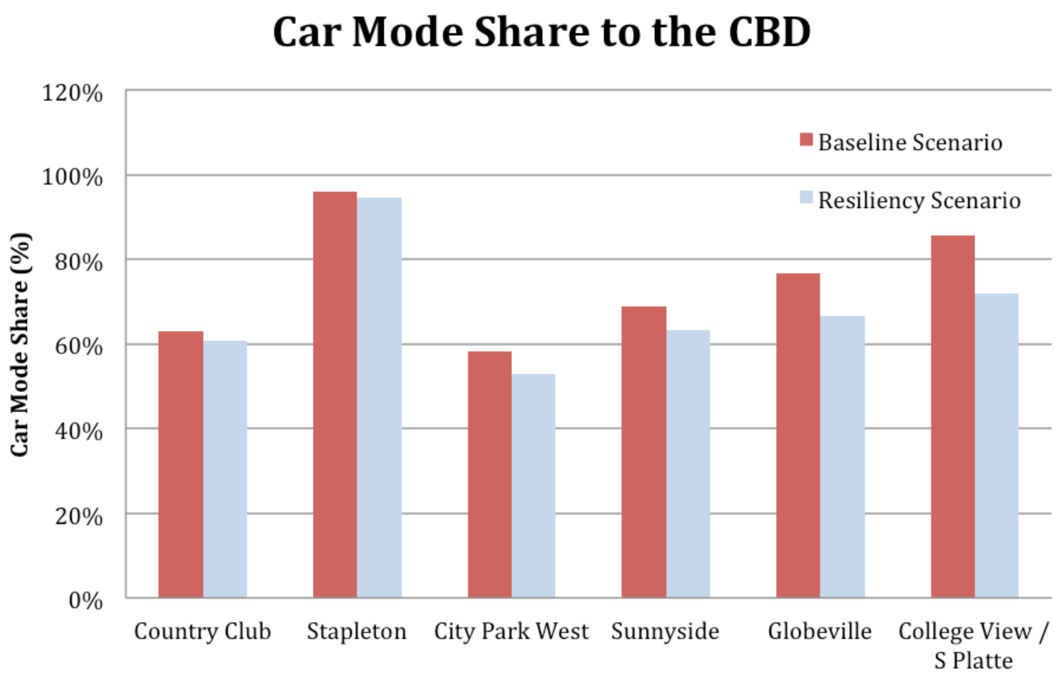

Figure 10.3 Car Mode Share to the CBD in the Baseline and Resiliency Scenarios for the Six Census Tract Study Areas

Another interesting trend related to the driving mode share is that all trips to the CBD, regardless of the origin, have lower driving mode share than those same trips to Aurora. So in addition to driving mode share being impacted by proximity to downtown, it is also impacted by the proximity to downtown of a household's destination. Figure 10.4 displays this trend.

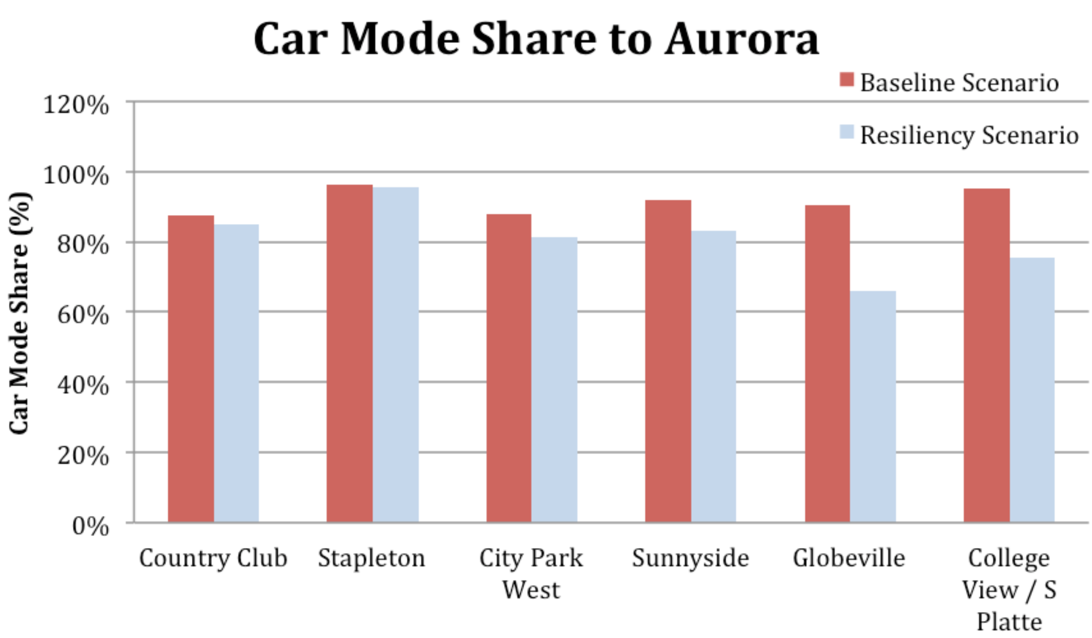

Figure 10.4 Car Mode Share to Aurora in the Baseline and Resiliency Scenarios for the Six Census Tract Study Areas

When comparing the trends in Figures 10.3 and 10.4, we see that the car mode share from Stapleton to the CBD (95%) and to Aurora (97%) for the resiliency scenario remains fairly unchanged. In these cases, nearly all the households are already opting to drive for both their trip to Aurora and CBD. However, most of the other study areas show a significant increase in car mode share for the trips to Aurora when compared with the CBD for the resiliency scenario. Because of this overall higher mode share across all study areas, the difference in car mode share between urban and suburban census tracts and Aurora is less dramatic than it was in Figure 10.3.

10.2.3 Income

One important impact of the trip distance differences for those people living in the urban and suburban origins, particularly as it relates to resiliency, is the fact that it directly impacts their household budgets in terms of gas expenditures. Those households in the suburban origins that have a farther distance to travel for work trips are spending more money on gas than their urban counterparts. This discrepancy impacts low-income households more than high-income areas in terms of the percent of income spent on gas. With high household income, these census tracts have more capacity to withstand increases in gas price than those areas with more constrained financial resources. For this reason, we would expect to see less of a change in driving mode shift for high-income areas when compared with lower-income areas after the resiliency scenario.

This trend is indeed apparent in Figure 10.4 for trips to Aurora. For the middle- and higher-income households, after the resiliency scenario, car mode share generally remains high. With more income available to these high-income households, they can better cope with higher costs of driving and do not necessarily have to change their travel behavior to mitigate the impact to their budget. On the other hand, for the low-income households (Globeville and College View/S Platte), car mode share falls more substantially after the resiliency scenario. The same trend occurs for trips to the CBD as displayed in Figure 10.3, although it is less acute. In Figure 10.3, the shift away from driving after the resiliency scenario is greater for the lower-income census tracts than for the middle- and higher-income households.

To further understand this trend, we determined the percent income spent on gas for each trip. As discussed in the "Materials and Methods" section, we were able to calculate this value based on the length of the trip in miles and assuming an average vehicle efficiency of 20.2 miles per gallon (EPA, 2007). Results revealed that higher-income households (Stapleton and Country Club) spent the least percentage of their household budget on gas for trips to Aurora than any other census tracts being reviewed – even after the resiliency scenario (see Figure 10.5). For trips to the CBD after the resiliency scenario, lower-income households spent more of their income on gas than other areas. When compared with percent of income spent on gas for trips to Aurora, trips to the CBD have less impact on household income – which again is due to the distance of these trips and amount of gas used. Finally, suburban trips have a higher percent of income spent on gas than their urban counterparts, except for the Stapleton to Aurora trip (which relates to the fact that this trip is shorter in distance than Stapleton to the CBD).

