

**Are Millennials Really All That Different Than Generation X?
An Analysis of Factors Contributing to Differences in Vehicle Miles of Travel**

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ABSTRACT

This paper is motivated by a desire to understand and quantify the extent to which millennials are truly different in their activity-travel behavior when compared with Generation X that preceded them. In order to conduct the inter-generational comparison and control for a number of confounding factors in determining the “millennial difference”, data from the 2001 and 2017 National Household Travel Survey (NHTS) are utilized. Subsamples of Generation X and millennials are drawn respectively from these data sets; both subsamples were constrained to be 26-30 years of age in the respective periods to control for age effects. The analysis involved estimating a simultaneous equations model system of car ownership, frequency of internet use, frequency of shared mobility services use, and driver vehicle miles of travel (VMT). The model system accounted for a number of effects including socio-economic/demographic effects, period effects (reflecting changing economic and technological conditions), geographic effects, and cohort (millennial) effects. In computing the sizes of various effects in explaining differences in driver VMT between the two cohorts, it is found that the socio-economic/demographic effect size is the largest. All other effect sizes are very small; the millennial effect, although statistically significant, is tiny in comparison to the socio-economic/demographic effect size. The isolation of the millennial effect size is, however, not straightforward because the other effects may themselves be influenced by the cohort effect. Nevertheless, the millennial effect appears very small, at least when comparing millennials in the 26-30 years range with Generation X individuals when they were in the same age range, suggesting that there is no substantial fundamental difference in attitudes, values, and preferences between generations at this age-mature lifecycle stage. It appears that changes in the transportation landscape are likely to be driven largely by technological innovation, economics, and public policy rather than by inter-generational differences.

Keywords: Millennials, Generation X, travel behavior, cohort analysis, age effects, longitudinal analysis, lifecycle stages

1. INTRODUCTION

Millennials are now all grown up, and yet there continues to be much interest in a multitude of domains in analyzing their choices, consumption patterns, lifestyle preferences, attitudes and values, and activity-travel behaviors (Lee et al., 2019; Krueger et al., 2019; Etezady et al., 2019). Based on the Pew Research Center (2019a) definition that anyone born in the years of 1981 through 1996 is a millennial, this generation of consumers surpassed baby boomers (generation born in the years of 1946 through 1964) in 2019 as the largest adult population group in the United States (Searing, 2019). Although Generation Z (the post-millennial generation), born 1997 and after, is larger in total numbers than any other generation in the United States (in 2019), many in the Generation Z cohort are not yet adults and hence do not yet command the marketplace as millennials do today (Kasasa, 2019). In 2019, all millennials are adults and they are projected to reach 73 million, while the boomer population is expected to decline to 72 million (Searing, 2019).

The commentary about millennials in the literature and popular press has evolved over time. When millennials entered adulthood in the early part of the decade, much was made about the many differences they depicted when compared with prior generations. In the transportation and urban planning literature, a number of studies documented that millennials made fewer trips, owned and used automobiles less, did not obtain driver's licenses at the same rate as prior generations, used transit and alternative modes more, preferred living in denser-multimodal urban environments, and embraced the sharing economy while shunning conventional models of ownership (Tiedeman and Circella, 2018; Tiedeman et al., 2017; Zhong and Lee, 2017). A number of articles in the popular press had also alluded to differences depicted by millennials – both in behaviors and attitudes, suggesting that this generation is going to fundamentally transform how the nation works, consumes, shares, interacts, and lives (Kasasa, 2019; Searing, 2019; Zipcar, 2015; Badger, 2014). There was considerable speculation that millennials are fundamentally different in their attitudes, perceptions, and preferences – and will therefore bring about a permanent and lasting shift in the urban ecosystem.

