Journal of Transport Geography 41 (2014) 315–324

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Evaluating public transit modal shift dynamics in response to bikesharing: a tale of two U.S. cities

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ARTICLE INFO

Keywords:
Bikesharing
Public transit
Modal shift
GIS
Ordinal regression analysis

ABSTRACT

Public bikesharing—the shared use of a bicycle fleet—has recently emerged in major North American cities. Bikesharing has been found to decrease driving and increase bicycling. But shifts in public transit have been mixed. The authors evaluate survey data from two U.S. cities to explore who is shifting toward and away from public transit as a result of bikesharing. The authors explore this question by mapping geocoded home and work locations of respondents within Washington DC and Minneapolis. Respondents were mapped by their modal shift toward or away from bus and rail transit. The results show that in Washington DC, those shifting toward bus and rail transit live on the urban periphery, whereas those living in the urban core tend to use public transit less. In Minneapolis, the shift toward rail extends to the urban core, while the modal shift for bus transit is more dispersed. The authors analyze socio-demographics associated with modal shift through cross-tabulations and four ordinal regression models. Common attributes associated with shifting toward public transit include increased age, being male, living in lower density areas, and longer commute distances. The authors conclude with a discussion of the final results in the context of bikesharing's impacts on other cities throughout North America.

1. Introduction

Bikesharing has emerged as one of the latest innovations in urban transportation to sweep North American cities and transform urban mobility. Public bikesharing systems operate by providing instant access to bicycles at docking stations located throughout an urban region. People who use bikesharing can be members of the system for an annual fee or can be walk-up casual users accessing the system on a trial or temporary basis. Bikesharing permits users to check-out a bicycle at any station and return it to any other station with an available dock. By facilitating one-way travel, bikesharing has opened new opportunities for individuals traveling by bicycle in situations that would otherwise not be possible. This new dynamic has resulted in modal shifts among those that use bikesharing.

In late-2011, the authors completed a survey of annual bikesharing members in collaboration with operators in four cities including: Montreal, Toronto, Washington DC, and Minneapolis/St. Paul (the Twin Cities). The survey was designed to understand the general profile of bikesharing users and to evaluate how bikesharing had changed annual member travel patterns.

Previous research has shown that public bikesharing almost universally reduces driving and taxi use and increases bicycling in most every city (Shaheen et al, 2012, 2013). In many of these same cities, bikesharing has been shown to also reduce the use of public transportation including rail, bus, and walking in favor of bicycle use. For example, in Washington DC, 48% of respondents indicated that they used rail less often as a result of bikesharing. In Montreal and Toronto, 50% and 44% reported the same respectively, while in the Twin Cities, only 3% reported using rail less often. Although these effects reflect the dominant trends in modal shifts among the survey population, all cities big and small have people that increased or decreased their public transit use as a result of bikesharing. For example, in Washington DC, 7% reported increasing their rail use, while in Montreal and Toronto, 11% and 9% respectively, also reported increasing rail use. However, in at least a few cities (that appear to be smaller), bikesharing has been shown to increase the use of some forms of public transit. For example, in the Twin Cities, 15% of respondents reported increasing rail use.

The dynamics of bikesharing that facilitate both increases and decreases to public transportation are unique to the direction of modal shift. As bikesharing systems position bicycles in locations

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http://dx.doi.org/10.1016/j.jtrangeo.2014.06.026
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throughout the city, new opportunities emerge to complete first-and-last mile connections to public transit networks that were not previously possible. At the same time, bikesharing also provides opportunities to move faster than public transit systems, particularly within the dense networks present in downtown areas. Thus, bikesharing can both increase and decrease public transit use depending on the specific circumstances of the traveler and the urban environment.

What are some key characteristics of people who increase and decrease their public transportation use in response to bikesharing? This paper advances understanding of modal shifts caused by bikesharing through a geographic evaluation of survey data collected through recently completed research (Shaheen et al., 2012). Working with surveys in two of the cities surveyed in the United States, the authors analyze the attributes of individuals who increased and decreased their rail and bus usage in a geospatial context along with the population density of respondent home and work locations. The results inform the nuances of bikesharing impacts on the modal shift of urban residents with respect to public transportation.

In the sections that follow, we proceed with a literature review of previous research in public bikesharing, including work that evaluates modal shift and the geospatial analysis of bikesharing systems, with an emphasis on North America. Then, we describe the data and methods applied in this analysis, followed by the results and conclusion.

2. Background: previous research on public bikesharing

Bikesharing evolution has been characterized as a generational process, passing through four generations to the present day technology (DeMaio, 2003; Shaheen et al., 2010). The first generation was established in Europe during the 1960s, comprising deployments of free bikes, often painted white that could be freely used by anyone without access controls. These programs eventually failed due to theft and vandalism. A second generation of bikesharing emerged that required deposits of either money or identification for bicycle access, and some of these systems still operate today in North America. The third generation of bikesharing programs constituted those that have rapidly expanded through North American cities today (DeMaio, 2009; Shaheen et al., 2010). These systems evolved as information technology was incorporated into remote management of rental and payment systems (Shaheen et al., 2013). A fourth generation is emerging; this generation is defined by flexible, clean docking stations; bicycle redistribution innovations (e.g., on-board computers with real-time information on redistribution trucks); smart card integration with other modes (e.g., public transit); and technological advances including GPS tracking, touchscreen kiosks, and electric bikes (Shaheen et al., 2010).

In 2011–2012, Shaheen et al. (2012, 2013) surveyed public bikesharing members in four North American cities: Montreal ($n = 3322$); the Twin Cities (Minneapolis and Saint Paul) ($n = 1238$); Toronto ($n = 853$); and Washington DC ($n = 5248$). Relative to the population within the four cities, bikesharing members had slightly higher incomes, were younger, more educated, and had a higher percentage of Caucasians than the general population. In addition, bikesharing members in all cities were of a male majority, even though females were in the majority of the population in three of the four cities. While bikesharing users were skewed toward the young adult demographic, there was notable representation among middle-aged and older respondents, as about 40% of all respondents were 35 years of age or older. Overall, 88% of respondents reported having a minimum of a four-year college degree, and nearly half of the entire sample (46%) also had an advanced (Masters or Doctorate) graduate degree. Such characteristics have also emerged as distinguishing features in carsharing (short-term vehicle access) members. For example, previous research has found that more than 80% of carsharing members had a four-year degree or more (Shaheen et al., 2012, 2013).

