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Commute well-being differences by mode: Evidence from Portland, Oregon, USA

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ABSTRACT

To understand the impact of daily travel on personal and so cietal well-being, researchers are developing more sophisticated quantitative measures of travel satisfaction. Metrics related to Subjective Well-Being (SWB), defined as an evaluation of one's happiness or life satisfaction, hold promise for better evaluating health impacts of transportation and land-use policies. This article examines commute well-being, a multi-item measure of how one feels about the commute to work, and its associated factors. The measure was adapted from the Satisfaction with Travel Scale originated by Ettema et al. (2010). Data were collected from a web-based survey of workers ($n=828$) in Portland, Oregon, U.S.A. with four modal groups: walk, bicycle, transit and car users. With some modifications from previous research, this research confirms that the commute well-being scale reliably measures commute satisfaction. A multiple linear regression model shows that along with travel mode, traffic congestion, travel time, income, general health, attitudes about travel, job satisfaction and residential satisfaction also play important individual roles in shaping commute well-being. Results in this study add further evidence that people who bike and walk to work are happier with their commutes and are relatively unaffected by traffic congestion compared to bus and car commuters. The findings suggest opportunities for policymakers to more effectively market active transportation policies.

1. Introduction

Transportation policy goals such as increasing mobility and reducing single occupancy vehicle trips and greenhouse gases do not often account for individuals' well-being explicitly. Because these goals also have limited appeal to the public, transportation research and planning could benefit from focusing more heavily on individuals' travel experiences, such as feelings of freedom, personal safety, and stress (Gärling and Schuitema, 2007; Anable and Gatersleben, 2005; Ory and Mokhtarian, 2009). These feelings and evaluations can affect people's lives. Commuting has been demonstrated to harm physical health and commute stress often carries over to work and home spheres (Novaco and Gonzales, 2009). Accounting for subjective well-being (SWB) in travel experiences can improve predictions of future mode choices and help policymakers evaluate positive and negative effects on health and well-being from these choices (Abou Zeid, 2009; Morris and Guerra, 2015).

This article focuses on “commute well-being” (CWB), a multi-item measure of the experience of commuting to work, and what influences it. Empirical models are estimated that build on a growing body of work covering subjective well being (SWB), satisfaction with travel, and their connections to travel mode (see De Vos, et al. (2013) for a review). This study represents one of the first applications of CWB in the U.S., utilizing data gathered in winter 2012 from commuters who travel to work in central Portland, Oregon via car, public transit, bicycle, and walking. Due to relatively high commute mode shares for bike and transit in Portland (6 and 12 percent of commute trips, respectively, according to the U.S. Census American Community Survey 2009), Portland is a suitable testing ground for evaluating the impact of modes on CWB.

Based on results from previous survey research from Sweden, England, and Canada (Friman et al., 2013, Gatersleben and Uzzell, 2007, Páez and Whalen, 2010), it is hypothesized that active travelers (walk and bike commuters) have higher commute well-being than bus, rail

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or car commuters, controlling for other variables (i.e. age, income, gender, education, vehicle availability, job satisfaction, residential location satisfaction, and accessibility). *T*-tests, ANOVA and multiple linear regression analyses are used to test this hypothesis.

Subsequent sections are presented as follows: section two briefly presents the development of SWB/satisfaction with travel research in previous literature; section three discusses the data and methods used, including modifications of the CWB measure from previous research; section four presents a description of the sample, the acceptability of the CWB measure, and findings from model estimation results, and; section five offers conclusions and practical implications of the findings, noting limitations and suggestions for further research.

2. Theory

Levels of satisfaction and happiness can have important consequences for people's lives. A growing chorus argues that policies should focus on well-being, rather than economic indicators. Nobel-prize winning psychologist Daniel Kahneman (1999) maintains that SWB measurements could complement conventional tools for measuring benefits and losses in a variety of domains, and in policy analysis. Transportation planning and policy relies heavily on benefit-cost analysis that have sometimes neglected impacts on people (and natural systems) that are difficult to measure or monetize. Dora and Phillips (2000) argues that "Psychosocial variables should become an integral part of impact assessments. This can only happen once appropriate indicators have been identified and methods developed to measure and analyse them" (p. 29). Measurements of travel well-being could be important indicators for impact assessments. They could also provide a measure of livability, a concern for cities competing to attract investment and improve their communities. There are strong ideas developing about the role of pedestrian, bicycle and transit facilities in making communities more livable. However, a better understanding of this role in actual experiences (and decision-making processes) is needed in order to properly plan future facilities that enhance livability.