More recently, however, the commentary has shifted. As millennials aged into adulthood and increasing amounts of longitudinal data became available (thus enabling a study of trends over time), it appeared that millennials are beginning to increasingly resemble and mimic behavioral patterns depicted by prior generations (Lavieri et al., 2017; Delbosc et al., 2019). A number of studies in the transportation domain alone suggest that millennials are not necessarily all that different from prior generations as they enter an age-mature lifecycle stage (e.g., Garikapati et al., 2016; Lee et al., 2019; Chatterjee et al., 2018; Ralph, 2017). Articles in the popular press have also begun to note that millennials are choosing to live, work, and travel in ways that are similar to generations that preceded them (Cox, 2019; Schwantes, 2018; Cappelli, 2019). A survey by the National Association of Home Builders suggests that two-thirds of Millennials want to live in the suburbs, 24 percent want to live in rural areas, and only 10 percent want to live in urban city centers (Hudson, 2015). Many of these studies and articles note that differences depicted by millennials in early stages of adulthood may have been due to circumstances wrought by the severe prolonged recession that began in 2007-2008, the effects of which continue to reverberate throughout the US and global economies despite the strong economic recovery and record low unemployment rates of the past few years (Thompson, 2012; Kasasa, 2019). Although millennials continue to evolve, in terms of their lifestyle and travel choices, and increasingly look like generations that preceded them, some differences in activity-travel patterns, residential location, and car ownership and use linger (Garikapati et al., 2016; Krueger et al., 2019; Lee et al., 2019). In addition, early millennials (i.e., those born in the early 1980s) are quite different in activity and time-use patterns than late

millennials (i.e., those born in the mid-1990s); the heterogeneity within the millennial generation makes it difficult (and potentially inappropriate) to draw broad and generalizable conclusions about the entire cohort (Garikapati et al., 2016).

The fundamental questions that motivate this research are largely identical to those which have motivated prior research studies: *Are millennials fundamentally different in their travel behavior than generations that preceded them, when they reach an age-mature lifecycle stage? What is the extent to which millennials are different, after controlling for all other confounding factors?* With the availability of recent national travel and time use survey data sets in the United States, it is now possible to analyze the extent to which millennials are truly different from the preceding generation (Generation X – born in the years of 1965 through 1980) while controlling for many other factors that have changed over time. In particular, the 2017 National Household Travel Survey (NHTS) data offers detailed socio-economic, demographic, and activity-travel information for a large national sample of individuals in the nation. The 2017 American Time Use Survey (ATUS) data set is also a rich source of information for analyzing activity-travel patterns of a large national sample but does not offer the same level of information about transportation choices as the NHTS does. Moreover, the ATUS series commenced only in 2003, presenting a shorter longitudinal window within which to study and compare multiple generations while controlling for myriad factors.

In the above context, the objective of the paper is to isolate and quantify the “millennial effect”, after controlling for all other factors that could contribute to differences between the two generations. The paper accounts for a number of effects of interest. In order to control for the *age effect*, the paper considers individuals in each of the two generations at the same (narrow) age range of 26-30 years old, thus minimizing the effects of within-generation heterogeneity (e.g., early millennials being different than later millennials). This is facilitated by combining data from the 2001 NHTS (from which a sample of Generation X individuals aged 26-30 years old can be extracted) with data from the 2017 NHTS (from which a sample of millennials aged 26-30 years old can be extracted). By comparing these two cohorts at exactly the same age range, this study strives to isolate and quantify the true millennial effect.

The study controls for several other important effects that could contribute to inter-generational differences. These include the *socio-economic/demographic effect*, the *period effect*, and the *geographic effect*. The socio-economic/demographic effect accounts for the usual household and person characteristics that affect travel behavior. The period effect accounts for the economic circumstances, technological systems, and modal options that prevail in the period under consideration. The geographic effect accounts for spatial and contextual differences that may contribute to inter-generational variance. Combined with the *cohort effect* (i.e., the millennial effect, which is the primary effect of interest in this study) and the *age effect* (which is eliminated by considering a constant narrow age range for both cohorts), this paper offers a comprehensive treatment of the measurement of effects to truly capture the extent to which millennials are different. The study involves the estimation of a simultaneous equations model system of car ownership, frequency of internet use, frequency of shared services use, and vehicle miles of travel (VMT) as a driver to capture endogeneity that is prevalent when modeling complex behavioral phenomena. Model estimation results are then used to quantify various effects, including the millennial effect.

