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FINAL REPORT

Mixed-Modal Household Vehicle Transactions

NITC-RR-586 ■ July 2016

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Transportation Insight for Vibrant Communities

Mixed-Modal Household Vehicle Transactions

Final Report

NITC-RR-586

by

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for

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<tr><td colspan="5">16. Abstract
This study examines household vehicle fleets with a specific focus on transaction decisions that lead to their formation over time. One main focus of this study is also non-motorized vehicles, more specifically bicycles, and their role in these household vehicle fleets. The overarching objective is to investigate factors that underlie the adoption of bikes, especially their transaction decisions. To accomplish this overarching objective, two main tasks were undertaken. (i) First, a retrospective vehicle ownership and transaction survey is developed, guided by the 2011 Oregon Household Travel and Activity Survey (OHAS) dataset. Although the OHAS contains information on motor vehicle fleets, such as vintage and make, transaction information is absent. Furthermore, while the OHAS also contained information on total household bicycle ownership counts, a more detailed delineation of these are not present; children's bikes used for relatively short neighborhood level distances are not distinguished adult bikes which may be used for daily work commutes. (ii) Second, this work will also provide a set of econometric models for observed vehicle transactions. The set of vehicles modeled includes those captured under conventional household travel surveys and bicycles. These econometric models are intended to address the probability of specific types of transactions, including disposal/retirement, replacement and acquisition decisions. The results indicate that there is much heterogeneity in the underlying factors for bike adoption, and more specifically transactions. An econometric analysis of revealed household bike ownership rates indicates that two regimes represent two distinct market segments comprised of (i) households that are considering owning bicycles and (ii) those that have selected out of bicycle ownership. An interesting result was that the coefficients for the same variables were different between the choice and count models. The retrospective survey revealed that significant variation exists in terms of which types of bikes were likely to be additions versus replacements. Overall, the results of the retrospective survey underscore this heterogeneity in transaction decisions, and bike ownership overall.</td></tr>
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DISCLAIMER

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1.0 Introduction

Vehicle availability significantly affects household travel behaviors and consequently affects the requirements for modeling and forecasting of household travel decisions under future or alternative scenarios. Household vehicle fleets evolve over time as a result of transactions, which include vehicle (i) disposal or retirement, (ii) replacement and (iii) acquisition decisions. Forecasting household vehicle ownership requires a closer examination of these transactions. Parallel to this forecasting need, is the increasing diversification of household fleets from all gasoline towards mixed-modal fleets that include alternative-fuel and non-motorized vehicles, such as electric vehicles and bicycles. This diversification provides the backdrop for this exploratory study that characterizes and models household vehicle transactions for non-motorized vehicles, in addition to personal gasoline automobiles. This backdrop also encourages a closer examination of bicycle ownership, collecting detailed information similar to those collected in conventional datasets for household gasoline vehicles.

To accomplish this overarching objective, two main phases of work are pursued. (i) First, a retrospective vehicle ownership and transaction survey is developed, guided by the 2011 Oregon Household Travel and Activity Survey (OHAS) dataset. Although the current OHAS contains detailed information on motor vehicle fleets, such as vintage and make, transaction information is absent. These include duration of ownership and whether an acquired vehicle was as an addition or replacement. Furthermore, while the OHAS also contained information on total household bicycle ownership counts, a more detailed delineation of these are not present; children's bikes used for relatively short neighborhood level distances are not distinguished adult bikes which may be used for daily work commutes. (ii) Second, this work will also provide a set of econometric models for observed vehicle transactions. The set of vehicles modeled includes those captured under conventional household travel surveys and bicycles. These econometric models are intended to address the probability of specific types of transactions, including disposal/retirement, replacement and acquisition decisions. A diagram representation of the analysis framework is presented below.

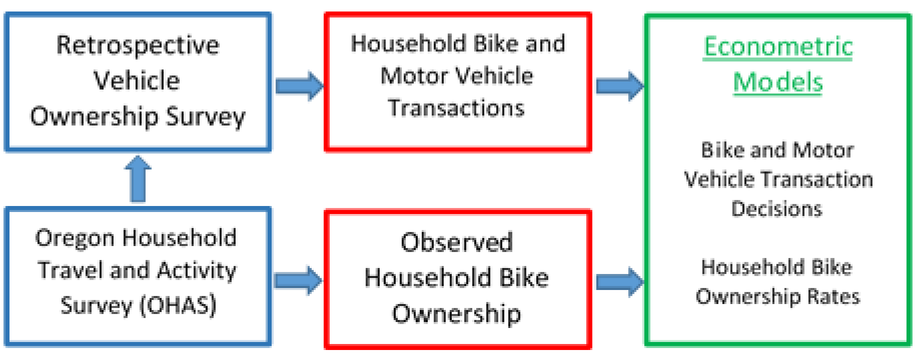

Figure 1: Study Analysis Framework

Characterizing these transactions permits a study of the evolution of household vehicle fleets. This evolution is important for assessing GHG emissions and the livability of communities, as households may move towards or away from more sustainable and "green" vehicle fleets due to lifecycle changes, fluctuating transportation costs and household member migration decisions. With respect to research questions, this study addresses the following three main questions:

1) *Which household factors, such as socio-demographics attributes or vehicle costs, trigger fleet transactions of non-motorized vehicles?* This study is interested in the range of sensitivity towards these factors in order to uncover the potentially effective policy levers for promoting adoption of mixed-modal household fleets.

2) *What is the relationship between vehicle transactions for non-motorized and motorized vehicles?* The nature of this relationship, which may be characterized as substitutability, complimentary or antithetical, has not been examined in the literature previously.

3) *Which residential, workplace and post-secondary education location attributes affect these fleet transactions, for example parking opportunities?* The vehicle transaction decisions of households likely depends on the parking availability at key destinations in households' set of daily destinations. Due to their relevance for fleet transactions decisions, this study will also survey respondents on their parking access at home and the workplace, with the intention of relating to these conditions.

Through answering these research questions, this study lays the foundation for future efforts on household vehicle fleet transactions for motorized and non-motorized vehicles. In responding and addressing these questions, the following three main outputs are produced:

1) The conclusion of this work provides guidance for designing similar future longitudinal household vehicle ownership and transaction surveys, or other similar survey. Along a similar line of thought, the conclusion of this work will also identify data requirements for investigating the evolution of household vehicle fleets;

2) The completed research work also provides detailed information on vehicle transactions of households based on the existing OHAS dataset. Data on household transactions for non-motorized vehicles are virtually non-existent, making this study pioneering. Additionally, this vehicle transaction information can be used to estimate the personal vehicle fleet for Oregon for both motorized and non-motorized vehicles.

3) Identify potential and effective policy levers for influencing vehicle transactions are also identified at the conclusion of this study. In particular, potential mechanisms for steering household fleet decisions towards more sustainable options, such as non-motorized and alternative fuel vehicles are uncovered.

Overall, the findings of this work have implications for integrating household fleet evolution into existing travel demand forecasting tools. Additionally, the findings will help identify the most effective policy levers, such as household/workplace location parking supply, vehicle costs and attributes for positively influencing household fleet transactions towards more sustainable and livable options. This work extends the body of literature by considering the multi-modal vehicle transactions of households, more specifically motor vehicle transactions, and their relationship with transactions for other non-motorized vehicle types, such as bicycles.

This report has five sections following this introduction. Next, a review of existing literature on bicycle ownership and household vehicle transaction studies is provided. Following the review of literature, the OHAS dataset is examined with respect to revealed bicycle ownership levels, since the primary focus is on bicycle vehicle transactions. A revealed preference analysis follows, through an estimated Poisson model of bicycle ownership levels. The presentation and analysis of the household bicycle transaction survey follows the revealed preference (RP) analysis. This report ends with some concluding remarks and identification of potential policies and mechanisms for positively influencing transactions in favor of bicycles in household fleets.

2.0 Literature Review

This section presents a review of literature related to vehicle ownership with a specific focus on household transactions. Forecasting vehicle fleets is necessary for evaluating future and alternative policy scenarios and for modeling applications, in particular estimating the number of household vehicles in travel demand models (Dissanayake and Morikawa 2002; Abu-Eisheh and Mannering 2002; Button et al. 1993). Vehicle holding/transaction models estimate the number of household vehicles, typically estimating the probabilities of households owning zero, one or two or more vehicles within a discrete choice framework (Ewing et al. 1998), structural equations framework (Golob et al. 1995; Golob et al., 1997), or combination (Kitamura 1987). One shortcoming of this approach is that vehicle holdings models assume households make frequent transactions and maintain an “optimal” number and type of vehicles at any one time.