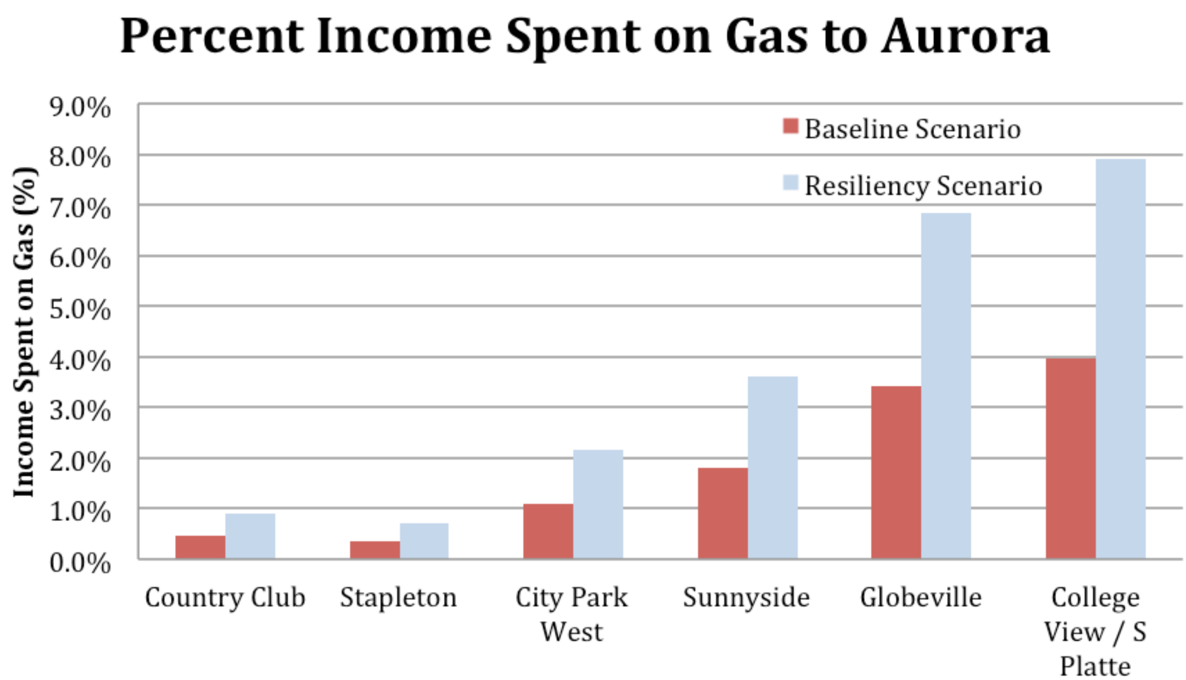

Figure 10.5 Percent of Income Spent of Gas for Households Traveling to Aurora for Both the Baseline and Resiliency Scenarios

In order to understand how other factors may be influencing mode share, we again hold income constant, this time specifically for the six census tract study areas. In doing so, we expect to better understand the extent to which proximity to downtown and other variables may impact mode share. With a median household income again adjusted to $59,230 for the six census tract study areas, car mode share in certain areas experience some interesting changes, as depicted in Table 10.1 (Metro Denver, 2013). Table 10.1 lists the changes in car mode share for the baseline and resiliency scenarios under their normal household income as well as the values before and after the resiliency scenario under the adjusted income.

Table 10.1 Car mode share shifts for census tract study areas and for normalized income of $59,230

	Car mode share under actual 2012 median household income			Car mode share with income held constant at $59,230		
	Baseline scenario	**Resiliency scenario**	**Change in car mode share**	**Car mode share, adjusted income**	**Resiliency car mode share, adjusted income**	**Change in mode share**
Country Club	73.50%	71.20%	-2.30%	75.80%	70.60%	-5.20%
Stapleton	94.60%	93.80%	-0.80%	95.10%	93.10%	-2.00%
City Park West	58.00%	53.30%	-4.70%	57.90%	54.00%	-3.90%
Sunnyside	81.90%	75.80%	-6.10%	82.10%	77.20%	-4.90%
Globeville	76.70%	64.60%	-12.10%	79.50%	76.00%	-3.50%
College View/S Platte	87.60%	76.80%	-10.80%	89.60%	86.20%	-3.40%

In Table 10.1, for both the actual and adjusted incomes, the baseline car mode share values are consistently higher than the resiliency scenario car mode share. Country Club and Stapleton (which normally exhibit median household income above $130,000) experience a greater driving mode share under this adjusted income level with the resiliency scenario. With less income at their disposal, the formerly higher income areas have a greater shift away from driving when their income is adjusted to $59,230. On the other hand, the lower income households in Globeville and College View/S Platte have less of a shift away from the driving mode share when their income is adjusted. In other words, these formerly lower income areas maintain a higher driving mode share during the resiliency scenario when their income is increased to the adjusted value of $59,230; with more income, these areas are less reliant on alternative modes of transportation in coping with the resiliency scenario.

Another trend under the adjusted incomes is that two of the more urban census tracts, Country Club and Globeville, have a higher shift away from the driving mode share after the resiliency scenario than their suburban counterparts. In these areas, more people are opting to take alternative forms of transportation with the resiliency scenario. However, City Park West, the third urban census tract, does not display this trend, which suggests that another demographic or environmental factor may be involved in favoring Sunnyside (suburban, middle-income census tract) to have a greater driving mode shift. Finally, the areas with the highest driving mode share under the adjusted income are Stapleton and College View/S Platte, which are farther from downtown.

10.2.4 Alternative Transportation Infrastructure

An important influence to mode share for certain census tracts is the availability of low stress, environmentally friendly transportation options. With more transportation modes available to urban origins, individuals, and households – particularly those with budget constraints – may choose transportation options other than driving for their work travel needs. Thus, in addition to proximity to downtown, another variable that impacts mode shift is availability of active transportation options – and the level of traffic stress of those options.

In the mode choice model, bicycle LTS was removed since it was highly correlated to walk LTS. Thus, we analyzed walk LTS to understand how bike LTS may also correlate with mode choice. For the walk mode, only three trips to the CBD from census tract origins are of the lowest traffic stress, LTS 3: Sunnyside, City Park West, and Country Club. Consequently, these trips have some of the highest walk mode share, respectively: 4%, 22%, and 10% (reported for the baseline scenario). It is interesting to note that Country Club and City Park West are urban areas (while Sunnyside is not); yet, they all have the highest walk mode shares of all six study areas. This suggests that the low traffic stress walking experience for those traveling from Sunnyside to the CBD is correlated with improving the walk mode share for this suburban area. During the resiliency scenario, these walk mode shares for Sunnyside, City Park West, and Country Club increase to 6%, 24%, and 11%, respectively. Because these trips are less stressful, traveling along streets with lower speed, wider sidewalks, and fewer lanes, individuals are more likely to shift to the walk mode for their work transportation needs.

Another area of analysis that indicated factors related to the transportation environment impacted the trips from Country Club, City Park West, and Sunnyside were the results in Table 10.1. We will recall that in Table 10.1, when income is held constant, the areas with the largest shifts away from driving mode share include these census tracts. Given that only two of the census tracts (Country Club and City Park West) are proximate to downtown suggests that other factors allow for the higher shift away from driving mode share for Sunnyside, which is not as near to downtown. After this analysis of alternate modes of transportation, it is clear that level of traffic stress is important in impacting that mode shift.

When compared with trips to the CBD, walking trips to Aurora are more stressful. No trips to Aurora by foot are less than LTS 4. This suggests the extent to which this suburban destination does not support the pedestrian mode of transportation and how the driving mode share to Aurora from households throughout Denver remains as high as it is (refer to Figure 10.4).

Transit LTS is measured by number of transfers and whether the trip includes light rail transit or commuter bus. Of all the trips in the study areas, the only trip of LTS 4 is from Stapleton to Aurora. At the same time, this trip has the lowest transit mode share of 3.2% at the baseline scenario. Trips of transit LTS 2 range in mode share from 3.7% to 21.0%, with the lower range value being impacted by a higher trip length and duration.

Sunnyside, the more suburban of the middle-income census tracts, has a higher transit mode share to Aurora than that same trip from City Park West, its urban counterpart. This is likely because the transit level of traffic stress from Aurora to Sunnyside is only a value of two, while to City Park West it is LTS 3. This indicates that the trip from City Park West is more stressful than the trip from Sunnyside with respect to the number of transfers (since light rail transit does not serve this trip). This further demonstrates how the transit experience, measured in traffic stress, can influence mode share even when there may be disparities in trip length and distance.

11. CONCLUSIONS

In measuring mode shift before and after a drastic increase in gas price, this study sought to understand how certain areas in Denver, CO, with various environmental and demographic characteristics, are better equipped to return to a normal level of service than other areas. In terms of this mode shift, we focused not on how individuals are behaving today, but on what they have the ability to do in a disruptive gas price event based on these environmental and demographic characteristics. Results of the model revealed that certain neighborhoods and individuals are better suited to withstand a disruptive gas price event. Three attributes appeared to be most relevant in these trends: household proximity to downtown, median household income, and the availability of multi-modal transportation options. All told, the closer to downtown, the higher the household income, and the better the accessibility to environmentally friendly modes of transportation, the better certain areas in Denver are able to react to the disruptive event.

Several limitations should be considered in this research. For the traffic stress analysis, lack of data about average annual daily traffic or actual speeds along roads limited the analysis of stress along certain roads. Additionally, the sidewalk data provided by the city and county of Denver were 10 years old and did not offer an up-to-date understanding of sidewalk presence and condition. In the assignment of traffic stress to trips, extrapolating from the TAZ to the census tract diminished accuracy of the trips, further exacerbated by the random selection of census tract or neighborhood centroid as the start and end of each trip. In the development of the mode choice model, it was assumed that the total of car, transit, walk, and bicycle modes would equal 100%, which is not necessarily accurate as some people telecommute and work from home.

Despite these limitations and assumptions, the contribution of this work to understanding behavior under a resiliency scenario is critical. This research offers an important approach to valuing transportation options and to understanding the latent worth of environmentally sustainable infrastructure, even if it is not heavily used today. Future direction of this research is promising. By utilizing a mode choice model to understand where reductions in traffic stress offer significant shifts to these alternative modes, we can better understand what infrastructure improvements to the current bicycling, walking, and transit network will facilitate additional resiliency. These improvements can be readily determined by analyzing the traffic stress of streets and trips, thereby ensuring that a lower stress environment exists through enhancements such as buffered bicycle lanes or better bus service. Such future applications of this research can be utilized to connect and improve bicycle, pedestrian, and transit networks, further strengthening these environmentally friendly transportation modes so they may support the communities they serve.