The remainder of this paper is organized as follows. The next section provides a review of some evidence about the behaviors of millennials and the differences they depict when compared with other generations. The third section provides a data description and the fourth section presents

the modeling methodology. The fifth section offers model results and estimation of effect sizes. Concluding remarks are offered in the sixth and final section.

2. THE MILLENNIAL DIFFERENCE – A MYTH OR REALITY?

Much has been said and written about the millennial generation. The millennial generation is the most diverse adult generation in American history (Pew Research Center, 2018). This generation is set to serve as a social, economic, and political bridge to chronologically successive (and increasingly) racially diverse generations (Frey, 2018). Besides diversity, technology-savviness is another differentiating characteristic of this group in comparison to prior generations. A quarter of millennials believe that their relationship to technology is what makes their generation unique (Admirand, 2019). Millennials have been badged as the frugal generation (O’Connell, 2015) with respect to their spending habits, and the ‘go-nowhere’ generation (Buchholz and Buchholz, 2012; McDonald, 2015) in their activity and travel patterns. Millennials have been found to exhibit lower rates of driver’s licensure, display lower rates of car ownership, and undertake fewer trips and travel fewer miles and minutes on a daily basis (Polzin et al., 2014; McDonald, 2015). Late millennials (born 1988-1994) spent more time at home than early millennials (born 1979-1985). The latter group tended to show time use patterns similar to those depicted by the prior generation (Generation X), suggesting that there is considerable heterogeneity within the millennial generation. Using the time series of ATUS data sets, Garikapati et al. (2016) found that millennials generally evolved to activity-travel patterns similar to those of the prior generation, but some differences in auto mode use persisted even as they aged.

Previous research suggests that millennials diverge from prior generations in their fundamental values. Millennials do not value home ownership, car ownership, and a steady job as much as prior generations; instead, they place greater value on leading a purposeful life and creating a better future for themselves and society (Guay, 2015; Delbosc and Ralph, 2017). Millennials have embraced the sharing economy and other technology-enabled services more so than previous generations (O’Connell, 2015). The adoption of these services is likely to have a significant impact on their activity-travel and consumption patterns. A recent study in California showed that millennials reduced driving by over 70 percent after beginning to use ride-hailing services such as Uber and Lyft (Alemi et al., 2018). It has been documented that millennials seek to live in dense urban environments that are less car-dependent (Nielsen, 2014), and that this residential preference among millennials could have significant long-term impacts on the built environment.

Millennials also depict socio-economic and demographic characteristics that are distinct from those exhibited by prior generations. Millennials grew up during the period of the great recession, and the economic hardships resulting from the recession influenced their attitudes and values, rendered it difficult for them to find a job and make a living, and forced them to stay in school and delay a number of lifecycle milestones such as entering the labor force, purchasing a home, marriage, and having children (Polzin et al., 2014; Lamberti, 2015; Van Dam, 2019; Pew Research Center, 2018). This delayed lifecycle milestones can contribute to differences in activity-travel patterns, residential location, and lifestyles.

The transportation-related literature devoted to millennials is quite extensive. Many papers have documented that, when compared with prior generations, millennials drive less, shun cars, and utilize alternative modes of transportation more (Badger, 2014; Lee et al., 2019; Eliot, 2019). There are a number of reasons that have been put forth to explain these differences (Delbosc et al., 2019; Delbosc and Ralph, 2017). Around the world, economies are shifting towards a more