Household vehicle transactions have been studied and modeled for both the (i) duration of holdings and between transactions and the (ii) probability of transactions. Vehicle transaction models are typically disaggregate and capture changes in the fleet over time by modeling household decisions to buy, sell, dispose and acquire vehicles (De Jong and Kitamura, 1992; Kitamura, 1992). The advantage of transaction models is their relaxation of the assumption that households have an optimal set of vehicles at any time. Transaction models closely represent the household vehicle decision process and can be observed over time (De Jong and Kitamura, 1992). Hocherman et al. (1983) and Smith et al. (1991) both developed a dynamic discrete choice transaction model of automobile ownership, accounting for a household’s previous car holding and transaction costs, using longitudinal data. Transaction models have also been estimated for the probabilities of disposing the current vehicle, replacing it with another vehicle or acquiring a new vehicle (Gilbert 1992; Mustti and Kockelman 2011). Hazard-based duration models have also been used to model and analyze the time between transactions and duration of holdings (Yamamoto et al. 1999; Mohammadian and Miller 2003). Similar to discrete choice studies on transactions, these studies relate duration of transactions and holdings to vehicle characteristics, household incomes and lifecycle stages. However, none of these studies examine their relationship with non-motorized vehicle holdings or transactions, such as decisions to adopt or discard bikes, and the factors driving these decisions.

The research literature on non-motorized vehicle ownership is less cohesive and rich, relative to the motorized vehicles. The motivation for bicycle ownership studies has been to identify measures and incentives that promote bicycle use. These studies generally show that bicycle ownership and use are strongly affected by individual attitudes and social environment factors, but show limited impacts from bicycle infrastructure (Beck and Immers 1984; Handy et al. 2010). Pinjari et al. 2011 show that endogenous correlations exist among bike ownership, residential choice and commute mode choice, and acknowledge that accounting for these endogenous effects is necessary to disentangle causal effects. However, virtually no studies have examined bicycle transactions in relation to the underlying factors. The proposed study extends this body of work to consider non-motorized vehicles transactions, specifically bicycles, and addresses two main gaps. First, although past studies addressed motor vehicle transactions, few consider their relationship with non-motorized vehicle ownership, such as bikes. Second, there has been a reasonable effort to look at factors that positively influence bike ownership; however, the actual related fleet transactions have received relatively little attention.

Several different approaches to modeling bicycle ownership have been undertaken in previous studies. The dominant approach is the application of random utility theory to disaggregate level analysis to examine the relationship between a set of explanatory variables and ownership. Under this framework, two different theoretical mechanisms are used in the models that address the number of vehicles owned; the first is an ordered-response mechanism and the second is an unordered-response mechanism. In an ordered-response, the choices made imply an ordering of the alternatives. For example, choosing to own three bikes implies an ordering that three is chosen over owning two bikes or one bike. In an unordered situation, choosing three does not imply any ordering of the alternatives. To examine the impact of self-selection from residential decisions on travel, a joint model of residential neighborhood type choice, bicycle ownership, car ownership, and commute mode choice was estimated (Pinjari et al. 2008). In this joint model, an ordered logit model structure was assumed for bicycle and car ownership. These authors find that considering different market segments within a transportation-land use context necessitates a consideration of "bundles" of choices, similar to the one defined in the paper. Consequently, from a modeling perspective, these decisions should be modeled simultaneously to consider their correlative effects, instead of a sequence of independent decisions typically characterizing conventional transportation-land use models. Yamamoto (2009) examined the ownership among a choice set of auto, motorcycle and bicycle using a trinomial binary probit model, where decisions to own a particular vehicle type were binary decisions, but a correlation structure exists among these binary choices representing the "vehicle bundle" for a particular decisions maker. This probit model was compared with the equivalent multinomial logit model. Interestingly, Yamamoto suggested using a multinomial logit model for representing the ownership structure of vehicle bundles over the trinomial binary probit model. The coefficient estimates from the two types of models were found to be consistent with each other. With respect to bicycle and car ownership, Yamamoto (2009) found that population density at the residential location negatively affects car ownership. For bicycle ownership, the opposite is found with bicycle ownership, with bicycle ownership higher in high population density areas. Both Pinjari et al. (2008) and Yamamoto (2009) suggest that bicycle ownership is a key decision dimension that can define market segments, especially in the context of other vehicle ownership decisions, such as auto ownership. Additionally, there is a strong relationship between bicycle and car ownership, and the residential location. With respect to modeling, the dominant approach seems to be an application of random utility theory to disaggregate level analysis to examine the relationship between a set of explanatory variables and decisions, most notable the use of ordered choice models for bicycle ownership levels. Based on this review of methods for modeling bicycle ownership, most studies apply a random utility approach, as opposed to a count variable perspective.

To address both bicycle ownership and use, Handy et al. (2010) specified and estimated a nested-logit model. The main purpose of this research was to find factors associated with bicycle ownership and use for six small cities in U.S. To accomplish this, Handy et al. (2010) tested different nesting structures for three dimensions: (i) owning a bicycle; (ii) frequency of bicycling, segmented into frequent and infrequent and (iii) attitudes towards transportation, segmented into transportation-oriented and non-transportation orientated. Handy et al. (2010) find that attitudes towards bicycling, revealed through statements such as ''I like riding a bike,'' are important variables associated with bicycle ownership and regular use. The authors also find that infrastructure conditions are important for bicycling for both transportation and recreational purposes, particularly distances to destinations as determined by land use patterns, off-street bicycle path networks. Furthermore, their model shows that effects from the social environment on bicycle use are also important, encapsulated by who else is bicycling rather than the perception that bicycling is common or normal in the community. Maness (2012) similarly investigated regional differences in bicycle ownership, but by applying an ordered logit model of ownership level. This study found that larger households were more likely to own bicycles. With respect to age, children aged 11 to 15 years old were most likely to own bicycles, while middle-aged adults (25-55 years old) were the second-most likely to own bicycles.

A review of literature revealed several characteristics of bicycle ownership research, from both a methodological and market characterization standpoint. Lifestyle and attitudinal factors strongly affect ownership and use, but there is no delineation between the factors that affect general ownership (should we own bikes or not) and those that affect the number of bicycles to own. Predominantly, past studies have modeled the number of bicycles using ordered choice models under a random utility framework. However, count models, such as the Poisson, negative binomial and gamma are also possible alternatives. Additionally, the literature reveals that bicycle ownership needs to be investigated as part of a "bundle" of choices; several papers talk about this, although the bundles are different in each case. A review of the literature reveals that a significant gap exists with ownership. While the factors affecting bicycle ownership have been investigated, the factors affecting NOT owning a bike have not received much attention. At a coarse level, these two segments represent important contrasting segments.

Next the OHAS dataset is examined with respect to revealed bicycle ownership levels. A revealed preference analysis follows, through an estimated Poisson model of bicycle ownership levels. The presentation and analysis of the household bicycle transaction survey follows the revealed preference (RP) analysis.

3.0 Oregon Household Travel Survey (OHAS) Characteristics

The sample of households used in the analysis is from the 2011 Oregon Household Travel and Activity Survey (OHAS) which has observations of the number of bicycles owned per household, in addition to household attributes and geocoded travel decisions for one weekday. Market segments are identified using a latent class model based on observations of bicycle ownership count. The count observations are modeled using three different specifications: (ii) Poisson regression model; and (iii) zero-inflated Poisson regression model. A comparison is first made among these three models to determine the most explanatory specification, followed by a latent class approach. To supplement this data, the residential locations in the sample were tagged with a residential density classification based on the population density surrounding the home location. Five classes were identified:

1) *Major Urban Center*: households within five miles from 50,000 people and within a mile of 2,500 people, where the majority of households are within an MPO ;

2) *City Near Major City*: household with 2,500 people within one mile of the residential location, that is also within 15 miles of a Major Urban Center;

3) *Rural Near Major City*: household that is immediately surrounded by an area of less than 2,500 people, but is within 15 miles of a Major Urban Center;

4) *Isolated City*: household is within two miles of 2,500 people and more than 15 miles away from a Major Urban Center; and

5) *Rural*: household is more than two miles away from 2,500 people and more than 15 miles away from a Major Urban Center.

A map of the study area and distribution of these residential density classes is shown below in Figure 2. These classes are intended to capture different levels of accessibility of each household based on their location. In addition to tagging each residential location with a residential density class, households were segmented by their life stages, which can range from single households just finished with college to retired couples. In the literature, household lifestyle or life stages have been broadly defined as a pattern of behavior revealed under constrained resources, such as income budgets or time constraints, that is related to the factors of household formation, labor force participation and orientation toward leisure (Salomon and Ben-Akiva 1983; Walker and Li 2007) all of which evolve over the long-term and impact short-term decisions such as day-to-day travel (Krizek 2006, Kitamura 2009). A broader definition may also include societal roles of household members defined by gender, marital status and lifecycle stage. For this study, life stages are defined on the basis of three attributes: (i) household size; (ii) age of the household head; and (iii) relationship status of household members (e.g., married). Other attributes considered in the literature include workforce status of the members, which is correlated with income, and transportation resources, such as number of vehicles owned, none of which were used in this round of analysis. However, to limit the complexity, these attributes were not considered in this study.

