City Resiliency & Active Transportation Infrastructure

Rachael Bronson, M.E., Civil Engineering
Wesley Marshall, Ph.D., P.E., Civil Engineering

University of Colorado Denver
Department of Civil Engineering
1200 Larimer Street
Campus Box 113
Denver, CO 80217

rachael.bronson@ucdenver.edu
wesley.marshall@ucdenver.edu

phone: 303-352-3741
fax: 303-556-2368

City Resiliency & Active Transportation Infrastructure

Abstract

Transportation resiliency is the ability for a transportation system to maintain or return to a previous level after a disruptive event. The goal of this research is to understand how the availability of mode options contributes to transportation resiliency under economic shocks to the system caused by an abrupt gas price change. We assess the ability of Denver's population to shift to these modes using a multinomial logistic regression mode choice model. Results of this study suggest that areas with lower stress transportation choices are more resilient. Other significant factors include being nearer downtown and higher income. There is a cumulative effect as well: lower-income, more suburban households with poor active transportation options are the most vulnerable. We also measure the financial benefit and resiliency value of various multi-modal transportation infrastructures – even if few people are using those facilities today – and how these investments may support more resilient communities.

Keywords

Transportation resiliency, bicycling, walking, transit, multi-modal transportation, mode choice, mode shift, neighborhood

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 and economic activities of a community. Given this 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 ("Weekly U.S. All Grades All Formulations Retail Gasoline Prices (Dollars Per Gallon)" 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.

When such a crisis arises, the households that are already vulnerable because of their poor access to transportation and other vital resources tend to be most deprived (Fitzgerald 2012). Such vulnerable households are often those who 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 a disruptive 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). To truly overcome these hazards, the goal must be to build resilient cities that offer a network of sustainable systems and communities. According to Newman et al., resilient cities are energy efficient, offer sustainable transport options, and possess power, water, and wastewater systems that are sustainable and built on a small scale; such cities build the local economy and nurture a sense of place (2009). A city without these resiliency measures is vulnerable to a threat that arises (Godschalk 2003).

Broadly, resiliency is a system's capacity to manage unexpected events without catastrophic failure (Heaslip, Louisell, and Collura 2009). 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 (2009). VMT is linked to negative effects of traffic safety, environmental health, public health, energy consumption, and other social and economic costs of automobile use (Ewing and Cervero 2010). Reducing VMT, thereby reducing societal and household costs and energy consumption while improving health and safety, is fundamental to building resiliency. However, the capacity to reduce VMT – even if a community is not doing so today

– is equally important. Understanding this capacity is where our study looks to make its contribution.

Transportation mode choice, for the individual and community, is the opportunity to use multiple means of transportation. Providing such options better facilitates resiliency to potentially threatening events. If only one mode choice were viable after an event, 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 be less compromised (Freckleton et al 2012). Thus, creating a built environment with transportation alternatives and land uses that support them is an important and effective strategy for lowering total transportation costs (Haas et al 2008) and building resiliency into a system (Freckleton et al 2012).

The goal of this work is to measure resiliency under a drastic gas price increase in terms of mode shift from driving to walking, bicycling, and transit use. Unlike the existing literature on resiliency, 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. 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 this way, this research offers an approach to measuring the transportation resiliency in Denver after a dramatic gas price event, and in the process, reveals how certain communities and neighborhoods demonstrate different mode shifts based upon varying environmental and demographic circumstances. This work also presents us with a unique understanding of the option value of multi-modal infrastructures.

METHODOLOGY

The analysis in this paper focuses on the mode share for work trips in 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-based planning model. This model was based on an in-depth travel behavior survey of 12,000 households in the Denver region, called the Front Range Travel Counts (Denver Regional Council of Governments 2013).

There were a total of 143 home origins, which comprises the total number of census tracts in the City and County of Denver as configured in the 2010 US 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 572 in total. 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 the city limits 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); and
  - Whether the trip required limited access highway travel.
- For the bicycle and pedestrian modes,
  - Travel time (minutes);
  - Trip length; and
  - Level of traffic stress for the trip.
- For the transit mode,
  - Travel time (minutes) and
  - Level of traffic stress for the trip.