Our work reveals that to build more resiliency into communities and neighborhoods, policy makers and leaders need to improve accessibility to low stress alternatives to driving, particularly in areas that possess lower-income households and are farther from the central business district. Increasing the supply of affordable housing in closer proximity to jobs is another possible solution. By better supporting the more vulnerable neighborhoods, we are supporting improved resiliency and strength of the community as a whole. These solutions will strengthen these communities by offering adaptive and alternative transportation choices, supporting the economic, social, and environmental strength of cities and towns.

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PART 3: TRANSPORTATION ECONOMIC RESILIENCE (TER) RATING SYSTEM[3]

13. INTRODUCTION

Transportation is the second largest expense in a typical U.S. household, lower only than housing expenditures and roughly consuming between 16% and 17% of total annual expenditures (BLS, 2012). For most households, purchasing fuel represents a large percentage of these transportation costs. As compared with most expenditures, the price of fuel, however, can be relatively volatile; such volatility can dramatically shift overall transportation expenditures and quickly affect household budgets.

The primary objective of this paper is to develop a rating system – called the Transportation Economic Resilience (TER) score – to measure the resiliency of households to significant fuel price shocks at different geographical levels. Such drastic shifts in fuel price can produce changes in travel behavior, car use, activities, as well as increases in transportation expenditures. The supposition is that areas with additional multi-modal options, such as a better walking, bicycling, or transit infrastructure, might be able to cope with such exogenous price influences. For instance, a community with considerable transit infrastructure – even if experiencing minimal ridership today – would theoretically be able to withstand a rising fuel price shock far better than an auto-dependent region that has not invested in transit.

The intent of this effort is to show the applicability of the TER rating system and its ability to measure the impact of fuel price shocks of a household's income and compare it across different geographical scales within a region. We model a baseline condition for the Denver Metropolitan area and compare it to a resilience scenario where fuel price doubles from the baseline condition. The scenarios were derived from the activity-based regional transportation model, known as the Focus model, developed by the Denver Regional Council of Governments (DRCOG). The Focus model is an advanced transportation planning tool that relies on disaggregated real-world data, gathered over a time period when gasoline prices more than tripled, to model regional travel. We then assess these scenarios with respect to additional transportation expenditures in terms of the extra percentage of income spent on transportation. For the sake of illustrating the TER rating system, the emphasis is on work tours because they represent travel that people would likely still need to make even under a gasoline price increase. However, the proposed rating system would be applicable to all trip purposes.

While there are many travel behavior studies that assess the elasticity of relatively minor shifts in fuel prices, this conceptualization of a fuel price shock – when the price is sudden and drastic – is not directly comparable to the previous strand of research. The focus is instead on how different areas would respond to a major shift in gasoline prices. Moreover, the underlying assumption of our model is that travel behavior will adapt with increased fuel costs to be more like households with a similar percentage of household income being dedicated to transportation. The resulting TER score is based on this additional percentage of income spent on transportation for work tours at the transportation analysis zone (TAZ) level of geography. After a literature review, we detail the development of the rating system and test it for the Denver Metropolitan region. Using the TER scores, we map zones that are resilient or vulnerable to fuel price shocks. We then identify several variables that contribute to differences in transportation economic resilience.

[3]This portion of the report is currently under peer-review: Henao, A. and Marshall, W. Transportation Economic Resilience Rating System. *Transportation Research Part A* (under review).

This study contributes to the overall body of literature by creating a transportation economic resilience metric index based on the additional percent of income spent on transportation due to a sudden and drastic fuel price shock. The findings of this study will also help increase our understanding of transportation economic resilience to fuel price shocks. These results have policy implications for automobiles, energy consumption, land use, future transportation infrastructure investments, as well as developing regional resilience plans. This research also offers a better understanding of the risks that might be mitigated by a diverse transportation infrastructure that can help shape more livable and resilient cities.

14. LITERATURE REVIEW

Communities are vulnerable to unexpected events such as natural disasters, terrorist attacks, or geopolitical disruptions. When these events occur, the priority becomes human survival, and in many cases, transportation is a key component. The general strand of resilience research primarily evaluates the ability of a community to perform under shock effects (shock absorption), to avoid the shock altogether (shock avoidance), or the ability to recover quickly from a shock (shock counteraction) (Briguglio et al., 2009). Transportation resilience, in particular, has to do with the ability of the transportation system to maintain a desired level of service or the time it takes to return to that level of service given a shock to the system (Heaslip et al., 2009). While transportation resilience research related to natural disasters and terrorist attacks is extremely important, there has been little research on transportation economics due to other shocks that focused on issues such as a drastic fuel price increase (Dodson and Sipe, 2007; Motte-Baumvol et al., 2010; Zheng et al., 2011).

Fuel price prediction is a dilemma. Economists and financial institutions have a poor record when it comes to estimating oil price fluctuations, such as with some of the most recent shocks that occurred in 2008 (Shafiee and Topal, 2010). One reason for the lack of success with predicting fuel prices is the multitude of factors that contribute to drastic fuel price increases, including diminishing fossil fuel reserves, resurgent demand, a lack of investment in oil, geopolitical disruptions, natural disasters, and terrorist attacks (Simmons, 2005). Prior to the run-up of oil prices in 2007-2008, four international events spanning over the last four decades (i.e., Yom Kippur War on October 6, 1973; Iranian revolution in the fall of 1978; Iraq's invasion of Iran in September 1980; and Iraq's invasion of Kuwait in August 1990) played significant roles in the dramatic global disruption of oil production and resulting drastic price increases (Hamilton, 2009). The impacts of such global events are difficult to predict, and rarely would one consider them having an impact on the everyday lives of Americans. However, these shocks do have a local impact, which affects communities with gasoline shortages and fuel price. Similar sharp increases in fuel price can also stem from natural disasters. For example, the recent Hurricane Sandy on the U.S. Eastern seaboard led to fuel scarcity and drastic fuel price increases across the region (Honan, 2012). The impact of Hurricane Katrina was similar in 2005 (Mouawad and Romero, 2005).

Resilience research has been studied primarily through the lens of natural disasters such as hurricanes, earthquakes, tsunamis (Bruneau et al., 2003; Chang and Nojima, 2001; Foster, 1995) or terrorist attacks (Battelle, 2007). More recently, the concept of resilience has become more quantitative and expanded to transportation (Berdica, 2002; Heaslip et al., 2010; Husdal, 2004; Murray-Tuite, 2006; Serulle et al., 2011). The majority of these studies focus on analyzing the ability of the transportation system to maintain a desired level of service or the time it takes to return to a level of service in the face of disruptive events including natural disasters and man-made events. Not one of these studies covers the impact of fuel price shocks with respect to economic household impacts.

Several academic research papers have studied the elasticity of petroleum demand to fuel price increases using several economic models and resulted in different findings (Dahl and Sterner, 1991; Espey, 1998; Lin and Prince, 2013). Most of these studies have shown the price elasticity of demand for gasoline to be small (Ferdous et al., 2010; Nicol, 2003; Puller and Greening, 1999; Small and Van Dender, 2007). For example, Hughes et al. (2008) estimate that the short-run price elasticity of gasoline purchased was between -0.034 and -0.077 for 2001 through 2006, while the estimated short-run income elasticities ranged from 0.21 to 0.75. Other studies (Cooper, 2005; Gicheva et al., 2007), along with data from the Bureau of Labor Statistics, have found that household-level fuel expenditures increase in proportion to increases in fuel prices, reiterating the notion of fuel price inelasticity. In addition to the increase expenditures, households adjust their consumption expenditures (including savings), car use, and activities in response to increases in fuel prices (Anas, 2007; Dargay and Gately, 1997; Ferdous et al., 2010; Yang and Timmermans, 2011). A 1975 study investigating travel behavior changes in the U.S. versus those in Europe during the oil embargo revealed that Europeans significantly increased their transit use while Americans were much more likely to stay home and forgo non-essential travel (Pisarski and Terra, 1975).

As noted above, changes in fuel prices suggest impacts in transportation expenditures, activities, and travel behavior. Unfortunately, the research aiming to examine the economic impact of extreme fuel price shocks on a household has received minimal attention in the literature, especially with respect to the immediate increase in transportation expenditures. The Center for Neighborhood Technology (CNT) developed a Housing + Transportation (H+T) Affordability Index to estimate total household annual transportation expenditures by a neighborhood (Haas et al., 2008). The interactive tool calculates the transportation cost added to the housing cost as a percentage of income for regions in the U.S. (CNT, 2010). More recently, with help from CNT, the U.S. Department of Housing and Urban Development, in conjunction with the U.S. Department of Transportation, developed the Location Affordability Index (LAI) (LAI, 2013). The LAI is based on data from the American Community Survey and Consumer Expenditure Surveys; it estimates the percentage of a household income for a typical combined cost of housing and transportation in a given location. Although the H+T Affordability Index and the LAI are great tools to help estimate the percentage of income spent on housing and transportation and to allow households to customize data for different market conditions, including fuel price, it does not take into account the potential travel behavior and mode share changes within a region. Our study aims to fill this gap in the literature by incorporating a mode shift option with fuel price increases in the Denver regional area.