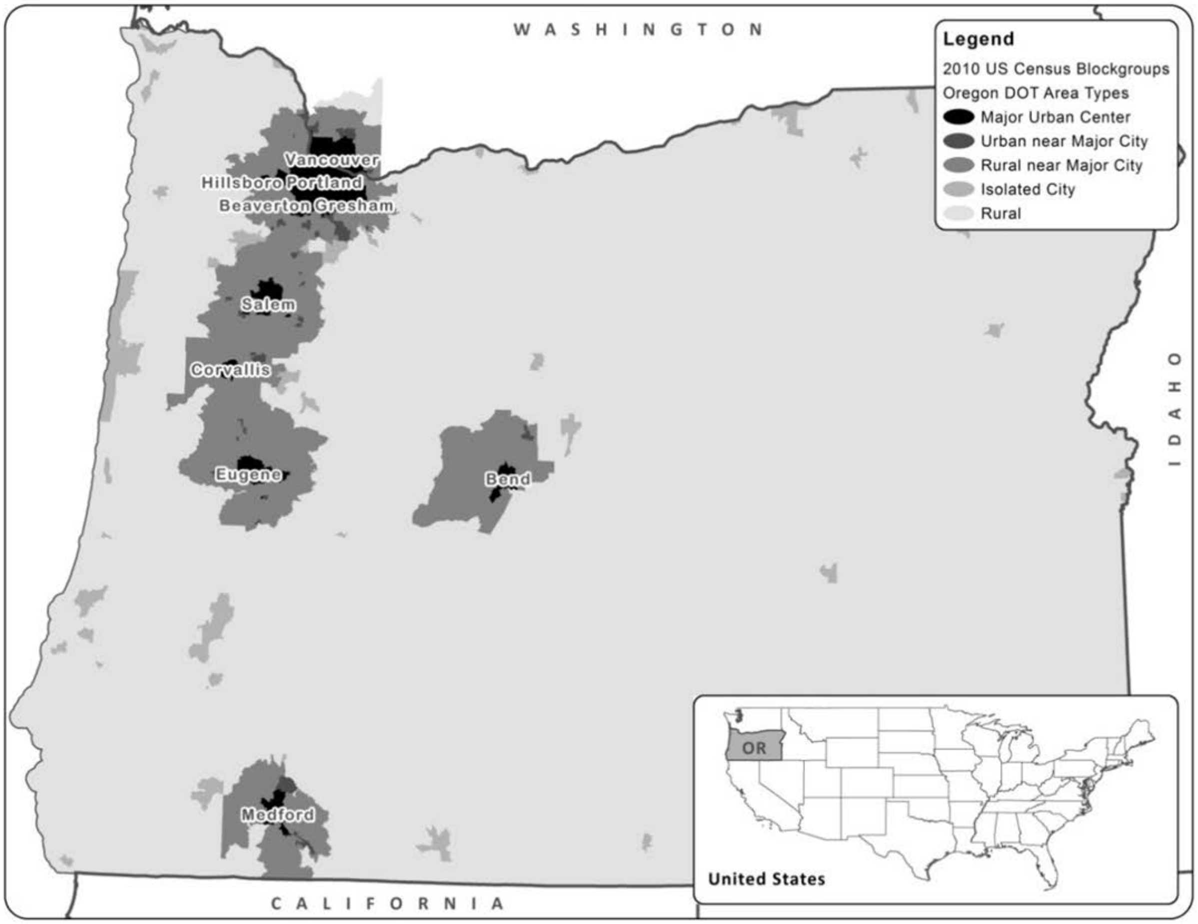

Figure 2. Study area and Residential Density Characterization

The framework for segmenting households based on life stage status begins by segmenting households into single and multi-member households. Next the single households are further segmented by age, with 65 year household head age as the cutoff. Multi-member households were segmented into related and non-related households. Related households were next segmented into households with children and those without, with children being defined as 17 years or less of age. Households with children are further segmented into single and non-single parent households. Households that are related without children are segmented into households where all adults are greater than 64 years of age and those where at least one member is below 65 years of age. This results in seven life-stages, with an eight segment for households with persons who did not give their exact age. These stages are as follows: (i) single adults ≥ 65 years of age; (ii) single adult, < 65 years and ≥ 18 years; (iii) non-related households; (iv) single parents with children; (v) parents with children; (vi) related adults, no children, ≥ 65 years; (vii) related adults, no children, < 65 years. From a methodological standpoint, segmenting household decision-making units serves two purposes. The first is to reduce the variation in observations within any one segment. The second is to facilitate a discussion of different types of households, since the spectrum of households is wide across Oregon.

The total number of households in the OHAS sample is 18,250 households. However, some households gave responses of "do not know" or did not respond for interested variables and were subsequently excluded from the sample, leaving 16,021 household for analysis. The distribution of household attributes across the analysis sample is shown in Table 1. The distributions of bicycle ownership counts across households are shown in Figure 3, shown for the entire sample and segmented by lifecycle class.

Life Cycle	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Sample**
Number of Households	1,809	2,220	535	464	3,386	5,579	2,028	57	16,078
Percent of Sample (%)	11.25%	13.81%	3.33%	2.89%	21.06%	34.70%	12.61%	0.35%	100.00%
Mean HH Size	1.00	1.00	3.01	2.91	4.09	2.22	2.12	1.00	2.34
Mean Num. of Students per HH	0.26	0.20	0.98	1.65	1.85	0.27	0.25	0.67	0.65
Mean Num. of Full-Time Workers per HH	0.06	0.54	0.81	0.52	1.18	0.99	0.13	0.30	0.73
Mean HH Annual Income ($/year)	39,535	44,228	47,251	49,510	78,794	77,361	60,320	46,087	64,766
$0-$14,999 (%)	1.69%	2.23%	0.44%	0.36%	0.49%	0.85%	0.27%	0.01%	6.34%
$15,000-$24,999 (%)	2.62%	2.14%	0.64%	0.47%	1.16%	1.69%	1.44%	0.08%	10.25%
$25,000-$34,999 (%)	2.45%	2.23%	0.73%	0.45%	1.71%	3.02%	2.21%	0.09%	12.89%
$35,000-$49,999 (%)	1.60%	2.39%	0.35%	0.42%	2.34%	4.27%	2.02%	0.06%	13.46%
$50,000-$74,999 (%)	1.62%	2.87%	0.52%	0.60%	5.02%	8.40%	3.10%	0.07%	22.19%
$75,000-$99,999 (%)	0.73%	1.21%	0.35%	0.33%	4.42%	7.53%	2.03%	0.03%	16.63%
$100,000-$149,000 (%)	0.26%	0.53%	0.16%	0.15%	4.14%	6.06%	0.96%	0.01%	12.27%
$150,000 or more (%)	0.27%	0.21%	0.14%	0.09%	1.77%	2.90%	0.58%	0.01%	5.98%
Mean Num. Telecommuters per HH	0.04	0.09	0.14	0.15	0.28	0.20	0.09	0.04	0.16
Mean Num. Licensed Drivers per HH	1.09	1.01	1.92	1.40	2.24	2.12	2.08	1.35	1.84
Car-Share Participation (%)	0.94%	1.71%	2.43%	0.86%	1.83%	1.52%	0.35%	0.00%	1.41%
Vehicle and Bicycle Ownership Attributes									
Mean Bicycle Owned per HH*	1.33	1.40	2.24	2.47	3.19	2.09	1.83	1.38	2.35
0 Bicycles (%)	9.52%	7.89%	1.41%	0.73%	4.56%	17.15%	9.21%	0.27%	50.75%
1 Bicycle (%)	1.36%	4.37%	0.66%	0.52%	2.64%	5.45%	1.43%	0.06%	16.48%
2 Bicycles (%)	0.27%	1.09%	0.70%	0.80%	3.91%	8.23%	1.53%	0.02%	16.56%
3 Bicycles (%)	0.06%	0.27%	0.24%	0.49%	3.57%	2.08%	0.22%	0.01%	6.95%
4 Bicycles (%)	0.02%	0.10%	0.19%	0.19%	3.53%	1.15%	0.15%	0.00%	5.32%
5 or more Bicycles (%)	0.02%	0.07%	0.12%	0.16%	2.85%	0.63%	0.08%	0.00%	3.94%
Mean Number of HH Vehicles	1.12	1.23	2.13	1.74	2.45	2.47	2.16	1.28	2.07
Mean Num. HH Retired Vehicles	0.02	0.03	0.05	0.05	0.06	0.04	0.03	0.02	0.04
Residential Location Attributes									
City near Major Center (%)	1.68%	1.37%	0.69%	0.35%	2.37%	3.76%	1.90%	0.06%	12.18%
Major Population Center (%)	6.18%	8.97%	1.83%	1.70%	12.06%	17.75%	5.33%	0.24%	54.06%
Rural near Major Center (%)	1.18%	1.09%	0.40%	0.25%	2.57%	5.64%	2.28%	0.04%	13.45%
Isolated City (%)	1.45%	1.44%	0.24%	0.34%	2.18%	3.68%	1.65%	0.02%	11.00%
Rural (%)	0.76%	0.94%	0.16%	0.24%	1.88%	3.88%	1.45%	0.01%	9.31%
Dethatched Single Family Unit (%)	8.29%	9.41%	2.71%	2.21%	19.71%	32.38%	11.99%	0.27%	86.96%
Attached Single Family Unit (%)	0.49%	0.86%	0.13%	0.25%	0.52%	0.67%	0.17%	0.01%	3.10%
Multi-Family Unit (%)	2.48%	3.53%	0.49%	0.43%	0.83%	1.65%	0.46%	0.07%	9.94%
Own (%)	8.46%	8.67%	2.41%	1.88%	18.20%	31.55%	12.10%	0.27%	83.55%
Rent (%)	2.79%	5.14%	0.92%	1.00%	2.86%	3.15%	0.51%	0.08%	16.45%