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 (2012). This methodology classifies streets based upon their bicycle level of traffic stress (LTS) that they exhibit to the user; a lower stress trip is one that does not require a bicyclist to exceed their tolerance for traffic stress and does not involve an excessive detour. The Mekruia et al traffic stress approach is measured through variables such as road width, traffic speed, presence of a parking lane and whether the bicycles are mixed in traffic, in bike lanes, or on segregated paths (2012). In this research, we applied our own adaptation of this methodology to the pedestrian and transit modes as well. 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.

Bicycle & Pedestrian Level of Traffic Stress

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. Our methodology focused on three traffic and street characteristics: speed, number of travel lanes, and the presence of bicycle facilities. 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). Table 1 summarizes these levels.

Table 1: Criteria for bicycle level of traffic stress (LTS), based on posted speed limit and number of travel lanes (adapted from 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 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.

As with the bicycle LTS methodology, the pedestrian approach we developed similarly intends to measure the stress that pedestrians experience on a roadway by using data that are measurable and readily available. The pedestrian LTS was based upon 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, the pedestrian LTS methodology was built upon the bicycle LTS designations. Additionally, the pedestrian analysis included sidewalk width. Table 2 describes each pedestrian LTS designation; in the criteria, the larger the sidewalk widths contribute to lower pedestrian level of traffic stress.

Table 2: Criteria for pedestrian level of traffic stress (LTS) based upon sidewalk width and bicycle LTS

	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

For both the bike and pedestrian traffic stress, additional variables could be included to calculate trip stress. However, given limitations in data and the fact that hundreds of trips were analyzed, only the aforementioned variables were investigated for both modal options.

After each street in Denver was assigned these traffic stress levels, the top four work commute trips for each of the 143 Denver census tract origins were assigned a traffic stress level based upon the stress of the streets along the trip route (route determined by Google Maps as described in the introduction to this section). 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 crosses one LTS 4 arterial, then that route was assigned the highest stress experienced by the user, or LTS 4. 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. These values were assessed and recorded for all 572 trips for the mode.

Transit Level of Traffic Stress

Instead of focusing on street and traffic characteristics for the transit LTS methodology, this approach analyzed the transit options available for these four trips using Google Maps. Research conducted in the US and Europe has shown an individual preference for light rail over bus (Scherer 2010); thus, in this methodology, light rail transit stress was based upon 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, as follows:

- 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 the transit traffic stress investigation, as with the pedestrian and bicycle mode, other variables may broaden the understanding of traffic stress. However, given the scope of this project, and the fact that hundreds of trips were investigated, the transit type and transfer option were the only variables explored.

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 present a realistic understanding of who might be able to access certain facilities in accessing their actual destinations. 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, used in conditions where the bicycle and vehicle share the lane of traffic) 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 everyday 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 trying to better model in this work.

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 speed of traffic; and functional classification of the street. Also considered were 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 AIC value. With respect to multi-collinearity, none of the variables used in the final models were highly correlated with one another.

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; 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, an in-depth household travel survey for the region from which our data were gathered, was being administered (Denver Regional Council of Governments 2013). This gas price was used to determine the average annual cost of gas for each of the 572 commute trips using upon an average vehicle efficiency of 20.2 miles per gallon (Environmental Protection Agency Office of Transportation and Air Quality 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 and was an important area of analysis that will be reviewed in the results section of this report.

Table 3 provides the descriptive statistics of all of 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. Table 4 shows the results of the mode choice model. Results of the mode shares for a given home census tract were weighted based upon the relative number of trips.