Buck et al. (2013) studied how the newest generation of bikesharing users differs from traditional cyclists in the Washington DC region. Survey data showed Capital Bikeshare users were split evenly between genders, although males tended to make more frequent trips than females. Males were predominant among traditional cyclists. Langford et al. (2013) conducted a study profiling the users of the first electric bikesharing system piloted at the University of Tennessee. Fifty-nine percent of users in the cycleUshare electric bikesharing program were male. Langford et al. (2013) noted that the majority of trips taken on the electric bikes were made by a small percentage of the subscribed users.

Webster and Cunningham (2013) conducted a study using data from a series of focus groups in Chattanooga, Tennessee on preliminary beliefs and attitudes toward biking to understand how to best implement a bikesharing program in the city. Participants revealed that they believed biking was a good form of physical activity but did not think that biking could be employed as a primary transportation mode. Langford et al. (2013) found some related results as 40% of all activity was due to school-related trips and 15% were for leisure and exercise. The only transportation mode that e-bikes replaced was walking. Overall, cycleUshare participants still relied on cars as their primary transportation mode, particularly during the winter months.

In larger cities, commute-related trip purposes were more common with public bikesharing. Our research in the four cities mentioned earlier found that the most common trip purpose was work or school-related. However, in the two U.S. cities, this trip purpose was not a majority (about 38%). While this was the most common single trip purpose, it could also be argued that "non-work" trips were the most common when aggregated together. In both Canadian cities, work trips comprised at least 50% of all trips (Shaheen et al., 2012, 2013). In addition, a study completed in Jiangyin, China, Tingting et al. (2011) found that 42% of public bicycle usage was to connect to public transit stations. This study found the main effect of public bicycles was to increase the travel reach of urban residents as opposed to increasing leisurely bicycle travel.

Recent work in bikesharing has also explored the dynamics of station network effects. Wang et al. (2013) used an ordinary least square regression to analyze the effects of socio-demographics, the built environment, availability of transportation infrastructure, and economic activity variables on bikesharing stations within the Nice Ride Minnesota network. Rixey (2013) studied the same four categories of variables using multivariate regression models across three bikesharing systems: Capital Bikeshare, Denver B-Cycle, and Nice Ride Minnesota. The study found a statistically significant correlation between variables in all four categories of independent variables at the one percent level, while most variables were significant at the five percent level in the Wang et al. (2013) study.

Rixey focused his spatial analysis on ridership and emphasized a strong positive correlation between the ridership levels at a station with the availability of other stations within 4800 m. For Wang et al. (2013), the proximity of food and restaurants nearby bikesharing stations showed a particularly strong positive correlation to ridership. Schoner and Levinson (2013) present another perspective by using survey data to study how public transit routes, neighborhood characteristics, trip purpose, and station area amenities affect station choice decisions. The study used data gathered from a survey of Nice Ride Minnesota subscribers and constructed a model predicting station use by using the subscriber's perceived expected utility. The study concluded that for commuter trips, members had a strong preference for shorter distances to their destination locations, with a strong preference for the least amount of walking. In the studies by Wang et al. (2013) and Rixey (2013), availability of recreational land was less important for determining station popularity as compared to other variables tested, and the correlation was highly dependent on favorable weather conditions.

This study builds upon this literature by exploring the dynamics of modal shift to and from public transportation in response to bikesharing. The authors use available geospatial data from the surveys completed in collaboration with Nice Ride Minnesota and Capital Bikeshare. The authors focus on this comparative case because the cities exhibited divergent shift patterns and their presence within the U.S. permits some comparability across external data resources. In terms of overall bicycle modal share, these two cities are highly similar. In 2012, Minneapolis recorded a bicycle mode share of 4.5% and Washington DC a mode share of 4.1% (US Census, 2012). In the following sections, the authors introduce the data used in this paper, as well as the methods applied to analyze the underlying dynamics of modal shift and bikesharing.

3. Methodological approach and data

The data applied in this paper are derived from three primary sources. The first is our 2011 survey of annual members of Capital Bikeshare in Washington DC and Nice Ride Minnesota in Minneapolis. The data from these surveys evaluated the modal shift of respondents in response to bikesharing. In addition, the survey collected key demographic and attribute data of respondent households, as well as home and work location data in the form of street intersections. Respondents were asked to provide two streets that cross near their home and near their work. Intersections are useful as geolocation information for a few reasons. First, intersections are precise enough to understand the local environment, commute needs, and available transportation options available to the respondent. However, intersections are not precise enough to identify an individual's actual home address or work location, which protects respondent privacy. Intersections, in the form of the cross-streets provided by the respondent, were geocoded. The geocoded locations were used to determine the distance between home and work locations. This spatial information was used in conjunction with the survey responses to evaluate the geospatial distribution of bikesharing members by the direction of their public transit modal shift.

The authors designed the modal shift question in the surveys to probe the general direction of modal shift due to bikesharing, as respondents would be the most knowledgeable of how bikesharing changed their personal behavior. The question was asked to evaluate the change in seven travel modes including: (1) bus travel, (2) rail travel, (3) walking, (4) bicycling, (5) driving, (6) taxi use, and (7) carsharing. An example of a question probing the shift in bus usage read: "*As a result of my use of < bikesharing>, I ride the bus...*," where <bikesharing> was a placeholder for the operator name (e.g., Nice Ride Minnesota, etc.). The respondent could select one response from: "Much more often," "More often," "About the same," "Less often," and "Much less often." Two other options were also available to aid the respondent in answering the question. They included: "I did not ride the bus before, and I do not ride the bus now." and "I have changed how I use the bus but not because of <bikesharing>." The scale applied has some useful features. First, it is ordinal, making the answers simple to understand and interpret for the respondent. It is also complete, in that all possible scenarios within the confines of modal shift and causality are on the seven-point scale. For the analysis, the "no change as result of bikesharing" options were aggregated together, as their disaggregation was primarily to aid the respondent in answering the question. These questions, which were asked in a standard format across multiple cities, were used to report overall modal shift in Shaheen et al. (2012) and are analyzed here in conjunction with geospatial data. The final data source applied in this paper is zip code-level population statistics derived from the U.S. Census but organized and made available by ESRI (ESRI, 2012). The authors used ArcGIS 10.2 to generate the maps presented in the results.

With these data sources, the authors map the regional distribution modal shift to and from public transit as a result of bikesharing. The authors also use this data to analyze the characteristics of members by direction of modal shift, including population density of their home and work locations. In the section that follows, the authors present the results of overlaying these data sets together on maps of the two cities, as well as a statistical analysis of modal shift data.