*** Mean bicycle owned per HH for sample households having bicycles; zero-bike owning households were excluded**

Table 1: OHAS Survey Sample Characteristics

Looking at Table 1, approximately half of the households in the entire sample do not own any bicycles. About 30 percent of total households in the sample own one or two bicycles and about 20 percent own more than two bicycles. On average, a household in the sample will own one bicycle. Segmenting by lifecycle class, Table 1 shows that bicycles owned per household is highest in segments three, four, five and six, (non-related households; single parents with children; parents with children; and related adults, no children, ≥ 65 years) with mean levels 1.29, 1.84, 2.50 and 1.06 bikes per household respectively. On average, households in the sample own two cars per household. Interestingly when segmenting by lifecycle class, the segments with high bicycle ownership levels do not necessarily have the highest vehicle ownership levels and vice versa. For example, segment six (related adults, no children, ≥ 65 years) has a mean bicycle ownership level of 1.06, but a mean vehicle ownership level of 2.47. In contrast, segment four (single parents with children) has a mean bicycle ownership level of 1.84, but a mean vehicle ownership level of 1.74. This suggests that the relationship between bicycle ownership and vehicle ownership per household is not exactly linear. Looking at the distribution of households across bicycle ownership levels in Figure 3 shows that across all lifecycle segments, there are a significant number of households owning zero bicycles, with a mass at the zero level. This suggests that the distribution of household observations across bicycle ownership levels may not be exactly Poisson in nature, due to the mass of observations at zero. Looking at the correlation between bicycle ownership and other household attributes in Table 2, the correlation seems strongest for household size, number of workers and income. This is intuitive, considering the number of bicycles owned is likely limited by the number of riders in the household. Additionally, if bicycles are viewed as recreational vehicles relative to personal motor vehicles, households with higher incomes may be more likely to own bicycles.

Variable	Correlation (r)	χ^2	Significance
Household size	0.48**	7102.36**	0.000
Num. of vehicles	0.19**	1115.86**	0.000
Num. of retired vehicles	0.03**	189.54*	0.013
Num. of telecommuters	0.14**	395.98**	0.003
Num. of workers	0.24**	1886.96**	0.000
Num. of students	0.37**	4964.26**	0.000
Num. of licensed drivers	0.18**	1395.75**	0.001
Household income	0.21**	885.61**	0.000
Life cycle class	---	5233.20**	0.000
Land use	---	146.75**	0.000
Residence type	---	340.64**	0.000
Home-ownership	---	166.71**	0.000

(Note: ** or * denoting the estimate is statistically significant to the 99% or 95% level.)