knowledge- and service-based societal structure; as the nature of work evolved, millennials had to stay in school and acquire the knowledge and skills to compete in such a globally connected knowledge-driven workplace (Millsap, 2018). Millennials have also come of age in a period dominated by the rapid evolution of technology and the emergence of several technology-enabled services. Many technologies, including high-speed internet, wireless connectivity, mobile phones and smartphones, internet enabled online gaming, e-commerce, and social media, evolved rapidly and became commonplace in households around the world during the 1990s and 2000s. The emergence of the smartphone in 2007 greatly increased the use mobile technologies to access goods and services and leverage crowdsourcing for fulfilling activity and travel needs. Ride-hailing services such as Uber and Lyft commenced operations in the early part of the 2010s; the convenience afforded by these mobility options enabled millennials to access destinations without the need to purchase and drive their own personal vehicles. Overall, it can be seen that the social and economic circumstances, technological context, and transportation ecosystem in which millennials came of age are different (than those experienced by prior generations), and hence their behaviors are likely to be different when compared with those depicted by prior generations.

A few studies have focused on millennials' use of time, with a view that an understanding of how millennials use time (and technology) would shed light on their travel choices. Malokin et al. (2017) found that the ability to undertake activities while traveling (multitasking enabled by mobile technologies and ubiquitous connectivity) has a substantial impact on millennials mode choice (besides traditional socio-demographic characteristics). This finding suggests that millennials place a premium on the value of (travel) time and seek to use technology to lower the value of travel time. Garikapati et al. (2016) analyzed trends in time use patterns using the ATUS series and found that millennials are beginning to mimic prior generations with respect to time use patterns as they age. They note that lingering differences are likely due to external factors such as delayed lifecycle milestones and economic recession effects as opposed to fundamental differences in attitudes, values, and preferences. Enam and Konduri (2018) found that millennials devoted less time to work and more time to non-mandatory and education activities. They also found that Baby Boomers traveled more than millennials and Generation X, and that the gap in travel between Generation X and Baby boomers is larger than the difference between Generation X and millennials.

Several researchers have explored the extent to which millennials are multimodal in their mode usage. Millennials are more multimodal than the previous generation, but the vast majority of millennials are still habitual single-mode drivers (Lee et al., 2019). In general, the evidence suggests that millennials have embraced alternative modes more so than prior generations. Ralph (2017) notes that 13.8 percent of young adults were car-less in 2009, with a majority of them living outside dense urban areas. Tiedeman and Circella (2018) examined public transportation usage patterns and found that, when compared to Generation X with children, millennials with children are more likely to be public transportation users. They also showed that lifestyle attributes characterizing millennials were associated with a high frequency of transit use, and hence the true millennial effect is difficult to decipher. In another study, frequency of use of emerging mobility options and technologies (such as Uber or Lyft) was significant in explaining variations in VMT among millennials, but not significant in explaining VMT variation among Generation X respondents (Tiedeman et al., 2017).

With respect to car ownership, lower levels depicted by millennials can be explained by attitudes (15 to 32 percent), delayed lifecycle (20 to 28 percent), and situational factors/recession effects (16 to 24 percent) (Zhong and Lee, 2017). Giallonardo (2017) notes that although the

association between employment status and travel behavior is clear, the differences in millennials car use cannot be explained by differences in socio-economic and demographic characteristics to the same degree that differences in Generation X car use can – suggesting that there is a significant and important effect (beyond socio-economic effects) that account for variations in millennial car use. After accounting for self-selection effects, Lavieri et al. (2017) found that age, parenting status, and location of residence influenced car-oriented mobility choices. The same study showed that millennials are a heterogeneous group when it comes to travel behavior. Even though younger millennials are more likely to adopt non-motorized modes, the majority of millennials still rely on car as their main mode of transportation; and as millennials age and overcome economic constraints, they seem to become more car-oriented – similar to previous generations.