The theoretical framework of the relationships between travel and subjective well-being is adapted from Ettema et al. (2010) and subsequent work by Friman et al. (2013) and De Vos et al. (2013). Their work posits that travel affects well-being, positively and negatively, both through the activities accessed from travel (or not accessed, for some) and the actual travel itself. As mentioned above, people's "travel well-being" is made up of affective (i.e. emotional) and cognitive (i.e. evaluative) components. Their work draws partly on earlier work from Mokhtarian and Solomon (2001) who found that the experience of travel is sometimes valued positively, contrary to what is assumed in most regional travel demand models.

Further work enhanced this theory, noting that people's perceptions of modes affect how much they like travel. (Ory and Mokhtarian, 2009, p. 26). For example, some people simply enjoy bicycling more than others. One study found that those who cycle longer distances on their commutes have more positive attitudes towards bicycling than those who cycle shorter distances on their commutes (Heinen et al., 2011). Travel liking can affect people's mode choices for other trip purposes besides the commute. Schneider (2011) used a mixed logit model to analyze data from people traveling to, from, and within 20 San Francisco Bay Area shopping districts, also found that enjoyment of walking and biking significantly impacts people's choice of walking and bicycling. Additional research is needed to better understand how specific travel attributes affect travel well-being.

This study focuses on only a portion of Ettema et al.'s model, measuring travel well-being from commuting as opposed to other trip purposes. The model integrates the following relationships:

- Indicators of affective and cognitive dimensions of commute well-being;
- How sociodemographic characteristics, residential location, commute mode options and choices relate to well-being;
- How instrumental factors such as travel time, traffic congestion, and bus crowdedness affect commute well-being; and
- How attitudes about travel and commuting interact with mode choice to affect commute well-being.

The addition of measures of socio-demographics, travel preferences, accessibility, and mode choice offers a way to expand Ettema et al.'s (2010) conceptual model. To keep the focus on the above relationships, other relationships in the model, such as participation in activities accessed by travel and its relationships with personal growth, life purpose and life satisfaction are not examined (De Vos et al., 2013). This study focuses on commuting to just one activity - work. The relationship between commute satisfaction and life satisfaction is also beyond the scope of this article.

3. Material and Methods

The survey instrument was developed during fall 2011. Survey questions were developed independently and borrowed from other researchers. Borrowed measures included questions on travel well-being (Ettema et al., 2011) and attitudes and preferences about travel (Ory and Mokhtarian, 2005).

Commute well-being is a composite measure adapted from the Satisfaction with Travel Scale (STS) developed by Ettema et al. (2011) and uses seven questions that measure both affective responses to the commute (i.e. feelings during the commute) and cognitive responses (i.e. evaluations of the commute afterwards). Questions are structured according to the following statement: "Please select the box that best corresponds to your experience during the [most recent commute] trip. For example, if you were very tense, select the box for −3. If you were neither tense nor relaxed, select the box for 0. If you were relaxed, select the box for 3."

Several changes were made to the STS scale in Ettema et al. (2011) in order to simplify the measure and reduce respondent burden. Three questions were removed, two of which (confident/worried and especially alert/tired) did not fit well in other STS studies (Friman et al., 2013; Olsson et al., 2012; De Vos et al., 2015). The wording on four questions was slightly changed. One question related to enjoyment was added based on its theorized relevance to well-being and mode choice (Schneider, 2011). These changes were made following pre-testing of the survey instrument. In addition, while Ettema et al. distinguish between two types of affect (positive activation and positive deactivation) as well as a cognitive evaluation of travel, this study only distinguishes affective from cognitive evaluation items. This was done to simplify the commute well-being measure while retaining its two main dimensions: affective and cognitive. These changes correspond with De Vos et al.'s (2015) recommendations.