Table 2: Correlation with Household Bike Ownership Counts in OHAS

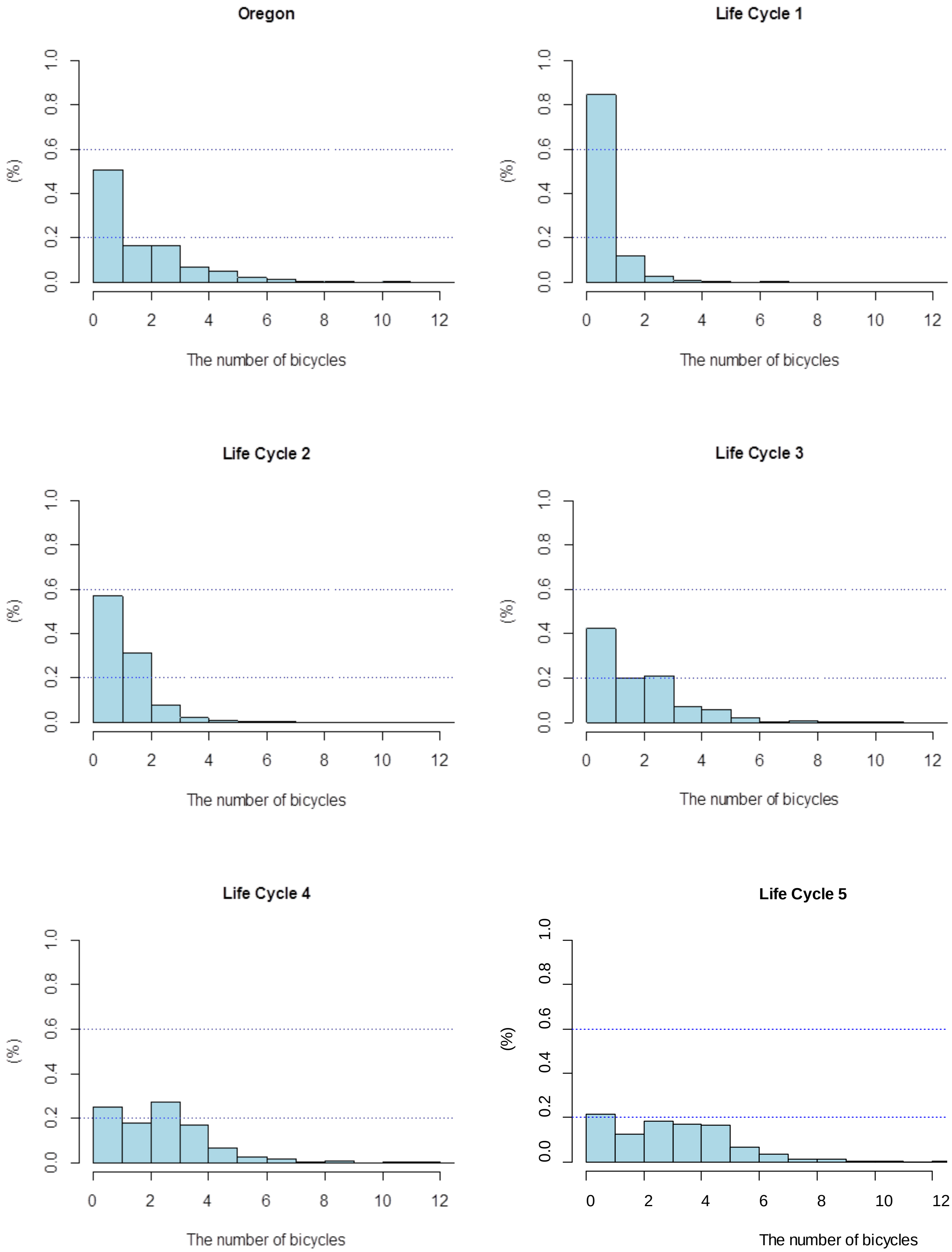

Figure 3(a): Distribution of Bike Ownership across Lifecycles

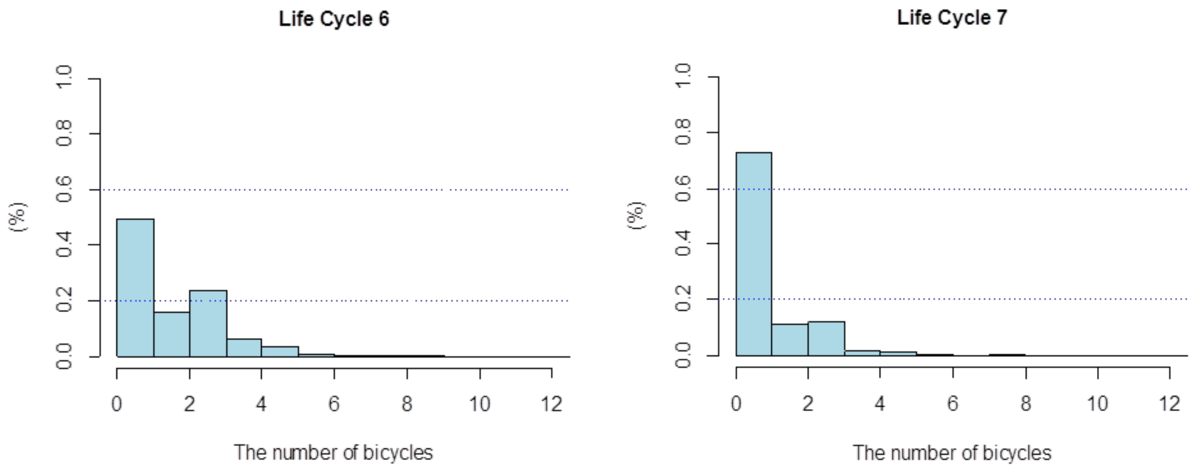

Figure 3(b): Distribution of Bike Ownership across Lifecycles

The next section presents the modeling framework for the relationship between bicycle ownership counts with respect household attributes. Based on the distribution of bicycle ownership count in Figure 3, one complication is the mass of observations at zero, suggesting that there are two regimes or segments of households at work. One segment would consist of households that own zero bicycles with certainty, possibly due to lack of feasible infrastructure for bicycling. The second segment would consists of households that own bicycles, where there exists a probability of owning both zero and non-zero values of bicycles. Thus, being selected in the second regime does not preclude owning zero bikes. The next section presents the modeling framework for examining the number of bicycles owned per household under this two regime perspective.

4.0 Analysis of Household Bike Ownership Levels

The sample of households used in the analysis is from the 2011 Oregon Household Travel and Activity Survey (OHAS) which has observations of the number of bicycles owned per household, in addition to household attributes and geocoded travel decisions for one weekday. Market segments are identified using a latent class model based on observations of bicycle ownership count. The count observations are modeled using three different specifications: (ii) Poisson regression model; and (iii) zero-inflated Poisson regression model. A comparison is first made among these three models to determine the most explanatory specification, followed by a latent class approach.

Bicycles have long been advocated as a zero-emissions alternative to the personal motor vehicle that can potentially reduce motor vehicle roadway congestion. Additionally, as a human-powered travel mode, bicycles also provide significant health benefits. However, based on recent travel surveys, bicycle mode shares are relatively low compared to transit and personal motor vehicles, even in urban areas where bicycle infrastructure and accessibility is extensive. According to the most recent iteration of the Oregon Household Travel Survey (OHAS), bicycles constitute about 2.3% of mode shares across all trips, compared with 80% for personal vehicle and 2.7% for public transit. The recent National Household Travel Survey (NHTS) shows that bike mode shares constitute about 1.5% of trips in the Portland Metropolitan Areas, compared with 78.8% for personal vehicles, and 3.2% for public transit. Long-term goals to improve bicycle mode shares, either in the context of sustainability or encouraging more multi-modal travel, requires identifying and understanding for whom bicycles are competitive when faced with key factors. The body of research into the factors associated with bicycle use over other modes has a long history (Axhausen and Smith 2002, Clarke 1992, Antonakos 1994, Baltes 1996, Moritz 1997, Nelson and Allen 1997, Hunt and Abraham 2007, Heinen et al. 2007). These factors range from the presence of facilities, such as bike racks to non-bicycle traffic characteristics, in addition to trip and decision-maker attributes (Hunt and Abraham 2007). A unique characteristic of bicycle mode share research, relative to traditional studies on mode shares for commute trips, is the consideration of latent factors, such as social interactions, safety perceptions and environmental attitudes, rather than objective measures such as travel times and costs. A critical condition for bicycle use and consequently improved bicycle mode shares is ownership, or at the very least having access to bicycles. Not surprisingly, bicycle use is closely related to its ownership (Handy, Cao and Mokhtarian 2006, Chatterjee et al. 2012, Owen et al. 2010, Heinen et al. 2007). However research work on bicycle ownership has received less attention in the overarching body of work on bicycles, especially with respect to non-attitudinal factors (Pinjari et al. 2008, Yamamoto 2009, Handy et al. 2010, Maness 2012).

The key variable modeled in this analysis is the number of bicycles owned by a household, with explanatory variables explaining both the count and the class memberships. Two basic classes considered here are households that own bicycles and those that own zero bicycles. When modeling count observations, several approaches have been investigated within the transportation literature, ranging from count specific models, such as the Poisson and negative binomial models, to ordered choice models. These models have been applied to the context of vehicle ownership, though to a lesser extent to bicycle ownership. The predominant modeling approach for modeling vehicle counts in household fleets has been the application of ordered choice models within a random utility framework.

Recognizing the mass of zero observations in the distribution of households across bicycle ownership levels (shown in Figure 3), a zero-inflated Poisson modeling approach is used. Under this approach observations have a probability of taking on zero or non-zero value. Conditional on taking on a non-zero value, there is a count model component that gives the probability of a specific integer number. First a choice model describes the assignment of households into zero bike ownership and non-zero regimes. For households which are assigned to the non-zero regime, a count distribution is used to describe and model the number of bicycles owned. For households that fall under the non-zero regime, the probability of owning zero bicycles is still non-zero in value. Both the choice model and count model are estimated jointly. The next section presents the Poisson count model, followed by a presentation of its integration with the choice model. A binary probit is used to model the choice between zero and non-zero regimes.

4.1 Poisson Count Model

In the OHAS sample, the number of bicycles a household owns takes an integer value, referred to as the count variable. Count variables are commonly modeled using the Poisson distribution or negative binomial distribution. Both distributions are restrictive in the sense that their mean and variance are dependent. For the Poisson distribution the mean and variance are restricted to be identical. For the negative binomial distribution the variance is proportional to its mean. Which model and set of restrictions to adopt and consequently depends on the assumption the analyst is willing to make regarding the data-generating process.

In this paper, the number of bicycles owned y_i by a household i is assumed to be generated by a Poisson distribution. Also, assume that a vector of explanatory variables x influences the probability of specific levels of bicycle ownership. Since the Poisson parameter λ is nonnegative, a convenient parameterization often assumed is:

$$\lambda(x) = exp(x'\beta) \qquad \text{Eq. 1}$$

Assuming a random sample of observations with sample size n, the likelihood function for estimating the Poisson model is:

$$L(\beta) = \prod_{i=1}^{n} \frac{exp\left(-exp(x_i{}'\beta)\right) \cdot [exp(x_i{}'\beta)]^{y_i}}{y_i!} \qquad \text{Eq. 2}$$

Take the log of Eq. 2 gives the following log-likelihood function:

$$LL(\beta) = -\sum_{i=1}^{n} exp(x'\beta) + \sum_{i=1}^{n} y_i \cdot (x'\beta) - \sum_{i=1}^{n} ln(y_i!) \qquad \text{Eq. 3}$$

Given K explanatory variable, the Hessian matrix of this function is negative definite if the K vectors $x_k = (x_{1k}, \dots, x_{nk})'$ are linearly independent (Greene 2007); meaning the model is identified (there are a unique set of coefficient estimates) using the maximum likelihood estimation methods.

In the case of bicycle ownership counts from conventional household surveys, there are likely several households with zero bicycles, resulting in a mass of observations at zero shown in Figure 2. To deal with this zero mass in the distribution, several extensions of existing count data models have been formulated in the literature. The specification for each of these "two part" models consists of three main components: (i) an equation describing the first decision of participating in each regime; (ii) a model for the event count that is conditional on the outcome of the first decisions; and (iii) an observation mechanism that links the participation equation with the count outcome model. The zero-inflated Poisson (ZIP) has specifically been established for dealing with a mass of zero observations, with extensions to allow for correlation between the regime and count variable also developed (Lambert 1992; Greene 2007). The preponderance of zeros in these data might be motivated by the possibility that the sample of households consists of those individuals for whom bicycle travel is infeasible, due to inaccessibility to destinations. An alternative interpretation of the ZIP model is a latent class Poisson model with two classes with respect to this paper, but the number of classes may be extended to situations beyond two.

4.2 Zero-Inflated Poisson Count Model

The latent class interpretation of the model suggests a two level decision process, the regime and the event count. The two regime model to account for zero mass observations consists of three parts. The first part describes decisions to participate in the zero regime though a latent construct as follows:

$$d_i^* = w_i' \cdot \delta + \mu_i$$
Eq. 4

$$d_i = \begin{cases} 1 & d_i^* > 0 \\ 0 & otherwise \end{cases}$$
Eq. 5

where

d_i^* is a latent variable describing the propensity towards owning a bicycle;
δ is a vector of coefficients relating the latent propensity with observed attributes;
w_i' is a vector of observed household attributes affecting the propensity towards owning a bike;
μ_i is a vector of normal disturbance terms distributed $N(0, \sigma)$.