Table 3: Descriptive statistics of the data used in the multinomial logistic regression mode choice model

	Variable	Obs	Mean	SD	Min	Max
Misc.	Population of origin census tract	2,288	4,129.42	1,567.84	314.00	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	25.20	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	27.40
	# of minutes driving to work (avg.)	2,288	13.80	6.61	0	40
	Whether car trip to work includes hwy driving (avg. of 0, 1 variable)	2,288	0.46	0.50	0	1
	Proportion of income spent on annual driving to work (avg.)	2,288	0.01	0.01	0.00	0.11
Transit	# of minutes for transit trip to work (avg.)	2,224	44.60	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	304.00
	# of minutes walking to work (avg.)	2,288	106.00	71.62	0	469
	Walking LTS score for trip to work (avg.)	2,288	3.60	0.66	0	4
Bike	# of biking miles to work (avg.)	2,288	6.22	4.28	0	26.80
	# of minutes biking to work (avg.)	2,288	35.35	23.30	0	138
	Biking LTS score for trip to work (avg.)	2,288	3.93	0.44	0	4

Table 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	0.00000294	**	0.000003639	**	0.000007592	***
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 to work (avg.)	0.4131	***	0.0249		0.3663	***
Whether transit trip to work includes light rail	0.7098	***	0.4461	***	0.2331	**
Walking						
Walking LTS score for trip to work (avg.)	0.313	***	0.3473	***	0.2145	***
Model Fit						
Observations	2,224					

* p <.10; ** p < .05; *** p< .01

RESULTS & DISCUSSION

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 for 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). Figure 1 depicts car mode share in the resiliency scenario while Figure

2 depicts car mode share with income held constant at the median. In 2011, the median household income in Denver was $59,230 (Metro Denver Economic Development Corporation 2013).

Those census tracts that have the highest change in driving mode share, displayed 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 Figure 2, where median income is held constant, 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: the southeast and southwest light rail transit lines service the area, as do multiple bicycle paths including the Platte River and the Cherry Creek bike path. Thus, it appears that there are factors in addition to income that may be impacting mode share, and our next step attempts to delve deeper into these issues.

Figure 1: Change in car mode share by census tract in City and County of Denver after the resiliency scenario, in relation to the major streets and highways, bicycle paths, and light rail transit network

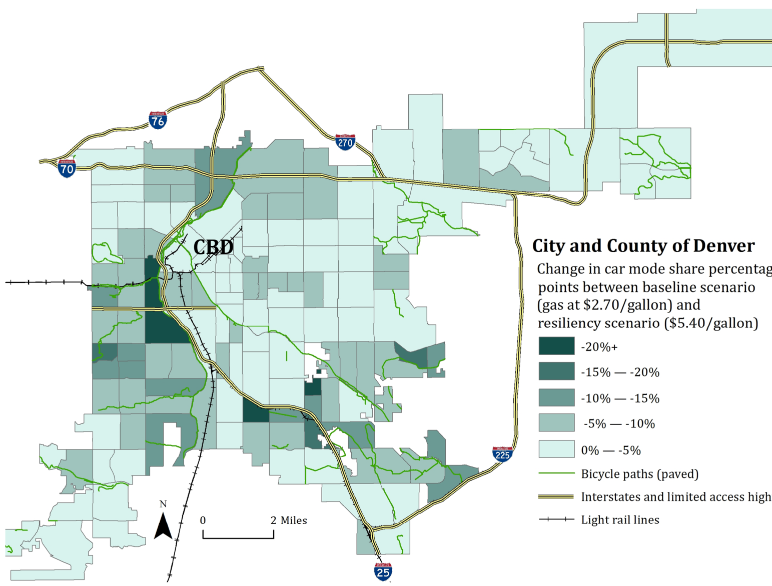
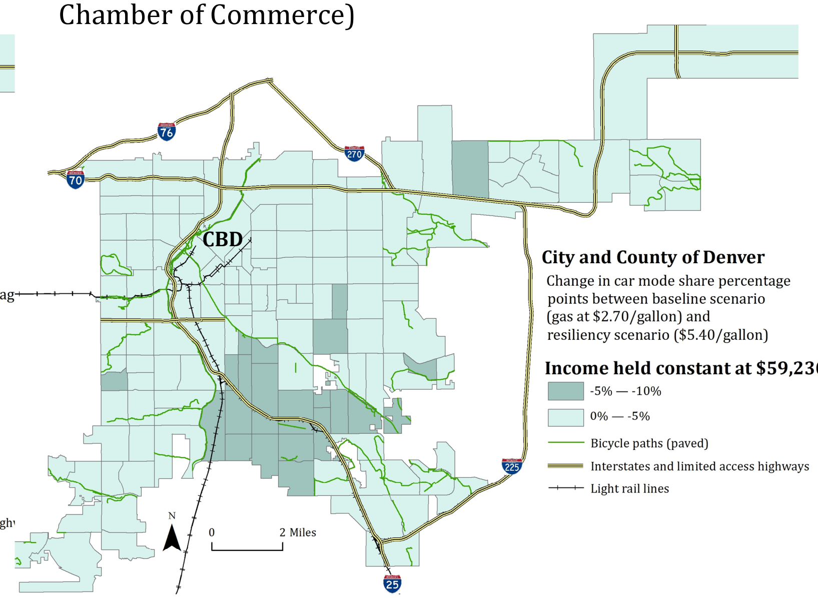