Data was collected via web-based surveys that were completed between January 16 and March 7, 2012. Participating organizations were recruited via phone calls and emails to personal contacts and employers (often HR managers) in central Portland. In this study, central Portland includes downtown Portland and a roughly one-mile perimeter that includes the adjacent Lloyd District, Pearl District, Old Town Chinatown, and Central Eastside. Most respondents were recruited via forwarded emails containing information on the study from contacts within their organizations. To increase representativeness of the sample, organizations from different sectors were contacted using the Portland Business Alliance directory. More than 50 organizations were contacted, usually through an email (see Appendix C) to office managers. Over 20 organizations from private, non-profit and public sector agencies (insurance, energy, planning, technology, social service, architecture, arts, government, and accounting) distributed survey information. In addition, bike commuters were recruited by receiving cards handed out during peak morning commute hours on three bridges leading to central Portland. Eligible participants must have commuted outside of the home to central Portland at least two days per week. 828 valid responses were collected. The response rate is estimated to be 30%, although only 75% of surveys received were from respondents at a workplace or intercept site in which a known number of surveys were distributed. A response rate for the entire sample could not be calculated.

Respondents' residential and work locations were geocoded using ArcGIS software. Street network data was drawn from Metro's Regional Land Information System (RLIS) database, which contains detailed layers of information on the Portland region's (including Vancouver, WA) transportation and land-use network. The street network for the Portland region was connected the network for the Vancouver region by editing vertices in ArcMap. ArcMap's Network Analyst and Shortest Path function were used to determine commute distances as well as distances from homes to the nearest bus and light rail stops. The survey asked for self-reported commute times, which was operationalized as a variable in the model presented in this paper.

The CWB measure was analyzed using confirmatory factor analysis (via a structural equations model). Variance in CWB was analyzed using *t*-tests, ANOVA tests, and a multiple regression model. SPSS, AMOS and Microsoft Excel software were used to compute the analyses.

4. Results and discussion

4.1. Respondent profile

A sample was obtained that represented three roughly equal groups of transit, bicycle, and car commuters. A small number (3.2%, $n=26$) of respondents walked for their most recent commute. Some of the analysis in this study includes findings related to walk commutes.

Locations of homes are well distributed throughout the Portland metro region. Seventy-one percent of commuters surveyed lived in Portland and 29% lived outside of Portland. Estimated commute distances (in miles) were longest for respondents that commuted by car ($M=8.6$, SD$=6.7$), followed by transit ($M=7.7$, SD$=5.9$), bike ($M=3.8$, SD$=1.7$), and walk commutes ($M=1.4$, SD$=1.3$). While approximately 80% of bicycle commutes were less than 5 miles long, car and transit were the dominant modes for longer commutes.

The demographic profile of the sample is somewhat different than of the population of commuters to Portland based on Census Transportation Planning Products (CTTP) data (2006–2008). This was expected because the study focuses on commuters to central Portland, a primarily white-collar population compared with commuters to all of Portland. Sociodemographic data for respondents is summarized in Table 1. Data for commuters to central Portland was unavailable.

The majority of respondents fall into the 25–44 year age group, while the age distribution is more spread out for the population of commuters in Portland. Bike commuters aged 25–44 are particularly overrepresented but there are relatively few bike commuters at least 60 years old (1.1%) in the sample compared to Census data for this group (7.2%). Household incomes of survey participants are somewhat higher than incomes of commuters to Portland overall although this is expected since jobs in central Portland provide higher wages than in other parts of the city.

4.2. Acceptability of commute well-being measure

The commute well-being scale shows acceptable internal consistency based on a Cronbach's alpha of 0.87 (Tavakol and Dennick, 2011). To further assess reliability and validity, illustrate the measure's two factor structure and the relative correlations for each question, a structural equation model of commute well-being was performed based on confirmatory factor analysis using AMOS Version 19.0, as shown in Fig. 1. At first, fit statistics indicate a marginally unacceptable fit ($\chi^2(9)=220.7$, CFI$=0.923$, RMSEA$=.169$) because the CFI is slightly less than the cutoff value of .95 recommended by Hu and Bentler (1999) for a good fitting model. When co-variances between error terms for two pairs of items – (1) Arrival time confidence and Stress and (2) Boredom/enthusiasm and Excitement items are estimated, as suggested by the modification indices, model fit improves substantially ($\chi^2(12)=121.7$, CFI$=0.963$, RMSEA$=.105$). These changes to the model are minor and theoretically plausible because the questions in each pair have similar meanings. Variable loadings change very little from the modifications.