When analyzing the activity-travel behavior differences of millennials, many different characteristics have been considered in the literature. One of the key variables that has garnered considerable attention is vehicle miles of travel (VMT), with a specific focus on miles of travel as a vehicle driver. Previous research has reported that 35 to 50 percent of the drop in driving can be explained by factors that are millennials-specific, such as virtual activity engagement and changes in attitudes, while 15 to 25 percent of the decrease in driving (compared to prior generations) can be explained by lifestyle-related demographic shifts such as decreased employment (McDonald, 2015). Another study found that, after controlling for socio-economic and life stage variables, there is a significant cohort effect with millennials driving less than Generation X (Tiedeman et al., 2017). However, these studies have not been able to sufficiently separate out various effects that are simultaneously at play. Most importantly, these studies have not been able to separate cohort effects from period effects, even if they are able to control for age effects. The inability to separate cohort effects from period effects is probably one of the biggest shortcomings of work to date in this domain.

The above discussion suggests that the final word has not yet been written on the extent to which millennials are truly different from prior generations in their mobility choices and characteristics. Are they different because of all of those circumstances and technologies (period effect), or are they fundamentally different in their attitudes, values, and preferences (cohort effect) – thus offering the promise that differences seen in early adulthood will prevail and continue into later adulthood even when they hit all of the lifecycle milestones of prior generations? It is undoubtedly difficult to separate out these effects because attitudes, values, and preferences may have themselves been shaped by the economic circumstances, environmental factors, and technological forces at play during the period in which millennials grew up. And separating the technology effect from the cohort effect is challenging when the technology has actually played a significant role in shaping the cohort to begin with (Bou-Mjahed and Mahmassani, 2018). These challenges have proven formidable in attempts to isolate and quantify the millennial effect, i.e., the extent to which differences can truly be attributed to the cohort as opposed to all other confounding effects (Krueger et al., 2019). It is in this arena that this paper attempts to make a contribution, while fully recognizing the complex intertwined nature of the problem being addressed.

Overall, it can be seen that there remains considerable interest in understanding the extent to which millennials are different from previous generations (Lee et al., 2019). The literature suggests that the isolation and understanding of the millennials difference is rather complicated given the many confounding factors at play. A number of previous studies have not been able to systematically tease out the millennial effect because of the lack of appropriate data to do so. Some studies compare generations without controlling for age effects (e.g., comparing millennials and

Generation X at the same point in time), while others attempt to control for age effects without adequately controlling for *period* effects. Given that economic and technological circumstances have changed dramatically in the past two decades, not controlling for *period* effects renders it impossible to determine the extent to which millennials are truly different from prior generations. This study attempts to clarify the “millennial difference” by leveraging data available from the 2001 and 2017 National Household Travel Surveys; through a combination of these two data sources, the study aims to compare travel characteristics between millennials and Generation X while explicitly controlling for many confounding factors as much as possible.

3. DATA ASSEMBLY AND DESCRIPTION

This paper employs NHTS data sets from two distinct time points. The 2001 NHTS data set serves as the source of information for Generation X, while the 2017 NHTS data set serves as the source of information for millennials. Within each data set, the cohort of individuals that is 26-30 years of age is extracted. In the 2001 data set, those 26-30 years of age were born in the years of 1971 through 1975 and hence they fall squarely within Generation X (born 1965 to 1980). In the 2017 data set, those 26-30 years of age were born in the years of 1987 through 1991 and hence they fall squarely within the millennial generation (born 1981 to 1996). For both cohorts, this study has chosen an age range (26-30 years) that represents young adulthood and places the cohorts in the middle of the respective generations (thus avoiding the inclusion of individuals who fall close to the borderline of a subsequent or preceding generation).

The samples were extracted from the data sets and pooled into an integrated data set in which all variables were reconciled and recoded (where necessary) to ensure consistency and uniformity in definitions. Where such reconciliation was simply impossible to accomplish, the variables were omitted to eliminate measurement effects that may impact the analysis. To further control for factors that may affect the results, the analysis sample is limited to those who provided travel diary information for the weekdays of Monday through Thursday. Thus, the day-of-week effect is eliminated (controlled) in this study, similar to the age effect. The total sample size of the final assembled data set is 10,838, with 3,478 (32 percent) belonging to Generation X (drawn from the 2001 data set) and the remaining 7,360 (68 percent) belonging to millennials (drawn from the 2017 data set).