4. Results and discussion

This section presents a basic overview of the overall modal shift observed in the two cities. Not surprisingly, the data influenced the geocoding process, as not all survey responses contained information that the authors could geocode. Table 1 presents summary statistics in the context of the modal shift reported from the member survey, as well as the same statistics for the reduced dataset, which was defined by the home and work location responses that the authors could geocode. For a complete demographic profile of the survey data, as well as responses to other questions, see Shaheen et al. (2012).

Table 1 displays the differences in overall modal shift between the two cities. A comparison between the percentages also shows that the attrition due to geocoding of survey responses did not impose much bias on modal shift percentages within the sample. For comparative purposes, the left side of Table 1 reflects results previously reported in Shaheen et al. (2012) for both cities. The "Full Survey" reported in the table reflects the actual modal shift reported in earlier research (Shaheen et al., 2012). The sample exhibits an increase in bicycling overall as a result of bikesharing, as evident in both Minneapolis (72%) and Washington DC (83%). In addition, driving reductions due to bikesharing in both cities were similar, as 52% reduced driving in Minneapolis and 41% did so in Washington DC. Taxi use declines in both cities and more so in Washington DC where taxis are more abundant. In Washington DC, carsharing use fell, while respondents in Minneapolis reported little change in carsharing usage. The change in walking, bus, and rail usage in both cities comprises one of the more significant departures in modal shifts between the two cities. In Minneapolis, more people shifted toward rail (~15% increase and 3% decrease) than away from it in response to bikesharing. The result was the same for walking (38% increase and 23% decrease), but not for bus, where a slight decline in overall ridership was evident in the sample (15% increase and 17%). This contrasts to the reported reduction in walking, bus, and rail transit in Washington DC (which was also observed in similar magnitude within Montreal and Toronto in the survey). The split between these shifts motivates deeper inspection of these two cities, which were early adopters of the public bikesharing service first established in Montreal.

The authors begin the analysis by presenting a series of maps that illustrate the combined modal shift data aggregated to geographic divisions defined by zip codes. Fig. 1 illustrates the geographic distribution of modal shift to and from rail for annual members of Capital Bikeshare in Washington DC. The map presents a pie chart for each zip code. The pie chart can have up to three divisions demarcated by the colors green,[2] yellow, and red. Each

[2] For interpretation of color in Figs. 1–4, the reader is referred to the web version of this article.

Table 1
Summary of modal shift activity for Washington DC and Minneapolis.

Washington DC	Full survey (N = 5248)			Survey with just gecoded home/work pairs (N = 4853)		
	Increased use	No change	Decreased use	Increased use	No change	Decreased use
Bus	268 (5.1%)	2907 (55.7%)	2042 (39.1%)	247 (5.1%)	2704 (55.7%)	1902 (39.2%)
Rail	353 (6.8%)	2390 (45.9%)	2467 (47.4%)	315 (6.5%)	2238 (46.1%)	2300 (47.4%)
Walk	904 (17.4%)	2685 (51.8%)	1594 (30.8%)	825 (17%)	2543 (52.4%)	1485 (30.6%)
Drive	24 (0.5%)	3092 (58.9%)	2132 (40.6%)	16 (0.3%)	2868 (59.1%)	1969 (40.6%)
Taxi	32 (0.6%)	2409 (46.3%)	2760 (53.1%)	27 (0.6%)	2260 (46.6%)	2566 (52.9%)
Bicycle	4304 (82.5%)	846 (16.2%)	69 (1.3%)	3999 (82.4%)	791 (16.3%)	63 (1.3%)
Carsharing	43 (0.8%)	4366 (84.9%)	736 (14.3%)	38 (0.8%)	4133 (85.2%)	682 (14.1%)
Minneapolis	Full survey (N = 1238)			Survey with just gecoded home/work pairs (N = 903)		
	Increased use	No change	Decreased use	Increased use	No change	Decreased use
Bus	177 (14.5%)	838 (68.7%)	204 (16.7%)	128 (14.2%)	611 (67.7%)	164 (18.2%)
Rail	179 (14.7%)	1007 (82.5%)	35 (2.9%)	129 (14.3%)	750 (83.2%)	22 (2.4%)
Walk	458 (37.5%)	479 (39.2%)	284 (23.3%)	330 (36.5%)	358 (39.6%)	215 (23.8%)
Drive	5 (0.4%)	581 (47.2%)	644 (52.4%)	3 (0.3%)	433 (48%)	467 (51.7%)
Taxi	13 (1.1%)	980 (80.2%)	229 (18.7%)	8 (0.9%)	734 (81.3%)	161 (17.8%)
Bicycle	871 (71.5%)	1531 (125.7%)	34 (2.8%)	637 (70.5%)	242 (26.8%)	24 (2.7%)
Carsharing	15 (1.2%)	1196 (97.4%)	17 (1.4%)	9 (1%)	884 (97.9%)	10 (1.1%)