Eq. 5 states that a household will likely belong to the bike ownership regime, given that the household's scaled latent propensity exceeds zero. Given the assumption that the disturbance terms are distributed $N(0, \sigma)$, the likelihood can be expressed as follows:

$$Pr\left(d_i \ = 0|w_i\right) = \pi_0(w_i'\delta)$$
Eq. 6

$$Pr\left(d_i \ = 1|w_i\right) = 1 - \pi_0(w_i'\delta)$$
Eq. 7

$$\pi_0(w_i'\delta) = \Phi(w_i'\delta)$$
Eq. 8

$$\Phi(w_i'\delta) = \left(\frac{1}{\sqrt{2\pi}}\right)\int_{-\infty}^{(w_i'\delta)/\sigma} exp\left[-\frac{1}{2}\left(\frac{\mu}{\sigma}\right)^2\right] d\mu \qquad \text{Eq. 9}$$

where $\Phi(.)$ = the standardized cumulative normal distribution. The scale parameter is set to 1 for convenience. The distribution of the count variable, in this case the number of bicycles owned, is assumed to be Poisson. Other distributions could be assumed, such as negative binomial. The probability distribution of observing a number of bikes owned by household i is:

$$\Lambda(y_i = Y_i) = \frac{exp\left(-exp\left(\lambda_i(x)\right)\right) \cdot \left[exp\left(\lambda_i(x)\right)\right]^{y_i}}{y_i!} \qquad \text{Eq. 10}$$

$$E[y_i^*|x_i] = exp(\alpha + x_i'\beta) = \lambda_i(x)$$
Eq. 11

The conditional mean is assumed to take the following parameterization in Eq. 11. Both d_i and y_i are random variable; we need the joint distribution between them. To obtain the joint distribution, define the probability that a household owns zero bicycles, given that it is in the zero regime ($d_i = 0$) as:

$Pr(y_i = 0|x_i, w_i, d_i = 0) = 1$
Eq. 12

Define the probability that a household owns bicycles, given that it is in the regime where household may own any number of bicycles, including zero ($d_i = 1$) as:

$Pr(y_i = Y_i|x_i, w_i, d_i = 1) = \Lambda(y_i = Y_i|x_i)$
Eq. 13

Given the probability that a household belongs to a particular regime, the probability expressed in Eqs. 12 and 13, the joint probability of a household belonging to a particular regime and owning y_i bikes is:

$Pr(y_i \text{ } and \text{ } d_i|x_i, w_i) = Pr(y_i|x_i, w_i, d_i) \cdot Pr(d_i|x_i, w_i)$
Eq. 14

Substituting Eqs. 5, 6 and 7

$Pr(y_i \text{ } and \text{ } d_i|x_i, w_i) = (1 - d_i) \cdot \pi_0(w_i'\delta) \cdot 1 + d_i \cdot [1 - \pi_0(w_i'\delta)] \cdot Pr(y_i^*|x_i)$ Eq. 15

The likelihood function of observations is:

$$L(\alpha, \beta) = \prod_{i=1}^{N} Pr(y_i \text{ } and \text{ } d_i|x_i, w_i) \quad \text{Eq. 16}$$

Substituting Eq. 15

$$L(\alpha,\beta) = \prod_{i=1}^{N}(1-d_i)\cdot\pi_0(w_i'\delta)\cdot 1 + d_i\cdot[1-\pi_0(w_i'\delta)]\cdot Pr(y_i^*|x_i) \qquad Eq.17$$

The log-likelihood function is:

$$LL(\alpha,\beta) = \sum_{i=1}^{N} ln\big((1-d_i)\cdot\pi_0(w_i'\delta)\cdot 1 + d_i\cdot[1-\pi_0(w_i'\delta)]\cdot Pr(y_i^*|x_i)\big) \qquad Eq.18$$

where $\Phi(.)$ = the standardized cumulative normal distribution, and the scale parameter is set to 1 for convenience. The joint model is estimated using a full information likelihood (FIML) approach. Standard maximum likelihood techniques were used to estimate the joint model. The next section presents the estimation results and discusses some of the insight provided by both the probit choice model for examining the split between zero and non-zero regimes, and the Poisson count model.

4.3 Estimation Results and Discussion

The estimation results for the model specified in the precious section are shown below in Table 3. The three models estimated are sequenced to show the progression of modeling and the improvement one model has over the previous iteration. The first model is a Poisson Count Model that does not delineate between different market segments, latent or observed. The second model Accounts for the presence of two latent regimes defined by households who are in the market for bicycles and those that are not. The third model further considers the interactive effects of lifecycle class and residential density combinations.

The Poisson model is often criticized for its assumption that the variance equals the mean. Overdispersion occurs when this assumption is violated and the variance is actually greater than the mean; testing for overdispersion is necessary. Cameron and Trivedi (1986) offered several tests for overdispersion, one of which states that if the overdispersion rate is greater than two, overdispersion is present. The overdispersion rate value for Model 1 in Table 3 is 15.17 which is greater than 2, suggesting the presence of overdispersion. One likely source for this overdispersion is the presence of a large number of zero bicycle ownership values in the sample. To address this, a zero-inflated Poisson model with a binary probit choice model for selection is estimated to account for differences between the zero and non-zero ownership regimes. One test for the appropriateness of the zero-inflated Poisson model is the Vuong test statistic which compares the zero-inflated model with the non-inflated model. The zero-inflated Poisson model is appropriate if the test statistic is greater than 2 (Greene 2007). For Model 2 and 3 in Table 3, the Vuong statistics are 16.97 and 19.04 respectively, where the zero-inflated Poisson model is tested against the standard Poisson model. Thus, in both cases the use of the zero-inflated Poisson model is appropriate.

The model estimation results in Table 3 suggest that the two-regime model is appropriate for modeling household bicycle counts in the sample data. Examining the coefficient values for both the choice model and Poisson count model reveals some key differences in the two latent regimes. Not surprisingly, if households own zero vehicles, the Poisson bicycle ownership rate increases, suggesting that on average, zero vehicle households, own more bicycles relative to household with at least one vehicle. Household size and number of students both have a positive impact on the Poisson rate, which is consistent with previous studies (Maness 2012). Additionally, the association of large bike ownership rates with large household sizes seems reasonable, given the need for riders. Interestingly, membership in all lifecycle classes lower the Poisson rate of ownership, relative to the base case, which is lifecycle class five, two parents with children. This suggests that the highest rates of ownership are households in lifecycle class five. One explanation is that the majority of bikes in the count are children's bikes. However, since there is no delineation of bicycle type within the OHAS, this is impossible to check. Interestingly, conditional on being selected into the regime of bicycle owners, living inside an MPO region slightly lowers the Poisson bicycle ownership rate. However, in the context of the regime selection model, these coefficients begin to seem reasonable. The Poisson model is "active" conditional on a household being in the non-zero bicycle regime. An initial examination of the MPO membership coefficient for both the choice and count model suggests conflicting effects. Table 3 shows that coefficient is negative (-0.154) in the choice model, indicating that households in MPOs have a lower likelihood of owning ZERO bikes. The coefficient for a household being in an MPO in the Poisson model is also negative (-0.091), indicating that the bicycle ownership rate tends to be lower for MPO households. This suggests an interesting divergence in MPO households; while their likelihood of owning bikes is higher relative to other land use classes, conditional upon being selected into the non-zero bike regime, MPO households tend to own less than households in other land use classes.