Additionally, the research aiming to understand the impact variability among areas with different mode shares that takes into account the presence of transportation options and local infrastructure to absorb fuel price shocks is minimal. This includes public transit, walking, bicycling, as well as shift trips from drive alone to carpooling.

Similar to the research of petroleum demand elasticity to fuel prices, there are some studies that investigate the relationship between gasoline prices and transit ridership (Currie and Phung, 2007; Haire and Machemehl, 2007; Lane, 2010; Maley and Weinberger, 2009). The American Public Transportation Association (APTA, 2012) summarizes these studies with average elasticity values of 0.254 for commuter rail, 0.188 for heavy rail, 0.266 for light rail, 0.139 for buses, and 0.181 for all modes. Each of these studies is based on the actual ridership change during periods of price change in the past decade. These studies also focus on elasticities and are sometimes constrained by the amount of transit service available and the excess capacity of that service. Rather than providing another elasticity analysis, this study examines the differing economic response across a region in terms of the additional income spent on commuting.

15. RESEARCH DESIGN

In this paper, we develop a metric index (rating system) tool to measure the impact of fuel price shocks of an individual's income and compare it across different geographical scales within a region. The implementation of this rating system is based on the additional transportation expenditures for home to work tours in the Denver Metropolitan area when the price of fuel doubles from a baseline condition. Work tours are the focus of this effort, as they represent travel that people would likely still need to make even under a gasoline price increase, but the methodology would apply to a study of all trip purposes.

15.1 Transportation Economic Resilience (TER) Rating System

The TER rating system is based on the additional transportation expenditures due to a fuel price shock. Fixed costs such as automobile ownership or insurance are not included since these costs are usually the same before and after a fuel price shock, and the focus of the scoring system is on the relative difference in expense. The following equation for additional transportation cost includes the mode share and corresponding mode cost for each geographical area being analyzed:

$$\begin{aligned}\Delta_{Transport\ Cost} = & \left[\left(DA_{MS} + SR2_{MS} * \frac{1}{2} + SR3_{MS} * \frac{1}{3}\right) * DA_{Cost} + (DT_{MS} + WT_{MS}) * T_{Cost} + (DT_{MS}) * DT_{Cost}\right]_{AFTER} \\ & - \left[\left(DA_{MS} + SR2_{MS} * \frac{1}{2} + SR3_{MS} * \frac{1}{3}\right) * DA_{Cost} + (DT_{MS} + WT_{MS}) * T_{Cost} + (DT_{MS}) * DT_{Cost}\right]_{BASELINE}\end{aligned}$$

where:

$\Delta_{Transport\ Cost}$ = additional transportation cost;
DA_{MS} = drive-alone mode share;
$SR2_{MS}$ = 2-person share-ride mode share;
$SR3_{MS}$ = 3 or more-person share-ride mode share;
DA_{Cost} = drive-alone cost;
DT_{MS} = drive-to-transit mode share;
WT_{MS} = walk-to-transit mode share;
T_{Cost} = transit-fare cost;
DT_{Cost} = drive-to-transit cost

After obtaining the additional transportation cost (Δ) by subtracting the baseline transportation cost from the scenario where fuel price increases, the Δ value is divided by the individual's mean income to calculate the additional percent of income spent on transportation.

$$\Delta PIT = \frac{\Delta_{Transport\ Cost}}{Mean\ Income}$$

where:

ΔPIT = additional percent of income spent on transportation;

The transportation economic resilience (TER) rating system was developed to assist in evaluating the results. Every additional percent of income variable is rescaled to range from 0 to 100 by the formula:

$$TER\ Score\ =\ 0\ if\ \Delta PIT > \left(0.05\ \times \frac{Fuel\ Price\ Shock}{Fuel\ Price\ Baseline}\right)$$

$$TER\ Score\ =\ 100\ if\ \Delta PIT < 0$$

$$TER\ Score\ =\ \left(\frac{100}{\Delta PIT_{MAX}}\right) \times (\Delta PIT_{MAX} - \Delta PIT_{variable})$$

where:

$\Delta PIT_{MAX} = 0.05 \times \frac{Fuel\ Price\ Shock}{Fuel\ Price\ Baseline}$ = maximum additional percent of income;

$\Delta PIT_{variable}$= additional percent of income variable being evaluated

Each geographical area receives a TER score. Higher TER scores (i.e., more resilient) represent lower values of additional percent of income spent on transportation. In contrast, a low TER score represents (i.e., less resilient) higher values of additional income spent on transportation.

15.2 Application

The TER rating system was applied in the Denver regional area using the TAZ unit level of analysis. The area includes the city of Denver and a surrounding area of approximately 40 miles, for a total of 2,832 TAZ (Figure 15.1). The analysis focuses on home to work tours, as they represent travel that people would likely still need to make even under a sharp fuel price shock.

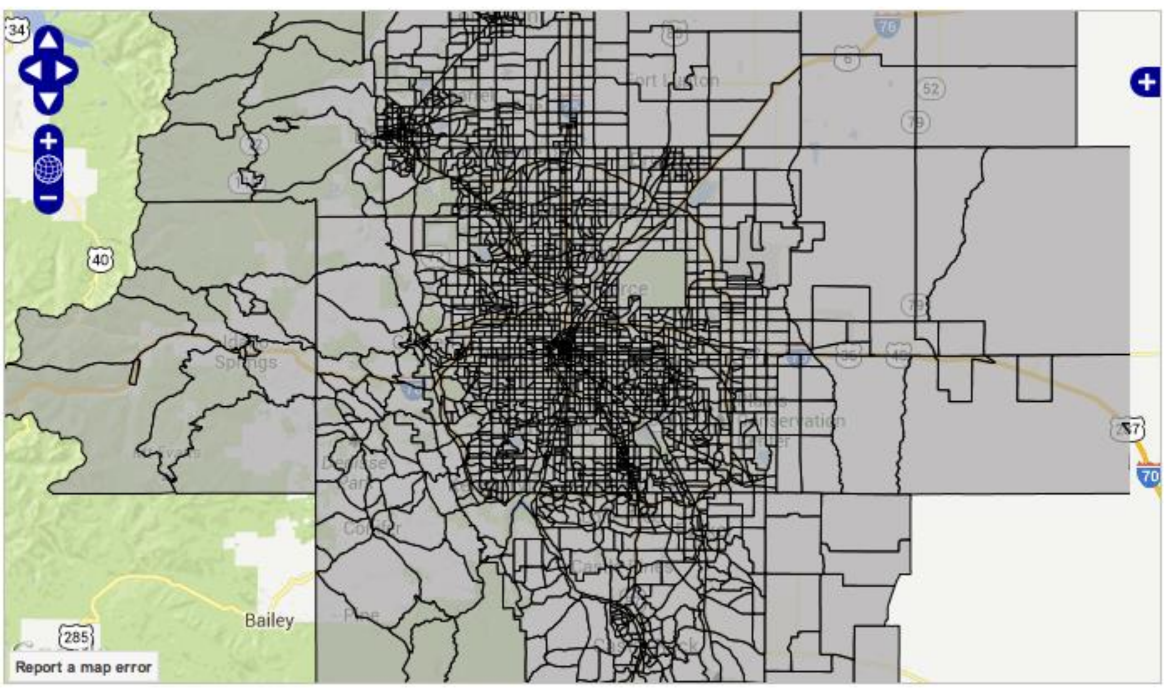

Figure 15.1 Regional Map of Transportation Analysis Zones
Source: DRCOG Regional Data Catalog (DRCOG, 2010b)

15.3 Data

The source of data for this analysis is the DRCOG Focus travel model, a regional-based activity model, with a baseline year of 2010. This model is based on an in-depth, 12,000 household survey of travel behavior in the Denver region, called Front Range Travel Counts (DRCOG, 2010a).

In order to facilitate the analysis and modeling efforts of this study, we applied a series of queries in Microsoft SQL Server and PostGIS (pgAdmin III) in the following manner:

- Selected tours with a home-based origin
- Selected tours with work destinations
- Grouped tours with the same home TAZ origin and the same work TAZ destination
- Selected tours with a total of five or more tours originating at the same home TAZ

The final sample of the analysis includes 1,154,673 home to work tours compromising 654,762 home-TAZ to work-TAZ combinations. The following information is included in the database:

- Home TAZ ID and Work TAZ ID
- Home to Work Distance
- Individual and Household Income
- Number of Tours
- Number of Drive-Alone Tours (DA)
- Number of 2-person Share-Ride Tours (SR2)
- Number of 3+ people Share-Ride Tours (SR3)
- Number of Drive-to-Transit Tours (DT)
- Number of Walk-to-Transit Tours (WT)
- Number of Walk Tours (W)
- Number Bike Tours (B)
- Drive Alone Cost
- In-Vehicle Travel Time (IVTT)

The database allowed us to calculate the number of tours from a specific home TAZ to a specific work TAZ as well as the respective mode share (DA, SR2, SR3, DT, WT, W, and B). It also contained several variables that contribute to the utility function such as home to work distance, income, drive alone cost, and in-vehicle travel time.