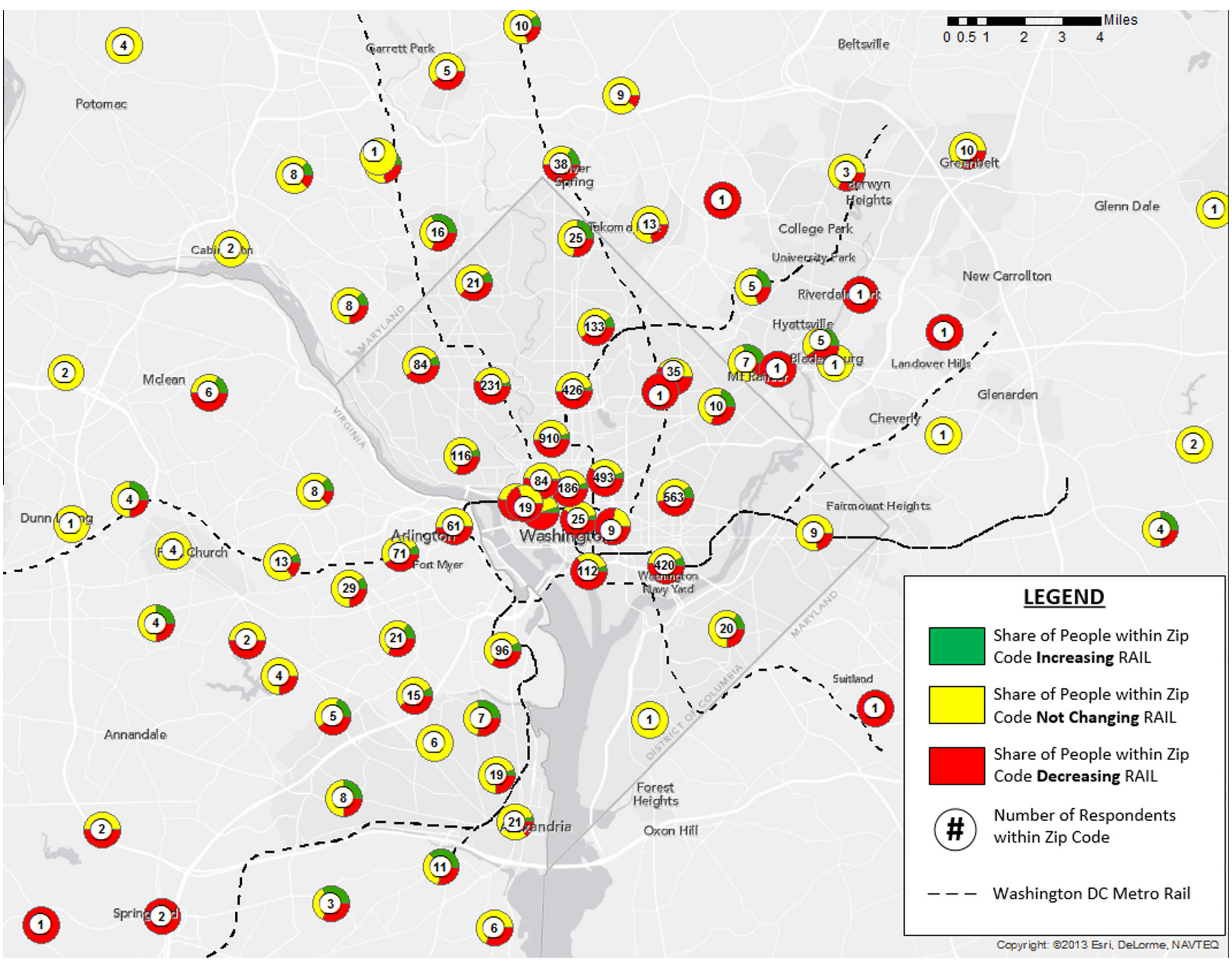

Fig. 1. Geospatial distribution of modal shift to and from rail in Washington DC.

division represents the share of respondents living (home location) within the zip code that *increased*, *decreased*, and *did not change* their modal use as a result of bikesharing. The *green* portion of each pie chart represents the share of respondents *increasing* their use of the mode. The *yellow* portion represents the share of respondents that *did not change*, and the *red* portion represents those that *decreased* their mode use. The number overlaid in each pie chart is the count of geocoded respondents in that zip code. The dotted line on the map shows that layout of the Washington DC Metro system operational at the time of the survey.

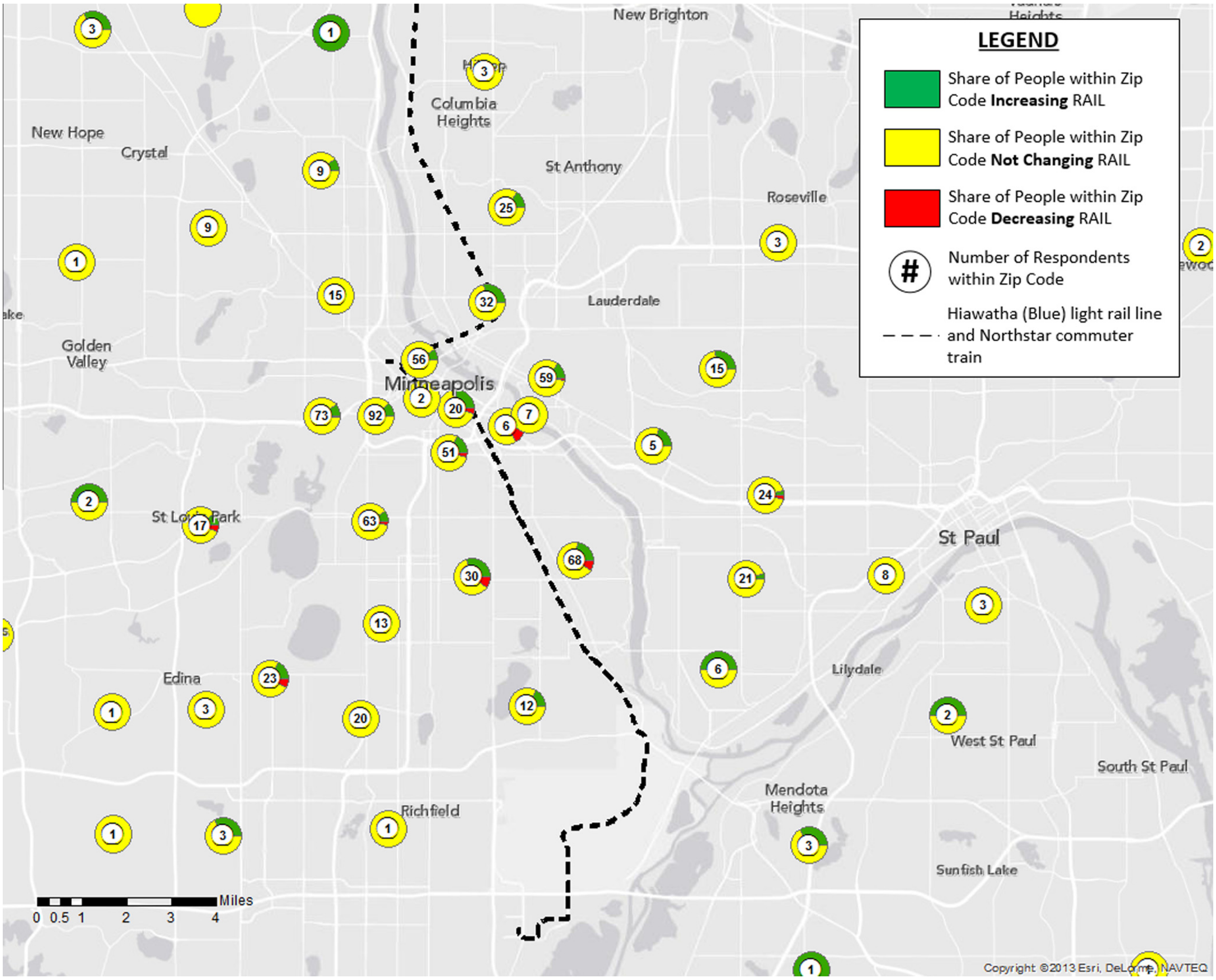

Fig. 2. Geospatial distribution of modal shift to and from rail in Minneapolis.