Figure 2: Change in car mode share by census tract in City and County of Denver after the resiliency scenario where income is held constant at $59,230 (based upon 2011 median household income as reported by the Denver Metro Chamber of Commerce)



Study Area Characteristics
For closer analysis, 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) (Social Explorer 2013). To facilitate the comparison, we also selected census tracts that share the following two top work destinations: the Denver Central Business District and the City of Aurora (located outside of Denver city limits). Table 5 describes these selections in more detail.

Table 5: Household and housing characteristics of each origin census tract in Denver (Social Explorer 2013)

	Low income		**Middle income**		**High income**	
	Globeville	**College View/ S Platte**	**City Park West**	**Sunnyside**	**Country Club**	**Stapleton**
Driving distance to the CBD (miles)	3.4	17.8	2.9	3.7	2.9	12
Median HH income	$24,190	$30,076	$51,371	$51,163	$130,321	$133,393
No. persons per HH	3.1	3	2.2	2.5	2.5	2.8
Home values	$164,200	$170,300	$325,100	$218,500	$723,100	$458,600
Monthly rent	$833	$710	$667	$714	$964	$1682
Pop density	1544	4258	7302	5705	4761	1686
% Non-white	30%	37%	30%	20%	16%	17%
% Hispanic or Latino	80%	64%	10%	62%	4%	16%

Before exploring active transportation infrastructure, we first look at two other factors seemingly important to resiliency: proximity to downtown and income.

Proximity to Downtown
Figures 3 and 4 illustrate the car mode share change from each of the six study sites to two common destinations – the CBD and Aurora – which are among the top four work commute destinations for each of our sites. The CBD and Aurora represent an urban and suburban destination, respectively. Overall, driving mode share is consistently higher for suburban census tracts origins as compared to their urban counterparts. Another interesting finding is that the low-income census tracts – Globeville and College View/S Platte – 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.

When comparing the trends in Figures 3 and 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, already nearly all of the households are opting to drive for both their trip to Aurora and the CBD. However, most of the other study areas show a significant increase in car mode share for the trips to Aurora when compared to 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 3.

Figure 3: Car mode share to the CBD in the baseline and resiliency scenario for the six census tract study areas