Variable	Model 1		Model 2		Model 3	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Poisson Count Model						
Constant	-0.764	-14.31	-0.091	-1.63	-0.092	-1.59
Household Size	0.092	8.06	0.100	9.54	0.096	9.15
Number of Telecommuters	0.116	8.26	0.060	3.85	0.060	3.84
Detached Single-Family Housing	0.521	20.26	0.396	12.73	0.414	13.27
Attached Single-Famlily Home	0.258	5.21	0.290	5.25	0.313	5.67
Number of Students per Household	0.186	16.50	0.131	10.97	0.145	12.15
Vehicles per Licensed Driver	0.146	8.86	0.137	8.57	0.135	8.42
Household Has Zero Vehicles	0.074	1.64	0.300	4.78	0.293	4.55
Household participates in Car-Share	0.492	13.79	0.254	5.95	0.260	6.03
Number of Retired Vehicles	0.042	1.62	---	---	---	---
Lifecycle Class 1, Single Adults <=65 (0/1)	-1.681	-26.29	-1.491	-22.44	-0.581	-1.69
Lifecycle Class 2 Single Adult, <65, >=18 (0/1)	-0.665	-17.04	-1.002	-24.49	-0.980	-23.55
Lifecycle Class 3 Non-Related (0/1)	-0.309	-7.02	-0.253	-4.85	-0.276	-5.03
Lifecycle Class 4 Single Parent w/Child (0/1)	-0.065	-1.88	---	---	---	---
Lifecycle Class 5 Parents w/Child (0/1)	---	---	---	---	---	---
Class 7 Related Adults, no Child >=65 (0/1)	-0.303	-12.83	-0.152	-6.21	-0.707	-6.19
Class 6 Related Adults, no Child <65 (0/1)	-0.934	-23.39	-0.484	-9.60	-0.436	-8.59
MPO (0/1)	0.227	9.03	-0.050	-1.77	-0.091	-2.80
Isolated City (0/1)	0.237	2.16	---	---	---	---
Lifecycle Class - Residential Density Interaction Terms						
Lifecycle Class 1 - MPO (0/1)	---	---	---	---	-0.916	-2.63
Lifecycle Class 6 - MPO (0/1)	---	---	---	---	0.632	5.53
Lifecycle Class 1 - Rural Near MPO (0/1)	---	---	---	---	-0.794	-1.93
Lifecycle Class 2 - Rural Near MPO (0/1)	---	---	---	---	0.199	1.95
Lifecycle Class 6 - Rural Near MPO (0/1)	---	---	---	---	0.559	3.92
Probit Choice Model (Zero-Inflated Component)						
Constant	---	---	0.443	6.70	0.092	1.07
Number of Telecommuters	---	---	-0.203	-5.32	-0.202	-5.29
Detached Single-Family Housing	---	---	-0.306	-6.09	-0.289	-5.65
Number of Students per Household	---	---	-0.254	-17.57	-0.159	-8.49
Household Has Zero Vehicles	---	---	0.599	6.61	0.620	7.00
Household participates in Car-Share	---	---	-0.893	-6.07	-0.888	-6.13
Number of Retired Vehicles	---	---	-0.298	-3.68	-0.229	-2.94
Lifecycle Class 2 (0/1)	---	---	-1.877	-4.70	-2.245	-3.01
Lifecycle Class 7 (0/1)	---	---	0.424	7.37	0.449	7.71
MPO (0/1)	---	---	-0.552	-12.40	-0.154	-2.21
Lifecycle Class - Residential Density Interaction Terms						
Lifecycle Class 1 - City near MPO (0/1)	---	---	---	---	0.837	2.43
Lifecycle Class 3 - MPO (0/1)	---	---	---	---	-0.355	-3.06
Lifecycle Class 4 - MPO (0/1)	---	---	---	---	-0.334	-3.96
Lifecycle Class 5 - MPO (0/1)	---	---	---	---	-0.308	-5.91
Lifecycle Class 2 - Rural Near MPO (0/1)	---	---	---	---	1.747	2.17
Lifecycle Class 5 - Rural Near MPO (0/1)	---	---	---	---	0.229	2.10
Lifecycle Class 6 - Rural Near MPO (0/1)	---	---	---	---	0.707	6.83
Lifecycle Class 5 - Isolated City (0/1)	---	---	---	---	-0.883	-1.59
Number of Households	16021		16021		16021	
Log-Likelihood at Convergence	-22376.45		-21060.70		-20987.10	
Log-Likelihood (0)	-26776.59		-26776.59		-26776.59	
Cameron and Trivedi Overdispersion Rate	15.17		---		---	
Vuong Test	---		16.97		19.04	

Table 3: Model Estimation Results

A similar divergence also holds for zero-vehicle households. Looking at Table 3, being a zero vehicles increases the probability of owning zero bicycles with a positive coefficient (0.620). This seems to contradict the Poisson model coefficient (0.293) which suggests that zero-vehicles households tend to have higher Poisson bicycle ownership rates. Like the MPO coefficient, interpretation of these coefficients indicates that conditional upon a household falling into the non-zero bicycle regime, owning zero vehicles increases the Poisson bicycle ownership rate. However, in general zero-vehicle households are likely to own zero bikes. Other household attributes, such as number of students, number of telecommuters and having a car-share membership are more consistent in their effects, increasing the probability of falling into the non-zero bicycle ownership regime, in addition to increasing the Poisson ownership rate. Similarly, being a member of lifecycle class two, which is single people under 65 years of age, increases the probability of owning a bicycle, but does not increase the Poisson bicycle ownership rate. This is reasonable, given a single person does not necessarily need more bicycles. Overall, while coefficients for the same variable may be contrasting between the choice and count model, as is the case of MPO household or zero-vehicle household indicator variables, for other attributes, there is consistency in the impact.
Looking at the interaction variables between residential density class and lifecycle classes show that the contribution of different lifecycle classes towards the probability of owning a bicycle are strongly related to the land use class. Figure 3 shows two patterns of impact across lifecycle classes, based on distinguishing shapes of the radial plots. Households residing MPO regions and rural areas near MPO regions share a similar pattern of impact on the Poisson bike ownership rate, where lifecycle class 1 (single adults ≥ 65 years of age) has a much more negative impact on utility relative to other lifecycle classes.

Relative to city near MPO, isolated city and rural land use classes, the other residential density classes show a more positive contribution across lifecycle classes. Similarly, Figure 4 presents the utility contributions of these density-lifecycle class interactions on the selection probability of not owning a bicycle (probability of being in the zero-bicycle regime). Rural, MPO regions and cities near MPO regions share similar patterns of contribution towards the utility of not owning a bicycle (bicycle ownership level of zero). Isolated cities and rural areas near MPO regions share very different utility contribution patterns across the different lifecycle classes. Several possible explanations exist for these differences. However, without a closer examination of the motivations behind bicycle ownership and decisions to locate in different residential density classes, these associations are difficult to explain due to self-selection. For example, whether or not households that reside in rural and isolated city classes exhibit different bicycle ownership patterns, both in counts and decisions to own bicycles, is due to the land use or other latent factors not observed in the dataset (and thus, not accounted for in the models) is difficult to distinguish without further information.

The focus of this portion of this study is on market segments for bicycle ownership. Two segments were examined differentiating between bicycle owners and household without bicycles. This work is interested in analyzing these latent market segments based on bicycle ownership counts and household attributes typically found in conventional surveys. A two-regime or latent class Poisson model is estimated for bicycle ownership levels, using household attributes to explain both the ownership levels and the latent class memberships with a probit selection model. The results show that the two regimes represent two distinct market segments comprised of (i) households that are considering owning bicycles and (ii) those that have selected out of bicycle ownership. An interesting result was that the coefficients for the same variables were different between the choice and count models. However, one possible explanation is that the coefficients in the count model are conditional upon an observation being selected into the regime of bicycle owners.

For example, although being located in an MPO region had a positive impact on the likelihood of being in the bicycle owner's regime, the same variable had a slightly negative coefficient in the count model. This underscores the importance of treating the selection of households into non-zero and zero bicycle ownership regimes.

This work contributes to the literature on analyzing bicycle count data. Most conventional surveys collect detailed information on household vehicle fleets, including the year, make, model and vintage of the vehicles, and whether the vehicle is leased or owned. Some surveys, such as the 2009 National Household Travel Survey (NHTS), even ask for odometer readings at the time of the survey to gauge vehicle usage. This gap in information for household bicycle fleets creates barriers to identifying market segments for bicycles based on these survey responses, and consequently is part of the motivation for this study. Future studies include more complicated correlation structures between the decisions to own bicycle relative to other travel options, such as car-share and transit adoption. One can think of a household's travel fleet as a collection of multi-modal options. As policy interests shift towards more multi-modal solutions and goals, it becomes increasingly important to consider the different market segments for these options and the economic tradeoffs that motivate the transactions among these options.

5.0 Household Vehicle Transaction Survey

In order to model the household vehicle transactions, a retrospective vehicle ownership survey was developed and administered to a sample of the 2011 OHAS participants who indicated willingness to participate in future studies. This transaction survey asks households about vehicle ownership and fleet transaction for a 10 year period from 2002-2012. Although the OHAS dataset has information on vehicle ownership and disposals, it lacks information needed for characterizing and modeling vehicle transactions, which include, but are not limited to:

i) Date and other time-related information on vehicle transactions; ii) Parking supply at home and work locations, and other location attributes; iii) Household member migrations (members entering and leaving); iv) Detailed Information on non-motorized household vehicles; v) General vehicle usage information on disposed vehicles; vi) Information and communication technologies (ICT) usage characteristics; vii) Attitudinal responses to non-motorized travel, such as bicycle travel.

The most recognized method for collecting information on decision processes over time are panel studies. However, panel studies are difficult and expensive to carry out and face problems of attrition, which affects sample accuracy. The second popular method relies on an individual's retrospective recall to approximate a panel study. The retrospective survey method is adopted in this research since vehicle ownership and transactions would be considered a major event in most households, and most details would be remembered; however, the questions for the supplemental survey will be designed with "recall" issues in mind.

5.1 Descriptive Statistics

Before presenting and discussing the estimation results, the distribution of responses from the household vehicle transaction are presented first. With respect to household characteristics, the survey responses indicated that most households were two person households with a mean size of 2.45 members per household. The majority of responses were married couples with children, married couples without children and single households. Single Family detached housing types dominate the sample, as does owning versus renting a household unit. Most households have two motor vehicles and own at least one bicycle.