The distribution of shift exhibited in Fig. 1 illustrates several dynamics related to bikesharing in Washington DC. First, it shows that at the time of the survey, the residences of annual members were highly concentrated in the downtown region of the city. The data show that within this tight region, which is at the center of the congested DC Metro rail network, the shift away from rail is highest, generally in both percentage (except a few outliers on the periphery) and overall count. This suggests that bikesharing may substitute for shorter trips that would have previously been completed by rail for a few stops. While the shift away from rail in Washington DC may dominate the numbers in Table 1 and in Fig. 1, it is important to note that bikesharing is also facilitating rail usage in the city as well (for 315 people just within this sample). Fig. 1 shows that those increasing their rail use are located on the periphery in relatively greater percentages within the zip code. Hence, the map suggests that public bikesharing in Washington DC, while certainly appearing to lower overall rail ridership, also appears to be doing so predominantly in the downtown area, where trips are shorter and the system is more congested. In contrast, bikesharing in Washington DC is aiding rail ridership in the outer suburban regions of the city, where trips are longer.

In Minneapolis, the net shift toward rail was found to be uniquely positive in the survey. The two main options at the time of the survey consisted of the Hiawatha light rail line (now called the Blue Line) that ran from the Mall of America in Bloomington northward to downtown, passing the airport along the way. The other option was the North Star line, a commuter rail service arriving from the north of the city to Target Field near downtown. The authors' member survey inquired how bikesharing influenced each separately and found the vast majority of the shift toward rail occurred with the Blue line (94% of it). This is not surprising, as the bikesharing network only covered the downtown end of the North Star line at the time of the survey, whereas stations close to the Hiawatha Line were far more pervasive further along the corridor. In the same format as Fig. 1, Fig. 2 shows the geospatial distribution of modal shift to and from rail for the annual members of Nice Ride Minnesota in Minneapolis. Fig. 2 also shows the layout of the two main rail lines that were operational at the time of the survey (the system has since expanded). The Hiawatha line terminated at Target Field in downtown Minneapolis and extended south to the Mall of America. The Northstar also terminated at Target Field, then it extended north to the suburbs terminating in Bike Lake.

Fig. 2 shows that the shift toward rail predominantly occurs in the downtown of the city. But it is also evident in the peripheral regions outside the center. Unlike the distribution in Washington DC, those shifting away from rail exist but are not so concentrated in the downtown area.

There are several possible explanations for the difference in rail modal shift found in Minneapolis in contrast to Washington DC. The simplest explanation may be related to the shape of the rail network. In a city like Minneapolis, the single light rail and commuter rail line do not compete with bikesharing over short trips, in contrast to the multi-line DC Metro with multiple transfer hubs. That is, there is less modal share for rail in Minneapolis to lose for these kinds of short trips. Another theory for the difference could be relative congestion, with the notion that the Hiawatha (Blue) line is not as highly used as the DC Metro. By one measure, public transit has a more prominent role in the Washington DC region. In 2012, the overall modal share of public transit for commuting to work in Washington DC was 37%, more than twice the 16% observed in Minneapolis (US Census, 2012). However, another measure of public transit usage is less convincing. In 2011, the Blue line serviced 58,788,888 passenger miles with 27 vehicles operating at maximum service, for a usage rate of 2,177,366 passenger miles per vehicle. That same year, the DC Metro serviced 1,626,750,032 passenger miles with 860 vehicles operating at maximum service, yielding a slightly lower usage rate of 1,891,570 passenger miles per vehicle (NTD, 2011). According to this averaged measure, both rail lines appear to be similarly used and congested. This leads the authors to believe that the reason for the difference is most likely infrastructure effects. The rail system in Minneapolis is very linear. The two lines terminate at Target field, one proceeding north and the other south. With its non-crossing rail lines, the system services less within-city trips that bikesharing could substitute for. Whereas the rail system in Washington DC, with its multiple transfer hubs and web of connections, serves far more trip types than bikesharing can support. In other words, the rail system in Washington DC may be losing modal share to bikesharing that the system in Minneapolis never had. One interesting point to note is that one of Washington DC's program objectives was to shift people off of public transportation during peak periods to increase transit's overall capacity.

The geospatial distribution of the modal shift in bus ridership tells a similar story as the shift in rail. As shown in Table 1, the share of respondents reducing bus ridership is lower than the shift away from rail (~39–47%). Fig. 3 presents the geospatial distribution of modal shift to and from bus. The pattern of modal shift is similar to that found with rail, in that few respondents in the urban core of Washington DC indicated increasing their bus usage as a result of bikesharing. However, as with rail, the respondents that reported increasing bus use due to bikesharing are distributed toward the edges of the district.

In Minneapolis, the respondents indicated a greater propensity to reduce bus use. This notably occurs in the downtown area, where very few respondents reported a commensurate reduction