Most of the variables load highly (i.e. greater than .6) on the affective and cognitive constructs. One item, Arrival Time Confidence (assessing "Worried that you would arrive on time *to* Confident that you would arrive on time") has a marginally acceptable standardized loading ($\lambda=.47$). Since arrival time confidence theoretically represents part of commute well-being and was used successfully in Ettema et al. (2011) and Friman et al. (2013), this item was retained. The path coefficients between latent variables show that both affective and cognitive components have significant and positive effects on overall commute well-being, as expected.

Table 1
Sociodemographic description of respondents.

		Study respondents					CTTP
	N	Car n=257	Bike n=261	Transit n=241	Walk n=26	% of total	% of total
Age 25 to 44	552	29.0%	39.4%	28.1%	3.5%	67.0%	48.0%
Age 60 or more	51	35.3%	5.9%	54.9%	3.9%	6.3%	8.9%
Income (% less than $35 K)	99	32.3%	33.3%	30.3%	4.0%	12.1%	16.1%
Income (% 75 K or more)	382	34.7%	30.7%	32.3%	2.4%	49.2%	48.9%
Vehicle Availability (1 or more)	757	34.6%	29.5%	33.1%	2.8%	93.2%	94.6%
Gender (% Female)	426	37.5%	22.6%	36.8%	3.1%	52.3%	44.9%
Race/ethnicity (% white)	684	32.0%	33.8%	31.0%	3.2%	86.8%	76.4%
Education (% 4-yr college)	669	28.7%	35.7%	32.1%	3.5%	81.2%	–
Education (% graduate degree)	272	23.1%	41.0%	31.7%	4.1%	32.8%	–
Children (% with children in hh)	266	29.2%	35.2%	34.8%	0.8%	37.8%	–
One-adult, no children	125	29.6%	26.4%	36.8%	7.2%	15.6%	–
Zipcar member	181	28.7%	43.8%	23.6%	3.9%	22.3%	–

Based on the theoretical relevance of these items, their use in other studies of commute well-being, and the statistical tests described in this section, the seven-item, two-factor measure of CWB is deemed to be reliable and valid.

To operationalize the CWB measure to compare modes, scores from the seven commute well-being questions were averaged to obtain a CWB score for each respondent. This procedure was used in Ettema et al. (2011), and Friman et al. (2013). The averages were incorporated as the dependent variable in regression models, allowing simpler model testing and reporting of independent variables than in SEM. SEM models were also tested and considered, but the regression results suggested similar effects from the variables under consideration. The sample showed a wide distribution of CWB. Average CWB scores range from −2.6 (indicating low CWB) to 3.0 (indicating high CWB). Mean CWB is 1.01 (S.D. = .995) and the distribution of CWB is somewhat skewed to the right (skewness = −0.490), as shown in