15.4 Methodology

The data analysis process began by first calculating the percentage share of the seven mode types in the model – drive alone, shared ride 2, shared ride 3, drive to transit, walk to transit, walking, and biking – using the processed data. We then investigated the statistical relationship between mode choice and a drastic increase in gasoline price via the multinomial logistic regression model developed for the Focus model. The intent was to provide an understanding of the mode shift by the different set of home TAZ to work TAZ tours. For the purpose of illustrating the TER rating system, we elect to model short-term travel behavior changes for work trips. We are less interested in absolute numbers with respect to the mode choice outputs and more interested in the mode shift trends. Thus, the regional multinomial logistic regression mode choice model was a good fit, despite the testing of a resilience scenario outside of the normal range. Furthermore, this mode choice model incorporates regional trends from both the 2010 Front Range Travel Counts as well as a similar survey undertaken in 1997. The development of this model using longitudinal data, across a time span when gasoline prices have more than tripled, made it an advantageous choice for our purposes.

The basic structure of a multinomial logistic regression mode choice model is derived from a basic logit model. The following generalized logit equation determines the probability of choosing a specific mode (Martin and McGuckin, 1998).

$$P_i = \frac{e^{u_i}}{\sum_{i=1}^{k} e^{u_i}}$$

where:

P_i = probability of somebody choosing mode i = 1, 2, . . . , k;
u_i = utility function describing the relative attractiveness of mode i; and
$\sum_{i=1}^{k} e^{u_i}$= sum of the functions for all available mode alternatives

The probability of choosing a particular mode depends on the above utility function relative to the utility functions for all the other mode options. The utility function of the logit equation is based on the four-step transportation planning model. It contains variables associated with each mode for a particular type of tour between two specific zones. For example, the variables of the utility function describing the relative attractiveness of driving alone include: cost associated from each home to work zones, individual income, in-vehicle travel time, out-of-vehicle travel time, a binary variable representing whether the tour happened at the AM peak or not, and tours remaining after the work trip.

Since the intent was to evaluate the immediate impact of doubling the cost of fuel, the utility function of a particular mode was only affected by the variables containing a cost component associated to the particular mode. While the utility function for walk to transit, walking, and biking remains the same after doubling the fuel price, the utility function for driving alone, shared ride 2, shared ride 3+, and drive to transit, was reduced. The probability of the seven modes was calculated for each of the 654,762 home-TAZ to work-TAZ tour combinations. Resulting average distance and mode shares for a given home TAZ were weighted based on the relative number of tours. For example, let us assume that a home zone has 100 total tours and 60 of them are going to destination A with 80% drive-alone mode share, 20 to B with 60% drive-alone share, 15 to C with 90% drive-alone mode share, and 5 to D with 40% drive-alone mode share. Given this breakdown, the home TAZ drive-alone mode share would be 75.5%, as follows:

$$0.755 = \frac{0.8(60) + 0.6(20) + 0.9(15) + 0.4(5)}{100}$$

After obtaining all mode share percentages for: i) baseline conditions; and ii) doubling fuel price scenario, we calculated the additional annual commuting expenditures using the assumptions below. They were derived from the DRCOG Focus model TAZ to TAZ matrices.

- Fuel cost baseline for driving alone is \$0.15 per mile and \$0.30 per mile when fuel price doubles;
- Fuel cost for shared ride 2 is equal to 1/2 the fuel cost for driving alone;
- Fuel cost for shared ride 3+ is equal to 1/3 the fuel cost for driving alone;
- Transit cost equals \$3.20 per tour or 2 times \$1.60 per trip; and
- The cost for walking and biking is negligible.

Since this specific TER application focus on modeling short-term travel behavior changes including the transportation options available as opposed to what might happen over the long term where we are using working tours as our scenario, we calculated the additional annual commuting expense (ΔTransport Cost) for each TAZ by subtracting the baseline annual commuting cost from the scenario where fuel price doubled. We then calculated the additional percent of income spent on commuting (ΔPIT) by dividing the additional annual commuting expense and the individual annual median income for each TAZ. Finally, we calculated TER scores for all TAZs using the TER score formula with:

$$\Delta PIT_{MAX} = 0.05 \times \frac{Fuel\ Price\ Shock}{Fuel\ Price\ Baseline} = 0.05 \times 2 = 0.1\ or\ 10\%$$

16. RESULTS

Table 16.1 presents the results for the 2,446 home TAZ zones by listing specific characteristics such as the number of tours, average distance home-to-work tours, median income, share for each of the seven modes before and after the fuel price shock, additional annual commuting expenses per capita, and additional percent of income spent on commuting.

Table 16.1 Home TAZ Summary Statistics Variables

(n=2,446)		Mean	Std. dev.	Min	Max
# of Tours		472.3	461.5	5.0	3950.0
Average Tour Distance		22.1	10.2	3.0	83.8
Median Income ($)		$37,100	$15,586	$9,389	$114,500
Mode Share Before	**Drive-alone**	68.6%	11.17	7.1%	100.0%
	Share-ride 2	16.8%	5.20	0%	53.8%
	Share-ride 3+	6.7%	3.19	0%	36.4%
	Drive-to-transit	1.3%	1.45	0%	16.7%
	Walk-to-transit	2.8%	4.20	0%	45.5%
	Walk	3.3%	9.47	0%	68.0%
	Bike	0.5%	0.93	0%	9.1%
Mode Share After	**Drive-alone**	67.6%	11.83	0%	100.0%
	Share-ride 2	17.2%	6.16	0%	80.0%
	Share-ride 3+	7.0%	3.96	0%	60.0%
	Drive-to-transit	1.3%	1.62	0%	20.0%
	Walk-to-transit	2.9%	4.37	0%	45.5%
	Walk	3.5%	9.86	0%	75.0%
	Bike	0.5%	0.99	0%	12.5%
Additional Annual Commuting Expenses per Capita ($)		$701	$334	$61	$2,637
Additional % Income Spent on Commuting		1.9%	1.05	0.1%	10.2%
TER Score		80.6	10.5	0.0	99.0

On average, each home TAZ generates approximately 472 home-to-work tours with an average distance of 22.1 miles per tour (round trip). The minimum number of tours per home TAZ is five with a maximum of 3,950 tours. The TAZ individual median income is approximately $37,100 per year, with a minimum of $9,389 and maximum of $114,500.

After the fuel price shock (i.e., doubling of the fuel price), the mean proportion for the seven modes are: 67.6% for drive-alone, 17.2% for share-ride-2, 7.0% for share-ride-3+, 1.3% for drive-to-transit, 2.9% for walk-to-transit, 3.5% for walking, and 0.5% for bicycling. The commuting expense per capita increases on average by a value of $701 per year. The average TAZ individual commuting expense ranges from as low as $61 to as high as $2,637 per year.

When the fuel price doubles, the mean percent increase in income spent on commuting for the TAZ home zones is 1.9% (i.e., on average, residents spend an extra 1.9% of their income for home-to-work tours) with a standard deviation of 1.1. The mean TER score is 80.6. These scores range from a minimum of zero when the additional percent of income spent on commuting is 10.2% (ΔPIT_{MAX}) and a maximum of 99 when ΔPIT=0.1% (ΔPIT_{MIN}). Figure 16.1 displays the frequency histogram of TER scores for the TAZ home zones.