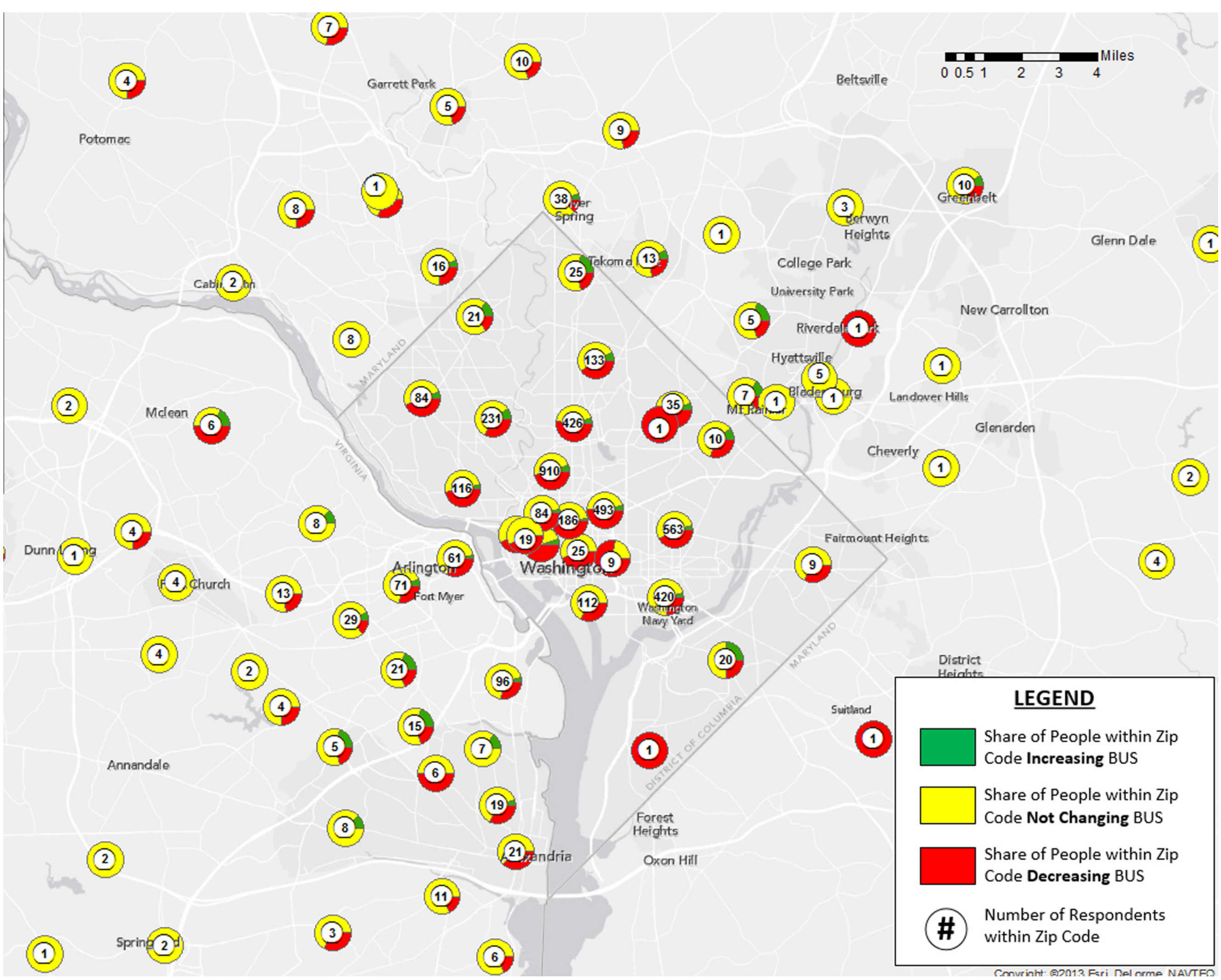

Fig. 3. Geospatial distribution of modal shift to and from bus in Washington DC.

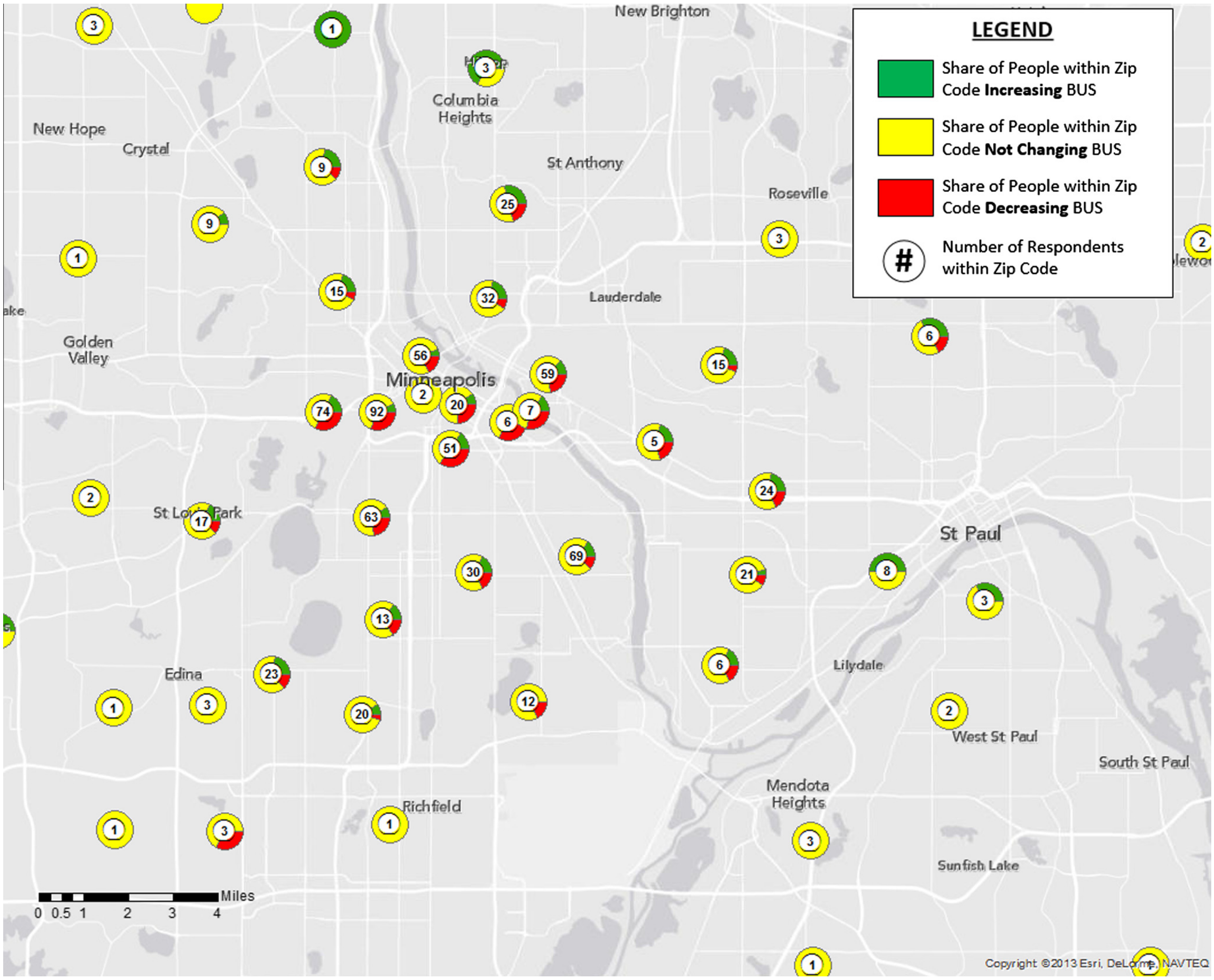

Fig. 4. Geospatial distribution of modal shift to and from bus in Minneapolis.

of rail use due to bikesharing. Rather, the modal shift to and from bus is distributed within the downtown of Minneapolis as well as within the suburbs. Also notable is the relatively even share of respondents within zip codes, particularly in the suburbs, that indicated they had increased use and decreased use of bus transit in Minneapolis. That is, members who reported reduced bus use, in a given zip code, were often counteracted by others who increased their bus use due to bikesharing. The geospatial distribution of the bus modal shift is shown in Fig. 4.