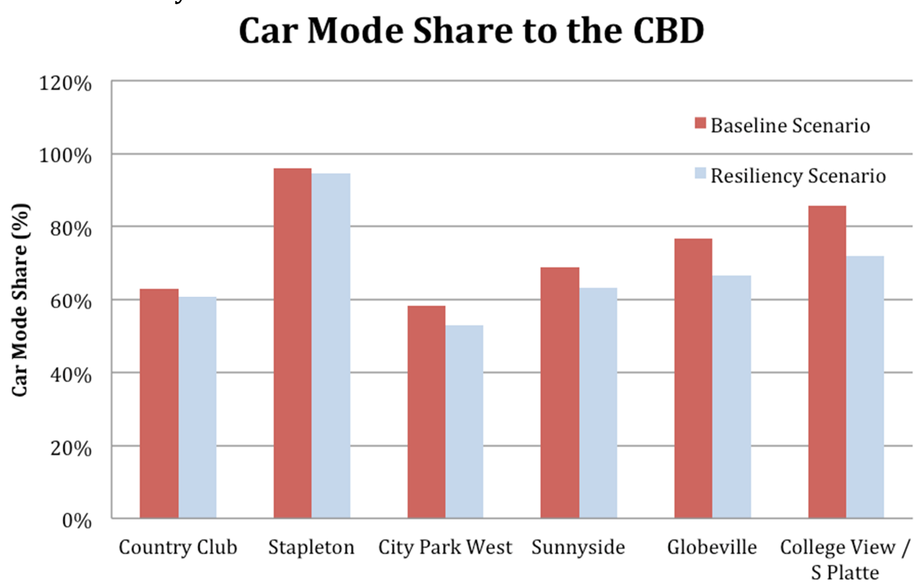
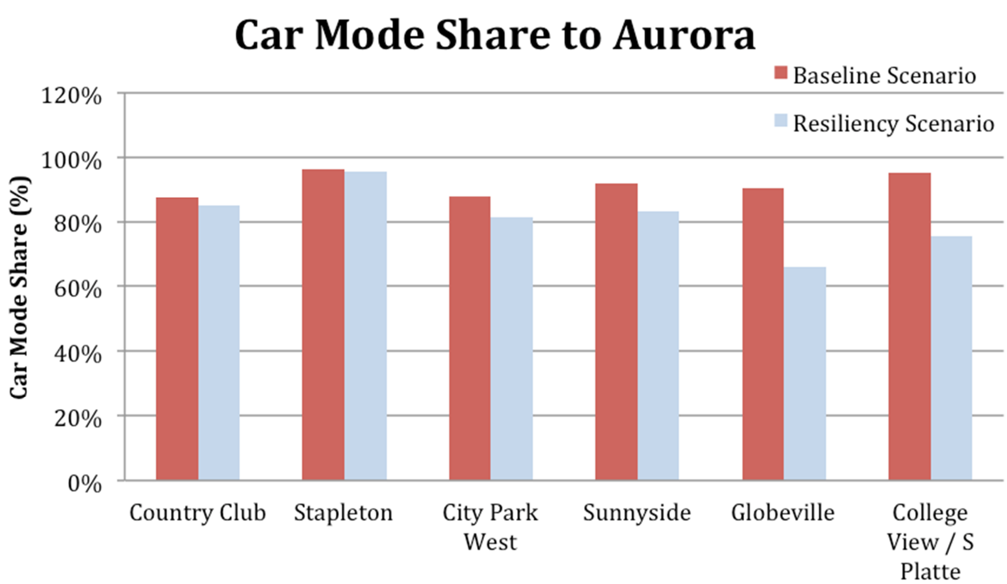


Figure 4: Car mode share to Aurora in the baseline and resiliency scenarios for the six census tract study areas