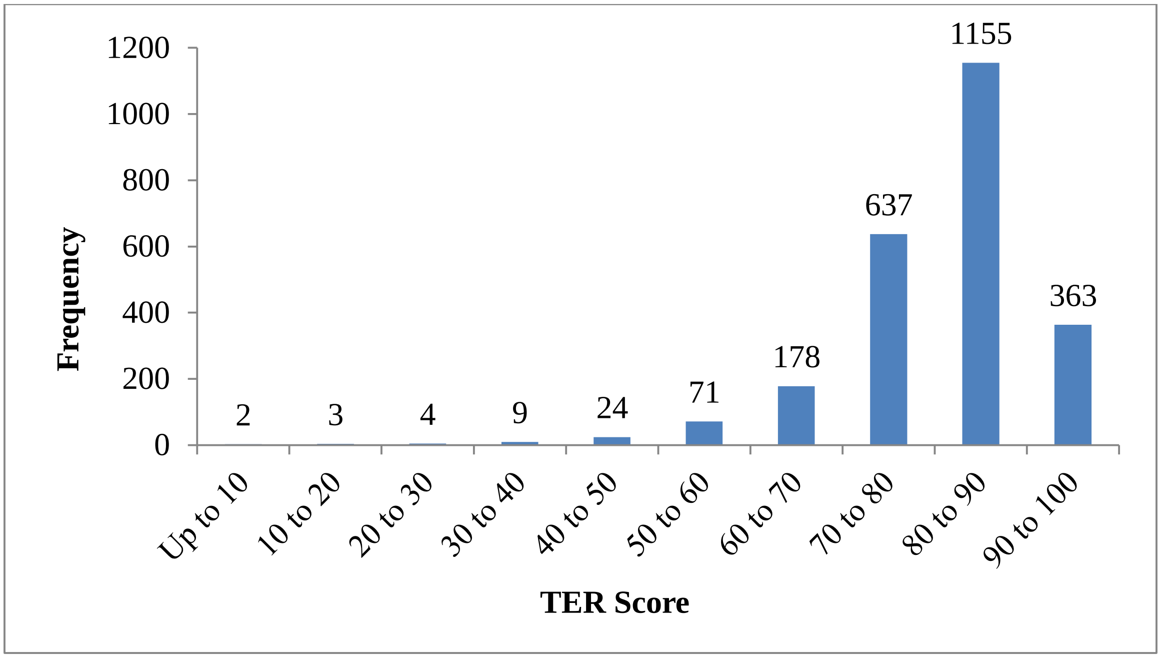

Figure 16.1 TER Score Histogram

Table 16.2 depicts the results for the 10 highest and 10 lowest TER scores as well as a selection of other zones intended to highlight variables that seem to be driving the differences in resiliency to fuel price shocks. For the *transit+walking+biking* variable, we combined drive-to-transit, walk-to-transit, walking, and biking into a single variable.

The TAZ with the highest additional percent of income spent on commuting ($\Delta PIT = 10.2\%$) has the lowest TER score of zero. The other zones with very low TER scores tend to exhibit:

- Higher than average tour distance
- Lower than average median income
- Low *transit+walking+biking* mode share

The highest TER score is 99.0. On average, a person living in this home TAZ would spend only 0.1% more income on transportation if the fuel price doubled. Other zones with high TAZ scores tend to have:

- Lower than average tour distance
- Higher than average median income
- High *transit+walking+biking* mode share

While these more resilient zones tend to have higher income levels, this was not always the case. For instance, the zone in position 4 has a median income of $37,213, which is just over the median income for all TAZs. The high *transit+walking+biking* mode share (81.8%) is what seems to be helping this TAZ exhibit resilience. Similarly, in position 172 is a TAZ with a very low median income of $17,579 but still considered relatively resilient with a TER score of 93.0.

In contrast, the TAZ in position 177 has a low *transit+walking+biking* mode share (0.8%) and high drive-alone mode share (95.8%). What helps the resilience of the TAZ with a TER score of 92.9 is the high value of median income ($112,591). This example where two TAZs have the same TER score as well as the same additional percent of income spent in transportation ($\Delta PIT = 0.7\%$) suggests that zones are economically resilient not only because of a high median income but also for a high non-auto mode share. Table 16.2 also displays TAZs in position 485, 1000, and 2000 to help illustrate the different TER scores and associated characteristics.

Figure 16.2 presents individual relationships between home TAZ TER scores and each of the following variables:

- Average tour home distance
- Median income
- Transit mode share (in the resiliency scenario).

The red lines in the figure represent mean values for the TER score (80.6), tour distance (22.1 miles), median income ($37,100), and transit mode share (4.2%). For the tour distance, we would expect resilient values to be located in quadrant II (low distance, high TER score) and non-resilient values in quadrant IV (longer distances, low TER score). Interestingly, there are several TAZ homes that lay in quadrant I, and despite longer commute, these TAZs still find high TER scores. In quadrant III are located the non-resilient TAZ that are not explained by the commute distance. In the two graphs for median income and transit mode share, quadrant I has the TAZs with high TER scores and high values for median income and transit mode share, respectively. In quadrant III lie non-resilient zones that might be explained by either the TAZ median income or the TAZ transit mode share. TAZ in quadrant II for median income are interesting; despite low median income, they experience high values of TER scores, such as the zones in positions 4, 11, and 172 showing in Table 16.2.

Figure 16.3 presents the distribution of TER scores for the 2,446 TAZ home zones. From this figure, we see that the lowest ratings are among home zones on the outskirts of the DRCOG region. Figure 16.4 depicts home TAZ zones located along the Denver – Boulder corridor in more detail. This illustrates TER ratings with significant higher values within the city of Denver and the city of Boulder. A final zoom into the Denver central business district (CBD) reiterates this result. Home TAZ with the highest TER scores are located within the CBD as shown in Figure 16.5. In contrast with the home TAZs located on the perimeter, these high rating TER home TAZ zones are the result of one or more of the following: low commuting distance, higher median income, and/or higher transit, and walking and biking mode shares.

Table 16.2 TER Scores including the 10 Highest and 10 Lowest Home TAZs

Position	Tour Distance (miles)	Median Income	Drive-alone Mode Share	Transit + Walking + Biking Mode Share	ΔPIT (Additional % Income Spent on Commuting)	TER Score
1	3.0	$61,133	19.9%	80.1%	0.1%	99.0
2	4.9	$114,500	33.3%	66.7%	0.1%	98.6
3	10.8	$86,914	16.7%	83.3%	0.2%	98.4
4	8.7	$37,213	18.2%	81.8%	0.2%	98.3
5	5.4	$62,828	38.5%	53.8%	0.2%	98.0
6	6.4	$79,090	24.5%	63.0%	0.2%	97.9
7	6.3	$44,818	15.5%	71.9%	0.2%	97.7
8	5.3	$58,066	22.9%	72.9%	0.2%	97.7
9	5.8	$40,097	16.7%	72.2%	0.2%	97.7
10	4.8	$40,853	13.3%	75.6%	0.2%	97.6
11	5.0	$34,521	15.0%	70.0%	0.3%	97.5
172	7.2	$17,579	15.2%	81.8%	0.7%	93.0
177	21.3	$112,591	95.8%	0.8%	0.7%	92.9
485	13.9	$38,293	71.2%	11.5%	1.2%	88.5
1,000	18.6	$36,882	75.7%	5.3%	1.6%	83.8
2,000	35.2	$41,679	68.3%	0.5%	2.6%	73.8
2,251	33.8	$44,941	87.5%	0.0%	3.4%	66.2
2,280	74.2	$60,285	59.9%	0.0%	3.5%	64.7
2,393	21.6	$14,146	58.2%	10.7%	4.7%	52.6
2,437	66.8	$32,133	76.3%	0.0%	6.9%	30.9
2,438	29.0	$12,681	66.3%	0.0%	7.1%	28.7
2,439	24.0	$9,698	62.2%	4.6%	7.1%	28.5
2,440	31.2	$13,328	67.3%	0.0%	7.7%	23.5
2,441	26.4	$10,583	70.9%	0.0%	7.9%	20.7
2,442	81.8	$29,828	60.3%	0.0%	8.1%	19.4
2,443	77.3	$32,357	85.3%	0.0%	8.1%	18.5
2,444	83.8	$30,381	67.6%	0.0%	8.2%	18.2
2,445	82.3	$27,566	67.8%	0.0%	9.0%	9.8
2,446	31.6	$10,176	65.7%	2.7%	10.2%	0.0

LEGEND

Tour Distance (miles)	Median Income (in $K)	Drive-alone Mode Share	Transit + Walking + Biking Mode Share
0 to 10	$60 or more	0 to 50%	20 to 100%
10 to 20	$45 to $60	50 to 60%	15 to 20%
20 to 30	$30 to $45	60 to 70%	10 to 15%
30 to 40	$15 to $30	70 to 80%	5 to 10%
40 or more	$0 to $15	80 to 100%	0 to 5%