Table 1 presents a descriptive summary of the analysis subsamples. All of the attributes are provided at the person level because the person is the unit of analysis in this paper. Differences and similarities between the Generation X and millennial samples are worth noting. The gender distribution is fairly similar. Millennials do not have driver’s licenses at the same rate as Generation X individuals, but the rate of driver’s license holding is quite high nonetheless. It is interesting to note that the employment status does not show a dramatic difference between the groups, except for the *Looking for Work/Unemployed* category where the percent of millennials in this group is nearly twice that for Generation X. The percent of millennials going to school is higher as well. In short, it appears that, even at the rather mature age of 26-30 years old, millennials are looking for work/unemployed or going to school at a higher rate than Generation X (did at the same age). Millennials are substantially more educated than Generation X, with 56 percent of millennials having a college degree or graduate/professional degree; the corresponding percentage for Generation X is just 37 percent.

Household attributes are computed at the person-level, and hence should be interpreted with caution. Average vehicle ownership is virtually identical between the two groups. The average household size is naturally inflated by the fact that the statistics are reported at the person

level, and hence larger household sizes factor in more heavily in the computation of averages. Nevertheless, it can be seen that millennial households are smaller, with a higher percentage of single-person households and multiple-adult households with no children. While more than one-half of Generation X (51.4 percent) reported residing in nuclear households by the age of 26-30 years, less than one-third (30.9 percent) of millennials reported doing so. In other words, millennials reside in households of a very different structure; they are largely in households with no children. As it is well known that the presence of children significantly impacts travel behavior and mode choice (Ye et al., 2018), millennials are naturally going to depict different travel behaviors when compared to Generation X. Although such socio-economic variables (household structure) are often treated as exogenous, they may actually constitute endogenous lifestyle choice variables in this instance – thus making it very difficult to separate the millennial effect from the socio-economic lifestyle choice effect. In other words, the differences in socio-economic characteristics may be intertwined with the millennial effects. Do millennials have different values and lifestyle preferences leading to these socio-economic differences (choices)? Or have circumstances associated with the period forced millennials into lifestyle choices and socio-economic situations that they would not have otherwise chosen? Although socio-economic and demographic variables could be endogenous in a study of this nature, they are treated as exogenous variables (consistent with tradition in the activity-travel behavior modeling literature) and their effect is computed separated from the millennial effect.

The household income has not been indexed to constant dollars. As such, one would expect a shift in the income distribution from 2001 to 2017. What is interesting to note is that nearly one-quarter of millennials reported living in households that make \$100,000 or more per year. There may be a couple of factors at play here. On the one hand, a healthy segment of millennials may have benefited from the recovery of the economy and the record low unemployment rate in 2017; consequently, many have jobs and their high level of education allows them to take advantage of high-wage jobs in the knowledge economy. On the other hand, there may also be a segment of millennials who continue to live with their parents (because they have not yet been able to establish and afford independent residence) (Polzin et al., 2014; Pew Research Center, 2019b) and they are reporting household income that includes their parents income.

A comparison of mobility attributes shows that millennials drive less per day than Generation X. They travel more by transit and other modes of transportation. In terms of total miles of travel, millennials travel 37.6 miles per day while Generation X traveled 41.5 miles per day. Although millennials travel less in mileage, they actually travel more in time. The total travel time expenditure for this sample of millennials is 79 minutes, while that for Generation X is 76.5 minutes. Millennials spend more time traveling by transit and other modes and about the same time driving alone – possibly due to worsening congestion in many metropolitan areas between 2001 and 2017. Moreover, millennial respondents in 2017 depicted a different geographic distribution than Generation X respondents in 2001. Millennials are drawn from Pacific, West South Central, and South Atlantic divisions to a greater degree than Generation X; the Generation X sample shows a higher geographic presence in Middle Atlantic and East North Central divisions. The definition of the census divisions are shown in Figure 1. These differences in geographic distribution of the samples may contribute to differences in travel mileage and minutes and are captured as an explicit effect in the analysis conducted in this paper.