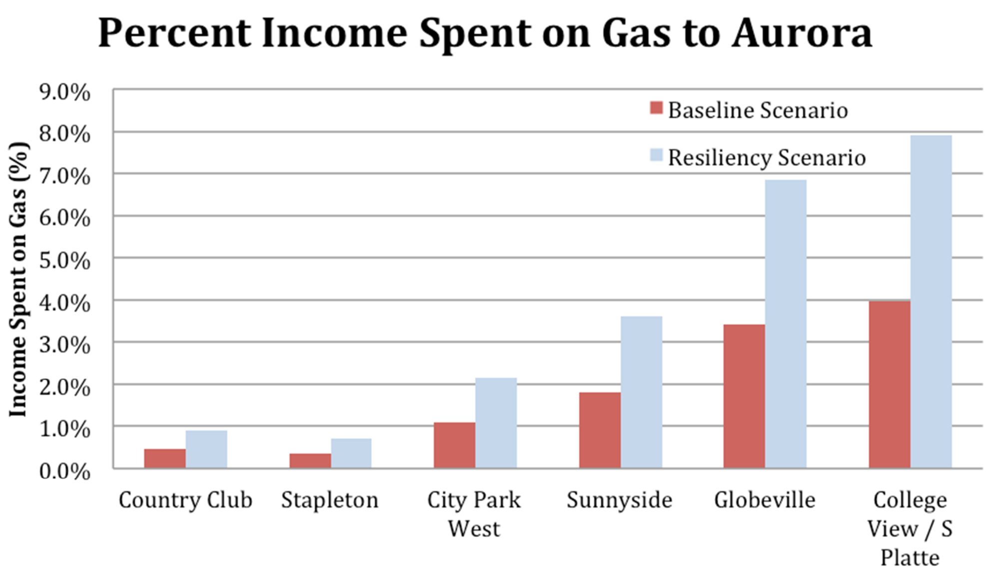


Income

A drastic gas price increase would impact low-income households more than high-income areas in terms of the percent of income spent on gas. In other words, a census tract with high household income has more capacity to withstand increases in gas price than 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 to lower income areas after the resiliency scenario. This trend is indeed apparent in Figure 4.

To further understand this trend, we determined the percent income spent on gas for each trip based upon the length of the trip in miles and assuming an average vehicle efficiency of 20.2 miles per gallon (Environmental Protection Agency Office of Transportation and Air Quality 2007). Figure 5 reveals that higher income households 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.

Figure 5: Percent of income spent on gas for households traveling to Aurora at both the baseline and resiliency scenarios



In order to understand how other factors may be influencing mode share, we again hold income constant. 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 shown in Table 6. Country Club and Stapleton (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. 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.

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. 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 census tract) to have a greater shift driving mode shift. This factor will be further discussed in the next section.

Table 6: Car mode share normalized for six census tract study areas under a normal and an adjusted income of $59,230 (based upon 2011 median household income as reported by the Denver Metro Chamber of Commerce)

	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	73.5%	71.2%	-2.3%	75.8%	70.6%	-5.2%
Stapleton	94.6%	93.8%	-0.8%	95.1%	93.1%	-2.0%
City Park West	58.0%	53.3%	-4.7%	57.9%	54.0%	-3.9%
Sunnyside	81.9%	75.8%	-6.1%	82.1%	77.2%	-4.9%
Globeville	76.7%	64.6%	-12.1%	79.5%	76.0%	-3.5%
College View/S Platte	87.6%	76.8%	-10.8%	89.6%	86.2%	-3.4%

Alternative Transportation Infrastructure
An important influence to mode share for certain census tracts is the availability of low stress 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, which includes the additional factor of sidewalk width. Thus, we analyze walk LTS to understand how bike LTS may also affect mode choice. Table 7 provides the walk and transit LTS values for all trips in the census tract study areas. 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 contributes in 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%. 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.

Table 7: Level of Traffic Stress (LTS) for biking, walking and transit, for all census tract origins to the CBD and Aurora

	Trips to the CBD		Trips to Aurora	
	Transit LTS	**Walk LTS**	**Transit LTS**	**Walk LTS**
Country Club	3	3	2	4
Stapleton	2	4	4	4
City Park West	2	3	3	4
Sunnyside	2	3	2	4
Globeville	2	4	3	4
College View/S Platte	3	4	3	4

Another area of analysis that indicated that factors related to the transportation environment impacted the trips from Country Club, City Park West, and Sunnyside were the results in Table 6. We will recall that in Table 6, 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 to trips to the CBD, walking trips to Aurora are more stressful. No trip to Aurora by foot are less than LTS 4; this is not surprising since most trips to Aurora require travel along busy roads with narrow or nonexistent sidewalks. All of the trips to Aurora are also over 5.6 miles in length. Although trip length was not a factor in the determining pedestrian LTS, these long trips are not realistic on foot. 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 4).

Transit LTS is measured by number of transfers and whether the trip includes light rail transit or commuter bus. Of all of 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 that are 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.

Conclusion

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 upon these environmental and demographic characteristics. Results of the multinomial logistic regression mode choice model revealed that certain neighborhoods and individuals are better able to withstand a disruptive gas price event. Three attributes are 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 multi-modal forms of transportation, the better able certain areas in Denver are 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 was ten years old and at times did not offer an accurate 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. Finally, the model did not take into account the fact that many modes can be combined for certain trips, such as walking to transit.