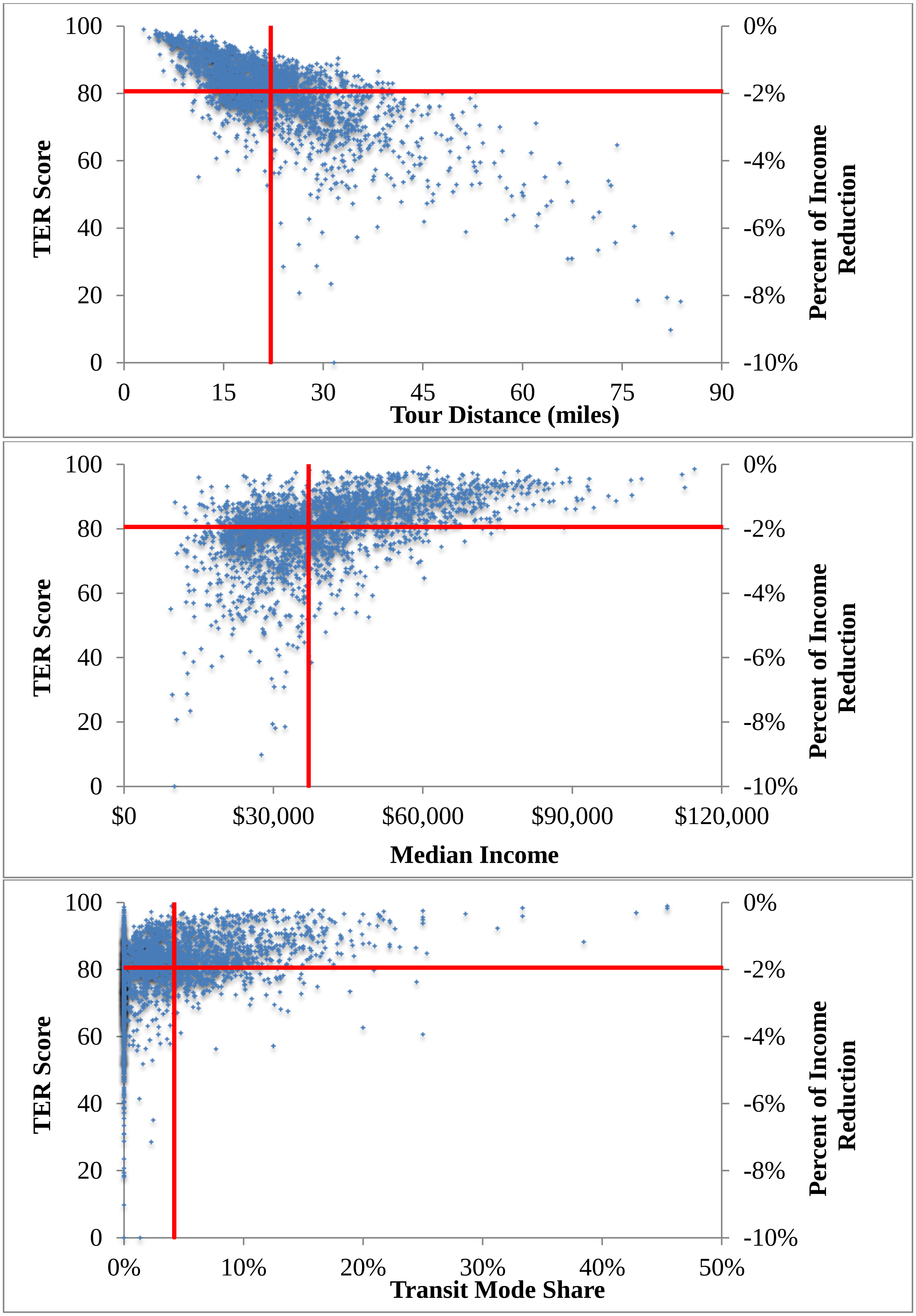

Figure 16.2 TER Scores vs. Selected Variables

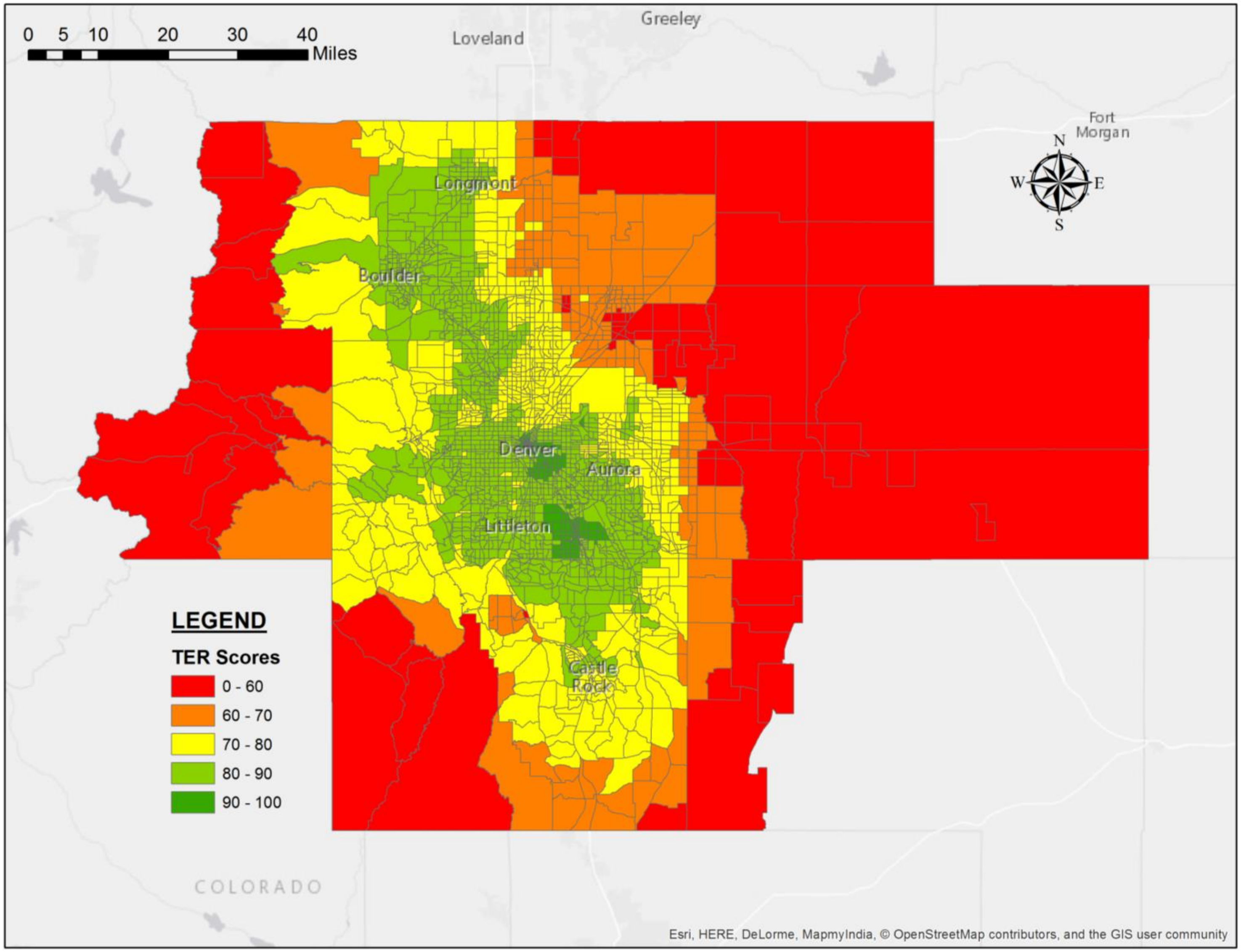

Figure 16.3 TER Scores

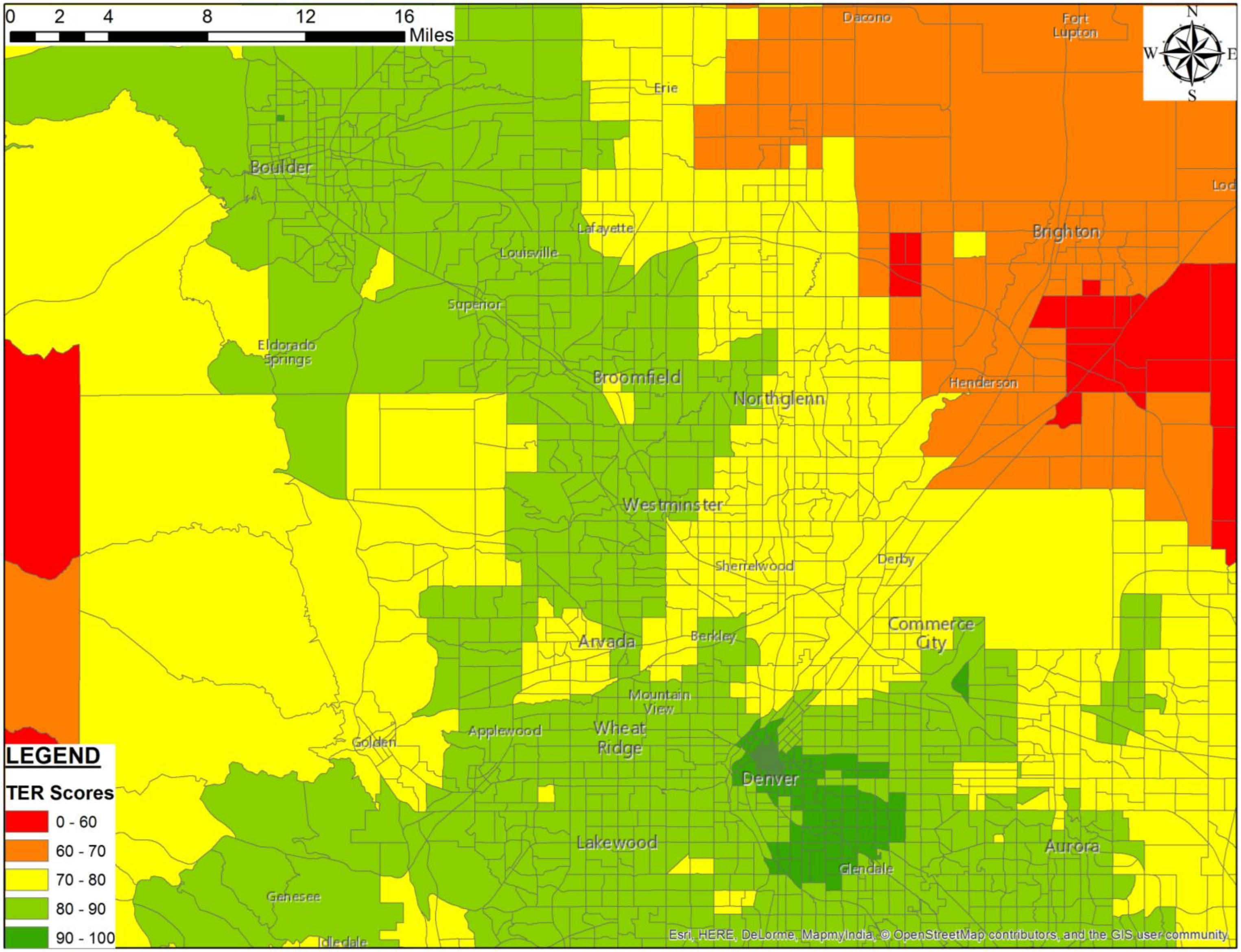

Figure 16.4 TER Scores Along the Corridor Between Denver and Boulder

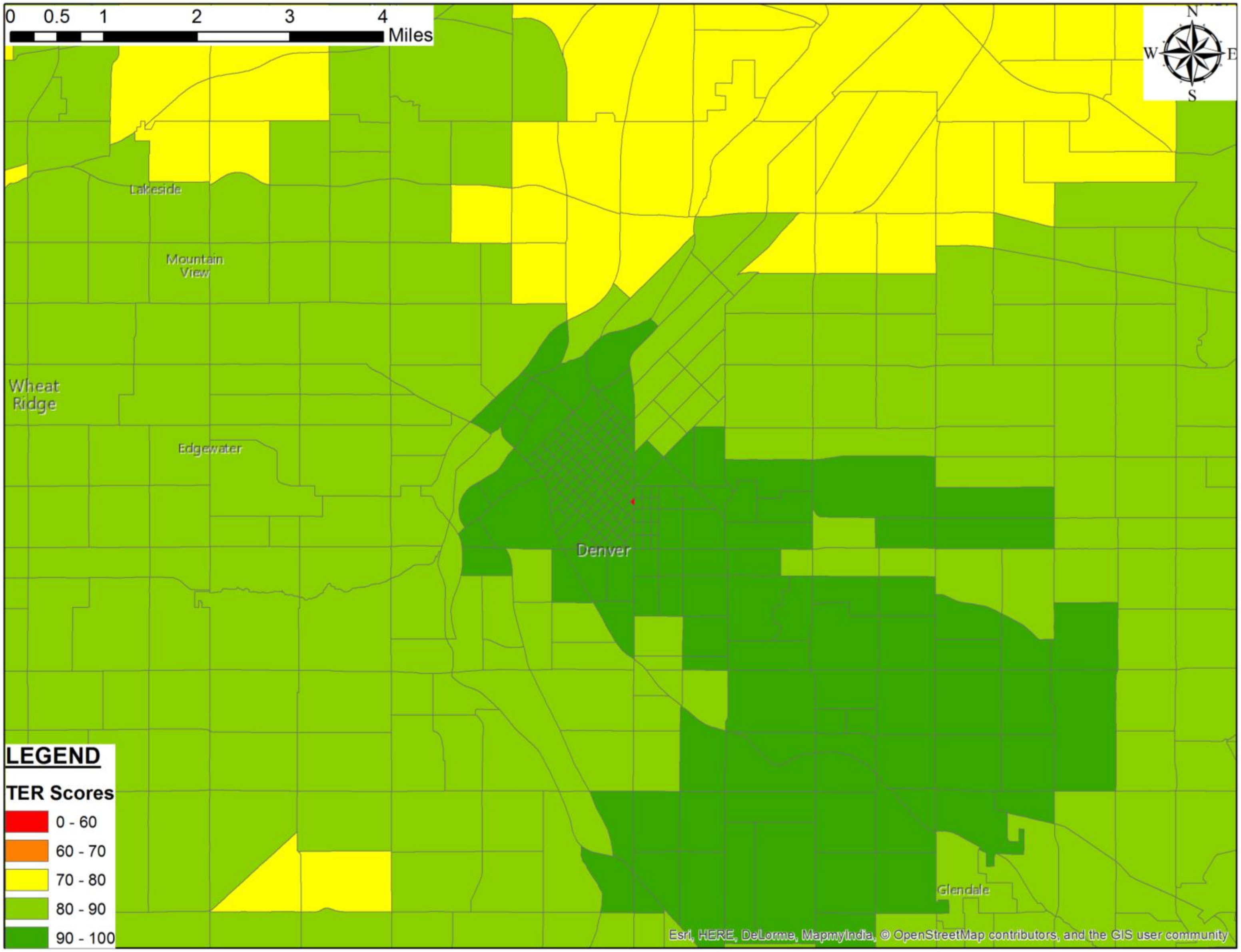

Figure 16.5 TER Scores Around the Denver CBD

17. CONCLUSIONS

Transportation cost is the second highest expenditure in a typical U.S. budget. With the high dependency on the automobile, a large portion of the variable cost fluctuates with fuel price volatility. Communities are vulnerable to unexpected events, including fuel price shocks.

This study sought to examine and develop a Transportation Economic Resilience (TER) score to help measure the impact of fuel price shocks on people's income for additional transportation expenses. We test the TER rating system by examining a database of 1,154,673 individual work tours and evaluating the additional percentage of income commuting expense in the short term when fuel price doubles. The underlying assumption is that work travel is non-discretionary. One limitation of the TER rating application in this study is that the mode choice model does not contain data on telecommuting or facilitate someone changing to telecommuting. For illustration purposes and data availability, we focus on modeling short-term travel behavior changes, but the TER rating system can be applied over the long term. The data would need to include other transportation trip purposes, working from home mode share, changes in the cost of transit, vehicle choices, land uses, residential and work location, etc.

The average increase of percent income spent on commuting due to a doubling of the fuel price was 1.9%. While this may seem like a relatively low number, the results suggested large disparities among home TAZs with some reaching more than a 10% increase and others at only 0.1%. The resulting TER scores ranged from zero to 99.0, with an average of 80.6. The home TAZs with the lowest TER scores are located on the outskirts of the geographical area analyzed, and the best ratings are closer to downtown Denver.

Home TAZs whose residents commute shorter distances are very likely to be economically resilient to fuel price increases. This is because the relative current cost of commuting is low, and there tends to be transportation options such as walking and biking available. High-income residents are also considered transportation economically resilient since their income would not be impacted as much by an increase in commuting expenditures. In contrast, residents in low-income home TAZs that have to drive alone and/or travel long distances for work tours would be the most impacted by a fuel price increase. Based on the TER rating, these areas are not considered economically resilient to fuel price shocks. A person living in these areas would still need to travel to work, and without realistic transportation options, the economic impact can be very serious.