To understand some of the underlying attributes of people shifting to and from public transit, the authors examined respondents more closely. The demographic variables tied to the respondent offer the first level of insight regarding the characteristics of bikesharing members that shift toward or away from public transit due to bikesharing. Key respondent attributes, including gender, age, income, and education, are provided in Table 2, which splits them by their shift to and from bus and rail in both cities. Table 2 shows several distinct features that appear to be associated with modal shift. First, those shifting toward rail and bus were more likely to be male. For example, 65% and 63% of all respondents that reported increasing their rail use due to bikesharing were male in Washington DC and Minneapolis, respectively. Similarly, 55% of respondents in Washington DC and 61% in Minneapolis who increased their bus use were also male. Table 2 also shows the median response for the demographics of age, income, and education. In Washington DC, the median age bracket is 24–35 for all subsamples. This by itself does not mean that age is not influential on modal shift, but it does indicate that the effect is damper or not strong enough to evoke a difference in the median. In Minneapolis, age seems to have a stronger association with increased public transit use, as those increasing their usage have an older median age than the broader sample. Income also appears influential. Those decreasing their rail and bus use in Washington DC have a lower median income than the broader sample, and a similar association is found for those decreasing their bus usage in Minneapolis. Education appears to have less association with the direction of modal shift, as those increasing and decreasing the two modes in all four cities had the same median education.

Finally, the last attribute of Table 2 is the average commute distance of respondents. Because this attribute is of a ratio scale, the difference of its mean from other values (or means) is testable using the *t*-test (not so with the other attributes, which are of ordinal or categorical scales). Using the *t*-test, the authors evaluated the degree to which the mean commute distance of those increasing and decreasing their use of each model are statistically different from each other. A higher commute distance appears to be associated with increasing rail usage in response to bikesharing. In both Washington DC and Minneapolis, the average commute

Table 2
Summary of respondent attributes and the modal shift in public transportation.

	Rail			Bus			Overall sample
	Increased	Decreased	No change	Increased	Decreased	No change	
Washington DC							
Gender							
Male	65%	56%	51%	62%	55%	53%	54%
Female	34%	43%	48%	37%	44%	46%	45%
No answer	1%	1%	1%	1%	1%	1%	1%
Total	100%	100%	100%	0%	100%	100%	100%
Median age	25–34	25–34	25–34	25–34	25–34	25–34	25–34
Median income	$75–100 K	$75–100 K	$75–100 K	$75–100 K	$50–75 K	$75–100 K	$75–100 K
Median education	Master's	Master's	Master's	Bachelor's	Bachelor's and Master's (tie)	Master's	Master's
Average commute distance (miles)	7.26[a]	5.93[b]	6.75	5.48[c]	5.59[c]	7.05	6.40
Total sample size	315	2300	2238	247	1902	2704	4853
Minneapolis							
Gender							
Male	63%	55%	52%	62%	55%	53%	54%
Female	37%	41%	46%	37%	44%	46%	45%
No answer	1%	5%	2%	1%	1%	1%	1%
Total	100%	100%	100%	100%	100%	100%	100%
Median age	35–44	25–34 and 35–44 (tie)	25–34	35–44	25–34	35–44	25–34
Median income	$75–100 K	$75–100 K	$75–100 K	$75–100 K	$35–50 K	$75–100 K	$75–100 K
Median education	Bachelor's	Bachelor's	Bachelor's	Bachelor's	Bachelor's	Bachelor's	Bachelor's
Average commute distance (miles)	7.08	5.31	6.29	7.21[a]	3.81	6.90	6.38
Total sample size	131	22	750	128	164	611	903

[a] Average commute distance of those increasing is statically different from those decreasing mode at 95%.
[b] Average commute distance of those decreasing is statically different from those not changing mode at 95%.
[c] Average commute distance of those increasing and decreasing is statically different from those not changing mode at 95%.

Table 3
Ordinal regression on modal shift.

Washington rail					Washington bus				
Coefficient	Estimate	Wald	*p*-Value	Sig.	Coefficient	Estimate	Wald	*p*-Value	Sig.
Threshold constant	1.20840	109.33	0.00	***	Threshold constant	1.021112	65.58	0.00	***
Age	0.09311	11.22	0.00	***	Age	0.050809	2.64	0.10	·
Commute distance	0.00324	1.36	0.24		Commute distance	−0.003217	0.90	0.34	
Female	−0.13635	6.50	0.01	*	Female	−0.104033	3.22	0.07	·
Household income	0.02173	3.07	0.08	·	Household income	0.016065	1.42	0.23	
PopDensityHomeZip	−0.00001	8.72	0.00	***	PopDensityHomeZip	−0.000004	2.26	0.13	
Link function	cloglog				Link function	cloglog			
N =	2502				*N* =	2060			
Minneapolis rail					Minneapolis bus				
Threshold constant	−2.3196	3.79	0.05	·	Threshold constant	1.6371	6.07	0.01	**
Age	−0.1126	0.36	0.55		Age	0.3926	10.10	0.00	***
Commute distance	0.0119	0.12	0.73		Commute distance	0.0812	7.19	0.01	**
Female	−0.1047	0.05	0.83		Female	−0.0239	0.01	0.93	
Household income	0.0553	0.28	0.60		Household income	0.0583	1.12	0.29	
PopDensityHomeZip	−0.0001	1.18	0.28		PopDensityHomeZip	−0.0001	7.11	0.01	**
Link function	logit				Link Function	logit			
N =	150				*N* =	286			

· Significant at .1.
* Significant at 0.05.
** Significant at 0.01.
*** Significant at 0.001.

distance of those increasing their rail use is higher than those decreasing it by nearly two miles (~3.2 km). In Washington DC, this difference is statistically significant, while in Minneapolis, it is not. This is in part due to the low sample size of those respondents decreasing rail use in that city, and thus the high standard error. In Minneapolis, there is a more striking (and statistically significant) difference between average commute distances among those that increase and decrease their bus usage. Commute distance appears to be less distinguishing among those that shift bus use in Washington DC. The average commute distance of both cohorts is near identical, but both are statistically different from the remainder of the sample that did not change their bus usage due to bikesharing.