The descriptive statistics show that vehicle retirements are rare among households, for both bikes and motor vehicles, resulting in less than 10% of observations in both cases. With respect telecommuting, a sizable percentage, about 40% of observations, engaged in some type of telecommuting in the past week. Mountain, touring and road bukes constitute the majority of bike frames owned and subsequently replaced. Surprisingly, road and mountain bikes are the two most common bike frames required. Touring bikes were also commonly replaced bike frames, but not so with respect to retirement.

HH Size	N	% Sample	HH Relationship	N	% Sample
1	82	22.04	Married Couple with Children	141	37.80
2	158	42.47	Married Couple without Children	119	31.90
3	47	12.63	Single Parent with Children	11	2.95
4	61	16.40	Single	82	21.98
5+	24	6.45	Other	20	5.36
Mean	2.45		**HH Income**	**N**	**% Sample**
HH Type	**N**	**% Sample**	$0-$14,999	10	3.38
SF	247	83.45	$15,000-$24,999	17	5.74
MFA	18	6.08	$25,000-$34,999	15	5.07
MF	27	9.12	$35,000-$49,999	30	10.14
Other	4	1.35	$50,000-$74,999	52	17.57
HH Tenure	**N**	**% Sample**	$75,000-$99,999	47	15.88
Rent	36	12.16	$100,000-$149,999	82	27.70
Own	260	87.84	$150,000+	29	9.80
			No Response	14	4.73

Table 4: Household Characteristics

HH Vehicles	N	% Sample	HH Bikes	N	% Sample
0	13	3.57	0	57	18.69
1	96	26.37	1	52	17.05
2	147	40.38	2	72	23.61
3	67	18.41	3	39	12.79
4	22	6.04	4	32	10.49
5+	19	5.22	5	28	9.18
Mean	2.14		6+	25	8.20
Retired Bikes	**N**	**% Sample**	Mean	2.54	
0	250	84.75	**Retired Vehicles**	**N**	**% Sample**
1	24	8.14	0	261	88.18
2	12	4.07	1	29	9.80
3+	9	3.05	2+	6	2.03
Mean	0.28		Mean	0.15	
Car Share	**N**	**% Sample**			
Yes	17	5.57			
No	288	94.43			

Table 5: Household Resources

Days Telecommute Last Week	N	%Sample
0	178	63.80
1	19	6.81
2	16	5.73
3	8	2.87
4	9	3.23
5	35	12.54
6+	14	5.02
Mean	1.35	
Work Freq. Activity Last week	**N**	**%Sample**
0	198	31.73
1	17	2.72
2	31	4.97
3	29	4.65
4	42	6.73
5	212	33.97
6+	95	15.22
Mean	3.48	
Maintenance Freq. Activity Last Week	**N**	**%Sample**
0	135	21.63
1	72	11.54
2	108	17.31
3	118	18.91
4	45	7.21
5	64	10.26
6+	82	13.14
Mean	3.03	
Recreation Freq. Activity Last Week	**N**	**%Sample**
0	95	15.22
1	70	11.22
2	106	16.99
3	105	16.83
4	64	10.26
5	64	10.26
6+	120	19.23
Mean	3.54	
Online Sales Transctions	**N**	**%Sample**
0	67	30.18
1	31	13.96
2	39	17.57
3	35	15.77
4	11	4.95
5	21	9.46
6+	18	8.11
Mean	2.50	

Table 6: Activity Frequency

Bike Frame	N	%Sample
Kids	4	5.97
Road	18	26.87
Mountain	26	38.81
Other, Touring and Hybrid	19	28.36
Replacement or Addition	N	%Sample
Repalcement	22	35.48
Addition	40	64.52
Trip Purpose	N	%Sample
Work/School Commute	55	19.37
Transit Access, Non-Routine Shopping, HH Errands, Other	56	19.72
Routine Shopping	11	3.87
Recreation and Social	162	57.04
Bike Replaced	N	%Sample
Road	32	31.68
Mountain	25	24.75
Kids	16	15.84
Touring, Hybrid, Others	28	27.72
Bike Retired	N	%Sample
Road	25	30.49
Mountain	24	29.27
Kids	17	20.73
Touring, Hybrid, Others	16	19.51

Table 7: Bike Ownership and Transaction Characteristics

5.2 Econometric Models of Transactions

The potential sample size is approximately 12,000 households who have indicated this willingness. The targeted response rate is 25% yielding a potential final sample size of 3000 households. However, the final response rate was below the projected rate. One possible explanation is the length of the survey, which was approximately 30 minutes in length depending on the vehicle ownership level characteristics of the household. A second explanation is the time between expressing interest in further OHAS studies and the time of this study, which was 3 years. Within this timeframe, several original respondents have reduced their interest in further study.

For this work, key outputs of these models are household tradeoffs among factors likely to affect vehicle transactions, which in turn determine vehicle fleet evolution. Using the supplemented OHAS dataset, the duration between transactions and of vehicle holdings, and the transactions themselves will be modeled within an econometric framework using discrete choice and hazard-based duration approaches. Both decision dimensions provide information on transactions in relation to factors which trigger them (i.e. kids becoming of driving age, etc.). The econometric modeling of household motorized vehicle transactions is rich. However, for non-motorized vehicles, such as bikes, this direction is still new and opens the door to methodological challenges, such as endogenous effects. For example, the data may show that households that migrate to urban from suburban areas and dispose of automobiles without replacement tend to acquire bikes, but whether or not this is a direct substitution is unclear.

A model of addition or replacement of bikes within a household fleet is given below in Table. 8.

Variable	Estimate	Std. Error	t-Statistic
Constant	-1.3582	0.36222	-3.750
Num. HH. Members w/ Dedicated Bike	0.6846	0.26140	2.619
Number of Household Bikes	-0.1565	0.04148	-3.774
Income Medium $50K-$79K (1/0)	0.2745	0.22751	1.207
Income High $80K+ (1/0)	0.4251	0.23940	1.776
Kid's (1/0)	0.6225	0.39256	1.586
Road (1/0)	0.7677	0.32169	2.387
Touring (1/0)	0.8058	0.41643	1.935
Mountain (1/0)	1.1224	0.32283	3.477
Hybrid (1/0)	0.5297	0.35698	1.484
Number of Observations (N - choices observed)	613		
Log-Likelihood Value (Model)	-379.54		
Log-Likelihood Value (Constants Only)	-400.15		

Table 8: Model Estimation Results – Bike Addition/Replacement

Estimations results indicate that the propensity to add a bike in a household fleet, relative to an addition increases with the number of household members with dedicated bikes. As the number of household bikes in the fleet increases, there is less likelihood to add and a greater propensity to replace. Both these trends are intuitive; households with more riders will tend to add more bikes to meet with demand. In contrast, as the number of household bikes in holding increases, the likelihood of addition over replacement decreases.

The coefficients on income also indicate intuitive directions and magnitudes. As household have membership in higher income levels, the propensity for addition increases. This propensity increases with increasing income. The following set of coefficients indicate that bikes that are kids, road, touring, mountain and hybrid have a higher propensity to be additions. With respect to these types, the top three additions tend to be mountain, touring and road bikes.

6.0 Conclusion

Vehicle holdings or fleets are important for examining household travel behaviors and consequently affects the requirements for modeling and forecasting of household travel decisions under future or alternative scenarios. These fleets evolve over time as a result of transactions, which include vehicle (i) disposal or retirement, (ii) replacement and (iii) acquisition decisions. Forecasting household vehicle ownership requires a closer examination of these transactions.

There is a growing diversification of household vehicle fleets that include alternative-fuel and non-motorized vehicles, such as electric vehicles and bicycles. This diversification provides the backdrop for this exploratory study that characterizes and models household vehicle transactions for non-motorized vehicles, in addition to personal gasoline automobiles. This backdrop also encourages a closer examination of bicycle ownership, collecting detailed information similar to those collected in conventional datasets for household gasoline vehicles.

An econometric analysis of household bike ownership rates indicates that two regimes represent two distinct market segments comprised of (i) households that are considering owning bicycles and (ii) those that have selected out of bicycle ownership. An interesting result was that the coefficients for the same variables across models were different between the choice and count models. This suggest that choice and count models for bikes may require further investigation. The retrospective survey revealed that significant variation exists in terms of which types of bikes were likely to be additions versus replacements. Overall, the results of the retrospective survey underscore this heterogeneity in transaction decisions, and bike ownership overall.

This study examines these mixed-modal household fleets. The final study outcome shows bicycle ownership at the household level is complex and cannot simply be characterized by number of bikes owned. Especially with respect to transaction decisions, these vary significantly with respect to type of bikes and households characteristics. The outcome of this study supports the need for a finer delineation of bicycle ownership at the household level and the data to support this analysis collected in conventional travel surveys.

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