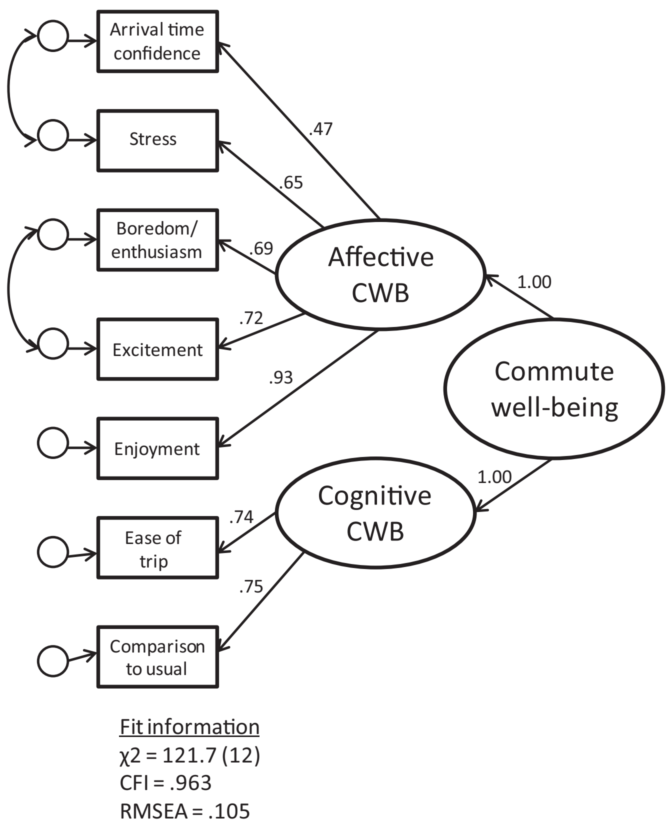

Fig. 1. Confirmatory factor analysis of the commute well-being measure.

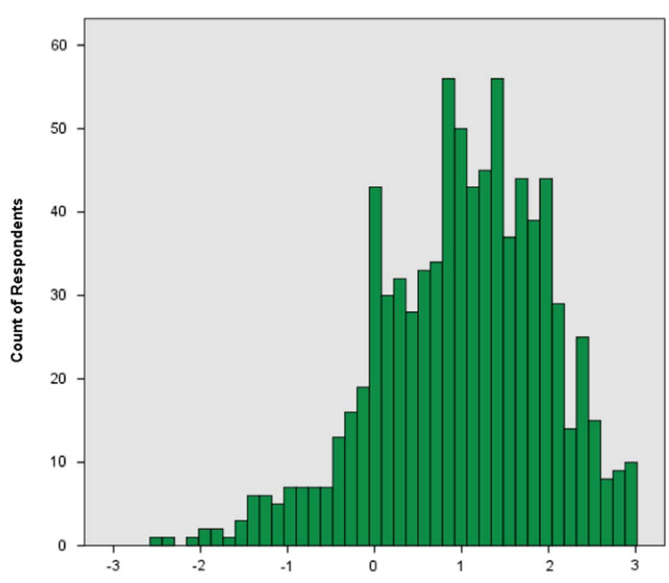

Fig. 2. Distribution of commute well-being among respondents (N=828).

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Fig. 2, meaning that the sample expresses positive commute experiences overall. Using the guidelines of West et al. (1995), the distribution of CWB does not substantially depart from normality as the Skewness is less than two and Kurtosis (0.193) is less than seven.

4.3. Variation in CWB by mode

Mean CWB among modes used by sample respondents are shown in Table 2. There is a statistically significant difference ($p < .001$) in CWB between the different modes used, a one-way ANOVA shows. Commuters that bicycle to work have the highest CWB, followed by walk commuters. *T*-tests suggest no significant differences between the two groups, although the sample of walkers is small. These results are in line with findings from similar research showing high commute satisfaction among active modes (i.e. Abou Zeid and Ben-Akiva, 2011, De Vos et al., 2015; Ettema et al., 2011; Friman et al., 2013; Gatersleben and Uzzell, 2007, Páez and Whalen, 2010; St-Louis et al., 2014).

Among car commuters, those who carpool to work have higher CWB than those who drive alone, however the difference is not statistically significant at the .05 level. The standard deviation for those that drive alone is relatively high, indicating high variability in CWB among this group. Travel time and the degree of congestion experienced likely explain much of this variability.

Among transit users, express bus (CTRAN) users have higher CWB than local bus (TriMet) users and the differences were significant using *t*-tests ($p < .05$). Express bus users likely use the express services from Vancouver, Washington to downtown Portland and Lloyd

Table 2
Commute well-being by mode.

	Mode	Mean	*N*	S.D.	
	Bicycle	1.59	261	.70	
	Walk	1.47	26	.89	
	Express bus	1.14	19	1.05	
	Light rail	0.84	100	.88	
	Local bus	0.65	137	.98	
	Carpool	0.77	79	1.01	
	Drive alone	0.59	176	1.01	
	Total	1.01	828	1.00	
ANOVA	Sum of squares	*df*	MS	*F*	*P*-value
Between groups	148.1	6	24.7	30.9	.000
Within groups	631.3	791	0.8		
Total	779.4	797			

Table 3
Estimation results of multiple linear regression models on commute well-being with all modes and condensed modes.