When the commute distance is long, home TAZ zones with current high mode shares for carpooling and transit – or the opportunity to shift to high share percentage in these modes – have a very high probability of being transportation economically resilient. Figures 16.3, 16.4, and 16.5 show the TER scores among all home TAZs for the area studied. Areas with a high density of jobs – such as Boulder, the Denver CBD, and the Denver Tech Center – tend to be very resilient. Areas with good transit service – such as the Denver-Boulder US36 corridor and along the light rail lines – also tend to be more resilient. The surrounding suburbs with less transit availability tend to be more vulnerable.

This study introduces a transportation economic resilience index and the concept of significant fuel price shocks on transportation expenditures. This work elaborates on earlier studies regarding the impact of fuel price fluctuations on travel behavior. In particular, this paper examines regional disparities with respect to preparedness to a major shift in gasoline prices for commuting expenses. Since the focus is on a drastic increase in fuel price, these results are different from elasticity studies that have considered how relative minor gasoline price adjustments impacted travel behavior. This paper builds on studies related to transportation costs across different geographic areas. For example, the Housing + Transportation Affordability Index (CNT, 2010) and the Location Affordability Index (LAI, 2013), which measure the cost of housing and transportation at the neighborhood level as a percentage of the household income, does not account for the ability to change travel modes. Our study incorporates a multinomial logistic regression mode choice model to help overcome this limitation. Future research should compare TER scores to output from the H+T Index and the Location Affordability Index in order to gain a better understanding of when and where these existing indices can serve as a TER score proxy and when they cannot.

This study helps increase our understanding of transportation economic resilience with respect to fuel price shocks and how commute distance, median income, and transit service impact the resiliency of different communities. These results have policy implications for automobiles (e.g., electric cars, fuel efficiency), land use (e.g., development of mixed-use, pedestrian, bicycling, and transit-oriented communities), and in facilitating other modes of transportation by investing in transit infrastructure or other transportation options. This research also offers a better understanding of the risks mitigated by a diverse transportation infrastructure. Such findings can support the development of regional resilience plans and, in turn, help inform planning for more resilient and livable cities.

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