To confirm the insights of Table 2, the authors conclude this analysis with a discussion of four ordinal regression models that incorporate the sociodemographic attributes presented, as well as two land-use parameters (population density) that are associated with the home and work zip codes of the respondent. Ordinal regression is an estimation procedure that is applicable when the dependent variable (modal shift) is on an ordinal scale. Here, the authors consider an ordinal dependent variable with distinct values for increasing rail and decreasing rail use (and similarly for bus). In each model, the authors only consider respondents that reported a shift toward or away from the mode. Ordinal regression also allows the application of different link-functions that can be better selected based on the distributional shape of the dependent variable. In this case, the authors apply the complementary log–log link function to the Washington DC data and the logit function to Minneapolis data. All estimations were completed with SPSS, with the parallel lines test validating the proportional odds assumption for all four models.[3] The motivation for this modeling exercise was not so much to generate a predictive application on modal shift but rather to evaluate the significance of different variables simultaneously on their influence and association with a positive or negative shift in both cities. The four estimated models are shown in Table 3. As increasing modal use was the higher value of the dependent variable, a positive coefficient means higher values for the independent variable are associated with a shift toward the mode, while negative coefficients indicate that higher variable values are associated with shifts away from the mode.

The estimated models show that the variables outlined in Table 2 are significant in some but not all of the models. Other variables, such as education, race, and the population density of work locations, were not significant or did not improve model fit. In all but one of the models, higher age was shown as significant and associated with shifts toward public transit. The age variables are all on the same scales across the models, and the model structures are all the same, so a comparison between age coefficient sizes is meaningful for determining where the effect of age is strongest. Age is most influential on increasing bus usage in Minneapolis, followed by Washington DC rail, and then by Washington DC bus. Surprisingly, commute distance, while always of the expected sign, was not significant in three of the four models. The one model in which it was significant was for the Minneapolis bus, where the difference in means was found to be largest in Table 2. This result was in part due to the significance of the population density of the home zip code variable. When this variable was removed from the model, commute distance was more often found to be of a positive sign and statistically significant. The close correlation of the two variables made their influence on the dependent variable less distinguishable, and ultimately, the population density of the home zip code offered a closer fit (albeit with the opposite sign). This dynamic would likely also confound the inclusion of other land-use variables aimed at capturing the impact of the surrounding environment on modal shift. For example, the density of rail stations or rail lines is another built environment variable that is related to the modal shift of rail, and it may uniquely influence its degree apart from population density. However, the correlation of this variable with the population density of home zip codes, along with the population density of respondent work zip codes being found to be insignificant, suggests that the contribution of such variables may be marginal. However, further exploration of these built-environment variables should be the subject of future research. The gender variable indicated that being female reduced the propensity to shift toward public transit. This variable was statistically significant in Washington DC but only of the expected sign in Minneapolis. Household income played a surprisingly weak role in all four models. It was significant just at the 10% level for shifts toward Washington DC rail. Finally, population density of the home zip code was negative in all four models, highly significant in two models, nearly significant in another, and not significant in the model where few peopled shifted away from public transit (Minneapolis rail). This counterintuitive dynamic is visually evident in the maps presented in Figs. 1–4. In general, bikesharing seems to play the greatest role in encouraging public transit use in lower density environments and peripheries of the regions studied, while facilitating perhaps faster or more direct travel than public transit in higher density environments. The Minneapolis rail system was one long line at the time of the member survey; bikesharing more likely played a role in enabling better access and egress within this system design. Other modes that had a denser network of stations tended to experience greater modal substitution due to bikesharing perhaps due to it is a faster, lower cost travel, which offers the opportunity for exercise. The dynamics of network design and its interactions with bikesharing would be a compelling subject for future research.

5. Conclusion

Public bikesharing has experienced rapid growth in North American cities, providing new options for mobility that are both independent and supportive of public transit. This and other research has confirmed that bikesharing is facilitating greater bicycle usage and is reducing the use of the personal automobile in the form of driving and taxis. The modal shift to and from public transit has shown an intriguing degree of variation within and across cities, meriting further exploration in this paper. The authors found, through mapping the modal shifts reported by members, that shifts away from public transit are most prominent in core urban environments with high population density. Shifts toward public transit in response to bikesharing appear most prevalent in lower density regions on the urban periphery.

As bikesharing continues to expand into new urban environments, different types of impacts may occur as bikesharing extends into different types of cities. Evidence is emerging from the early study of several North American cities that bikesharing may serve prominently as a first-mile, last-mile facilitator in areas with less intensive transit networks. These are areas in which bikesharing provides access to-and-from the broad public transit system. In areas with higher population density and more intensive public transit networks, bikesharing may offer faster, cheaper, direct connections over short distances that were previous completed by short transit trips. Cities that have more limited rail networks, such as Minneapolis or Salt Lake City, may exhibit the characteristics of an urban environment in which public transit ridership is more gained than lost throughout the region. Hints of this dynamic are present in the overall gain in rail transit usage throughout Minneapolis. Evidence from this study begins to suggest that the key issue governing how bikesharing influences public transit may be connected to the degree to which the existing transit services predominantly serve long trips in which a bicycle is not competitive or short trips in which a bicycle is a substitute. In this sense, the impact of bikesharing on transit ridership may be different based on the urban environment in which it is deployed. The denser the urban environment (particularly for rail), the more bikesharing provides new connections that substitute for existing ones. The less dense the environment, the more bikesharing establishes new connections to the existing public transit system. If this dynamic holds across multiple cities, public bikesharing may be more complementary to public transit in small to mid-size cities and more substitutive of public transit in larger and denser cities (perhaps alleviating crowded transit lines during peak periods). In all cases, as demonstrated by its remarkable ability to attract modal share in North America, public bikesharing appears to be improving urban mobility and lowering dependency on automobile travel.

[3] The Test of Parallel Lines evaluates whether the value of the coefficients are the same for all categories of the dependent variable. The test compares the model estimated to a hypothetical model with the same independent variables, but it is structured so that there is a separate set of coefficients for each dependent variable category. The null hypothesis is that the hypothetical model does not produce vastly different coefficient values for each dependent variable category (e.g., the lines/slopes of the coefficients are parallel for each variable). This is a hypothesis a researcher using ordinal regression does not want to reject. If this hypothesis is rejected, then the estimated ordinal regression model, with its single coefficient per independent variable is not correctly representing the true value of the coefficients, and the model violates the proportional odds assumption (UCLA, 2014; IBM, 2012).

Acknowledgements

The Mineta Transportation Institute and the Transportation Sustainability Research Center (TSRC) of the Institute of Transportation Studies at the University of California, Berkeley generously funded this research. The authors would like to thank Capital Bikeshare and Nice Ride Minnesota for their participation in our member survey. Thanks also go to Rachel Finson, Adam Cohen, Kailin Lu, and Nelson Chan of TSRC for their help in data collection and research assistance. The contents of this paper reflect the views of the authors and do not necessarily indicate acceptance by the sponsors.

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