Variable	B	Sig.
Intercept	.672	.000
Mode		
Carpool	.191	.075
Walk	.454	.006
Bike	.512	.000
Light rail	.046	.663
Bus	−.115	.268
CTRAN express bus	.223	.237
Trip attributes		
Travel time > 40 min (car)	−.373	.003
Congested (car)	−1.187	.000
Congested (local bus)	−.684	.020
Crowded transit	−.580	.000
To lloyd center by bike	−.365	.094
Job and home satisfaction and health		
Job – very satisfied	.124	.036
Home – very satisfied	.191	.001
Health – very good	.182	.002
Attitudes		
Transition useful	.154	.000
Use trip productively (bus+light rail)	.157	.001
Use trip productively (car)	.122	.007
Only good thing destination (bus+light rail)	−.103	.011
Car safer than bike (bike)	−.103	.036
Demographics		
Income > $75,000	.138	.015
Observations	762	
R^2	0.438	

Center, both within central Portland. Along with having very few stops, express buses are equipped with more comfortable seating than local buses. Light rail (TriMet MAX) users have higher CWB than local bus users but the difference is not significant at the .05 level.

4.4. Multiple linear regression on CWB

To test whether theoretically relevant factors have independent effects on commute well-being when controlling for each other, a multiple linear regression models was tested in which CWB is regressed on the full list of possible explanatory variables, such that:

$$N = \beta + \beta' T + \beta' M + \beta' J + \beta' S + \beta' A + u$$

where
N = CWB;
T = trip attribute variables;
M = mode variables
J = job and residential satisfaction variables;
S = sociodemographic variables;
A = attitudinal variables
u = regression error term.

All of the independent variables are categorical except the attitudinal variables, which are continuous. The attitudinal variables were also adjusted to control for the distribution of responses for each attitude. This helped show the strength of agreement for each respondent relative to the sample mean. The mean response for each item (for the sample) was calculated and then subtracted from the individual responses for each attitude. In addition, four of the five attitudinal variables in the model were interacted with variables for specific modes.

Results of the multiple linear regression analysis are provided in Table 3. Unstandardized coefficients and their significance are reported. For the most part, only significant variables ($p < .05$) were included in the estimation. However, all mode coefficients were included, even when non-significant, to provide a full explanation of their relative influence on commute well-being.

Results show that even when trip attributes, mode options, job and home satisfaction, health, demographic, and attitudinal variables are taken into account, both biking and walking to work have positive significant effects ($p < 0.01$) on CWB. This is consistent with many previous studies (Abou-Zeid, 2009; De Vos et al., 2015; Ettema et al., 2011; Friman et al., 2013; St-Louis et al., 2014). All other modes have insignificant coefficients, presumably because other elements in the model, such as crowding, congestion, and travel time explain a substantial portion of the variation in CWB among modes.

Commute time for car commutes (i.e. car commutes at least 40 min long) has a significant negative effect on CWB ($p < 0.01$) and its magnitude is moderate. It was expected that longer transit commutes would also significantly reduce CWB, but this factor is not statistically significant. Other ways of specifying travel time were examined, but only the forty minute "break point" was found to be significant, and only for car commuters. The findings add some support to findings in other research (e.g. Mokhtarian and Solomon, 2001; Páez and Whalen, 2010; Mokhtarian et al., 2014) that (1) travel time is not always something to be minimized and (2) people "budget" their travel time and will be satisfied as long as their commutes fall within a certain expected amount of time.

The magnitudes of the effects of traveling to work by car and bus on highly congested streets on CWB are particularly large and highly significant. This finding is in line with previous research (e.g. Anable and Gatersleben, 2005; Novaco and Gonzales, 2009) showing that the delays, reduced predictability, and stress caused by congestion have a negative effect on well-being.

As expected, commuting in crowded public transit vehicles has a highly negative and significant ($p < 0.001$) effect on CWB. While the question was subjective – people's conceptions of crowded transit vehicles may differ – having many people on one's bus or light rail vehicle clearly seems to reduce CWB.