Despite these limitations and assumptions, the contribution of this work to understanding household transportation mode choice under a catastrophic gas event is critical. This research offers an important approach to valuing multi-modal transportation and to understanding the latent worth of this infrastructure, even if it is not heavily used today. Future direction of this research is promising. By utilizing the 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 network will facilitate this resiliency. These improvements can ensure 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 alternative transportation modes so that they may support the communities that 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 communities by offering adaptive and alternative transportation choices, supporting the economic and social strength of cities and towns.

REFERENCES

"ACS 2006 to 2010 (5-Year Estimates)." 2013. Social Explorer. *Social Explorer Professional*.

"Consumer Expenditure Survey." 2013. *Bureau of Labor Statistics*. Accessed July 24. http://www.bls.gov/cex/home.htm.

"DRCOG - Front Range Travel Counts." 2013. *Denver Regional Council of Governments*. http://www.drcog.org/index.cfm?page=FrontRangeTravelCounts.

Ewing, Reid, and Robert Cervero. 2010. "Travel and the Built Environment: A Meta Analysis." *Journal of American Planning Association* 76 (3): 265–94. doi:DOI 10.1080/01944361003766766.

Fitzgerald, Gerald. 2012. "The Social Impacts of Poor Access to Transport in Rural New Zealand". 484. New Zealand: NZ Transport Agency.

Freckleton, Derek, Kevin Heaslip, William Louisell, and John Collura. 2012. "Evaluation of Transportation Network Resiliency with Consideration for Disaster Magnitude" presented at the 91st Annual Meeting of the Transportation Research Board, Washington, DC.

Godschalk, David R. 2003. "Urban Hazard Mitigation: Creating Resilient Cities." *Natural Hazards Review* 4 (3): 136–43. doi:10.1061/~ASCE!1527-6988.

Haas, Peter M., Carrie Makarewicz, Albert Benedict, and Scott Bernstein. 2008. "Estimating Transportation Costs by Characteristics of Neighborhood and Household." *Transportation Research Record: Journal of the Transportation Research Board* No. 2077: 62–70. doi:10.3141/2077-09.

Heaslip, Kevin, William C. Louisell, and John Collura. 2009. "A Methodology to Evaluate Transportation Resiliency for Regional Networks" presented at the 88th Annual Meeting of the Transportation Research Board, Washington, DC.

"Light-Duty Automotive Technology and Fuel Economy Trends: 1975 through 2007." 2007. EPA-420-R-07-008. Washington, DC: Environmental Protection Agency Office of Transportation and Air Quality.

Lipman, Barbara J. 2006. "A Heavy Load: The Combined Housing and Transportation Burdens of Working Families". Washington, DC: Center for Housing Policy.

Long, J.S. 1997. *Regression Models for Categorical and Limited Dependent Variables (Advanced Quantitative Techniques in the Social Sciences)*. Thousand Oaks, CA: Sage Publications.

Martin, W.A., and N.A. McGuckin. 1998. "Report 365: Travel Estimation Techniques for Urban Planning". National Cooperative Highway Research Program. Washington, DC: National Academy Press.

Mekuria, Maaza, Peter Furth, and Hilary Nixon. 2012. "Low-Stress Bicycling and Network Connectivity". Final Report CA-MTI-12-1005. Mineta Transportation Institute: San Jose State University.

"Denver, Colorado – Income Growth for Region." 2013. *Metro Denver Economic Development Corporation*. Accessed November 12. http://www.metrodenver.org/demographics-communities/demographics/income.html.

Newman, Peter, Timothy Beatley, and Heather Boyer. 2009. *Resilient Cities: Responding to Peak Oil and Climate Change*. Washington, DC: Island Press.

Scherer, Milena. 2010. “Is Light Rail More Attractive to Users Than Bus Transit: Arguments Based on Cognition and Rational Choice.” *Transportation Research Record: Journal of the Transportation Research Board*. No. 2144: 11–19. doi:10.3141/2144-02.

“Weekly U.S. All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon).” 2013. *US Energy Information Administration*. July 23. http://www.eia.gov/dnav/pet/Hist/LeafHandler.ashx?n=PET&s=EMM_EPM0_PTE_NUS_DPG&f=W.