Results show a marginally significant ($p < 0.1$) negative effect for bike commuters to in the workplaces in the NE (Lloyd Center) district. The auto-oriented environment of Lloyd Center, which is flanked by Interstates 5 and 84, may decrease commute well-being for cyclists.

Job and residential (including home and neighborhood) satisfaction variables both have positive and significant effects on CWB ($p < 0.05$ and $p < 0.01$, respectively), although the effect is larger and more significant for residential satisfaction. The job satisfaction result is in line with previous research (Abou Zeid and Ben-Akiva, 2011). The results suggest that people who can optimize their residential location choice with respect to their work location express both high home and commute satisfaction. It is possible that home satisfaction encompasses people's preferences for accessibility to different commute modes, such as a preference for a bike friendly neighborhood.

Having very good health has a positive and significant ($p < 0.005$) effect on CWB. For bike commuters, better health may facilitate greater enjoyment of the trip by allowing faster speeds with less discomfort. Bike commuters with relatively poorer health may have greater discomfort and more frequently be overtaken by other bike commuters, thereby reducing CWB. Greater health may allow car commuters to more effectively cope with the stresses of commuting. Better health may also increase CWB because the sedentary nature of the car allows people to be physically active during non-commute activities, such as running during lunchtime or after work.

For all modes, relatively strong agreement with the statement "The trip to/from work is a useful transition between home and work" positively and significantly ($p < .001$) increases CWB. For bus and car users, relatively strong agreement with the statement "I use my trip to/from work productively" increases CWB moderately based on coefficients for the interaction terms. Similarly, relatively strong agreement with the statement "The only good thing about traveling is arriving at your destination" appears to decrease CWB among bus and light rail users. For bicyclists, greater agreement that "Traveling by car is safer overall than riding a bicycle" decreases CWB slightly. These results support findings in other research (Páez and Whalen, 2010) that commuters who believe that the trip is a useful transition between home and work and use the trip productively have more positive views of commuting.

Of all the demographic variables examined in this analysis, only income has a significant effect ($p < .05$) on CWB. Income could affect CWB through a number of pathways. Higher incomes tend to reflect greater flexibility to optimize areas of one's life with respect to work

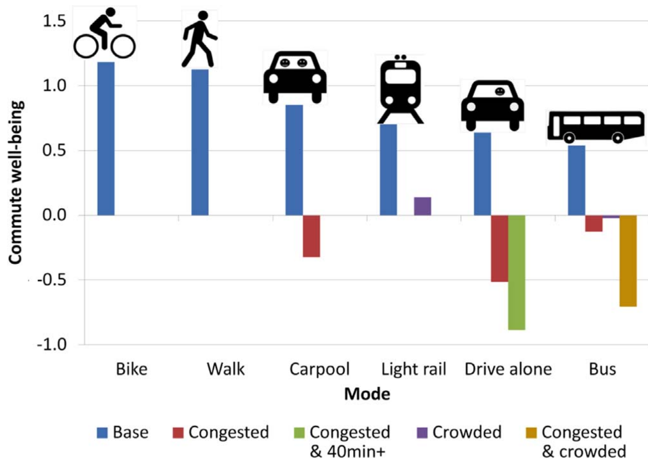

Fig. 3. Predicted commute well-being based on OLS regression.

environment, childcare, and time pressures that may result in better commute experiences. While the exact pathways of how income affects commute well-being are unknown, the significance of income was retained in the model.

The fit of the model (adjusted $r^2 = 0.438$) is high considering the use of a relatively new measure (CWB). However, commute well-being is multifaceted and these results suggest that other unknown factors explain more than one-half of the variation in CWB. While multicollinearity may be a problem in the regression, the independent variables in the model were not highly correlated (i.e. $r > .70$) in pairwise correlation tests and had intuitive coefficients.

4.5. Predicted commute well-being

Results from the multiple regression equation allow one to make predictions of commute well-being under various scenarios. Using the intercept value and coefficients in Table 3, CWB is predicted for 13 scenarios related to mode choice, traffic congestion, travel time, and transit crowdedness in Fig. 3. CWB for the "base" mode accounts for the other factors in the model (attitudes, income, job and home satisfaction, etc.). For carpool, drive alone, and bus modes, CWB is predicted for both "base" commutes and congested commutes. Drive alone commutes that are congested and at least forty minutes long are predicted, along with crowded light rail and bus commutes.

The model predicts the highest CWB for bike commutes (CWB = 1.18) and the lowest commute well-being for drive alone commutes longer than 40 min that also include congestion (CWB = −0.89). Using the bus, encountering high traffic and having a crowded vehicle (CWB = −0.71) is the second lowest CWB scenario. The following comparisons can also be suggested:

- A person that rides the bus and encounters traffic congestion will have seven percent higher CWB than if that person drives alone and encounters traffic.
- A person with a crowded light rail vehicle commute will have ten percent lower CWB than if he/she rides a light rail with no crowdedness.
- A person with an uncongested, uncrowded light rail commute will have three percent higher CWB than if he she had an uncongested, uncrowded bus commute.

5. Conclusions

The commute well-being measure used in this study supports the reliability of the basic structure of the Satisfaction with Travel (STS) scale developed by Ettema et al. (2010) and supported by Friman et al. (2013) and De Vos et al. (2015). This study improves upon the measure by adding an indicator of enjoyment, which better captures feelings of pleasure, escape, and thrill that do not fall clearly into previous iterations of this scale. It also adapts the scale by reducing the number of measured items from nine to seven and the number of latent items related to affective aspects of commute well-being from two to one. While further refinements could enhance this scale, expanded use of the commute well-being scale in future research (in other cities, population groups) could greatly improve our understanding of satisfaction and well-being related to commuting and other travel.

This study also found that commute well-being has many likely influences (i.e. mode, trip attributes, land-use, job and home satisfaction, and attitudes). Multiple regression analysis shows that walking and biking have a significant positive effect on commute well-being, while other modes have no significant effect when controlling for key variables. This finding confirms findings in previous research by Abou-Zeid and Ben-Akiva (2011), Friman et al. (2013), and Páez and Whalen (2010), among others and suggests that bicycling to work may benefit mental as well as physical health. Travel time is not a significant predictor of commute well-being for transit and bike commuters, supporting existing theories on a positive value of travel among some populations (Mokhtarian and Solomon, 2001). Attitudes about the usefulness of time spent commuting also seem to influence the commute experience as other research (e.g. Páez and Whalen, 2010) has reported. Many of these variables have been found in mode choice studies. It appears that similar factors affect both the mode choice decision and the ultimate experience following this decision.

The findings in this paper add evidence that could inform policymakers on how to increase well-being using sustainable transportation policies. Shifting travel modes away from single-occupancy car use is a primary goal of transportation planners. If people who bike and walk to work are indeed happier with their commutes, this suggests that policy efforts to make active travel options more available should continue. The survey asked about attitudes regarding environmental protection and exercise based on previous association of these variables with commute mode choice, but the variables were not related to commute wellbeing for any mode group and were thus not included in the model or discussion. Appealing to affective feelings of joy, excitement, or relaxation may be more effective ways to market bicycling to car commuters.

This research could be extended in several different ways. Other potential influences on commute well-being should be tested. For example, comparisons with previous commutes and peer's commutes have been shown to influence commute well-being (Abou-Zeid and Ben-Akiva, 2011). Commutes during the summer may also be quite different than commutes in other months, but it is uncertain how the associations of CWB may be different. Commute routes are estimates rather than actual routes and therefore preclude the inclusion of route-level attributes, such as the quality of bicycle infrastructure and actual congestion. Route-level attributes affect people's route choice decisions and likely also affect their commute well-being. Future studies could obtain greater detail on route choices through survey questions or GPS. Expanding the survey with additional questions could increase our understanding of social comparisons, seasonal influences, and route choices on commute well-being. Future research should also continue to explore connections between travel mode, commute well-being, and well-being in other life domains.

Unlike most previous studies on commute well-being, findings in this research come from a relatively large U.S. (Portland)-based sample using commuters from a non-university setting and are therefore more representative of American commuters. Nevertheless, employees from this study work in mostly professional office environments; future sampling frames could include people that commute to other workplace types such as industrial and retail. Testing similar research in other cities and among commuters to non-downtown locations could further deepen our understanding of commute well-being.

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