TABLE 1 Descriptive Characteristics of Analysis Sample

Variable	Gen X (N=3,478)	Millennials (N=7,360)	Variable	Gen X (N=3,478)	Millennials (N=7,360)
Person attributes			Mobility attributes		
<i>Gender</i>			<i>Miles of Travel</i>		
Male	45.1%	46.3%	Average miles driven on travel day	41.5	37.6
Female	54.9%	53.7%	Average miles by SOV driver	31.3	25.9
<i>Driver's License Status</i>			Average miles by SOV driver	21.3	18.8
Not a driver	5.5%	7.4%	Average miles by HOV driver	10.0	7.1
Driver	94.5%	92.6%	Average miles by HOV passenger	5.6	4.2
<i>Employment Status</i>			Average miles by Transit	0.6	1.2
Working	72.9%	73.3%	Average miles by Non-motorized modes	0.3	0.4
Looking for work / unemployed	2.8%	5.3%	Average miles by Other modes	3.7	5.9
A homemaker	11.3%	9.3%	<i>Minutes of Travel</i>		
Going to school	4.3%	6.1%	Average minutes by SOV driver	76.5	79.0
Something else	8.7%	6.0%	Average minutes by HOV driver	38.1	39.8
<i>Education Attainment</i>			Average minutes by HOV passenger	17.5	15.5
Less than a high school graduate	6.0%	2.4%	Average minutes by HOV passenger	9.7	8.8
High school graduate or GED	25.9%	14.4%	Average minutes by Transit	3.0	5.4
Some college or associates degree	31.5%	27.2%	Average minutes by Non-motorized modes	5.1	6.8
Bachelor's degree	24.6%	35.0%	Average minutes by Other modes	3.1	2.7
Graduate degree or professional degree	12.0%	21.1%	<i>Average Number of Trips</i>		
Household attributes			<i>Percent Reporting Zero Trips</i>		
<i>Vehicle Ownership</i>			8.2%		
Average vehicles in the household	2.13	2.13	Geographical distribution		
Average vehicles/adult in household	1.02	1.01	New England		
<i>Household Structure</i>			2.2%		
Average household size	3.10	2.70	Middle Atlantic		
One adult, no children	7.3%	12.5%	24.3%		
Multiple adults, no children	38.2%	54.0%	East North Central		
Single parent (1 adult w/ child)	3.2%	2.5%	40.1%		
Nuclear household (2+ adults w/ child)	51.4%	30.9%	West North Central		
<i>Household Income</i>			4.8%		
Less than \$10,000	4.5%	4.7%	South Atlantic		
\$10,000 to \$14,999	2.4%	3.1%	9.0%		
\$15,000 to \$24,999	10.2%	7.2%	East South Central		
\$25,000 to \$34,999	13.9%	9.3%	3.2%		
\$35,000 to \$49,999	22.9%	13.7%	West South Central		
\$50,000 to \$74,999	26.0%	21.3%	5.1%		
\$75,000 to \$99,999	12.5%	15.8%	Mountain		
\$100,000 or more	7.5%	24.9%	3.2%		
			Pacific		
			8.1%		
			20.3%		
			Period attributes		
			<i>Internet Use Frequency</i>		
			Never		
			17.7%		
			0.6%		
			Once a month or less		
			7.6%		
			0.1%		
			A few times a month		
			10.9%		
			0.3%		
			A few times a week		
			19.7%		
			1.2%		
			Daily		
			44.2%		
			97.7%		
			Average unemployment rate, 8 years before the survey date (1993 unemployment rate for 2001 respondents and 2009 unemployment rate for 2017 respondents)		
			5.9%		
			9.7%		
			<i>Frequency of Shared Services Use in Last 30 Days</i>		
			Never		
			100%		
			79.9%		
			1-2 times		
			0%		
			9.1%		
			3-5 times		
			0%		
			6.0%		
			>5 times		
			0%		
			5.0%		

U.S. Census Divisions

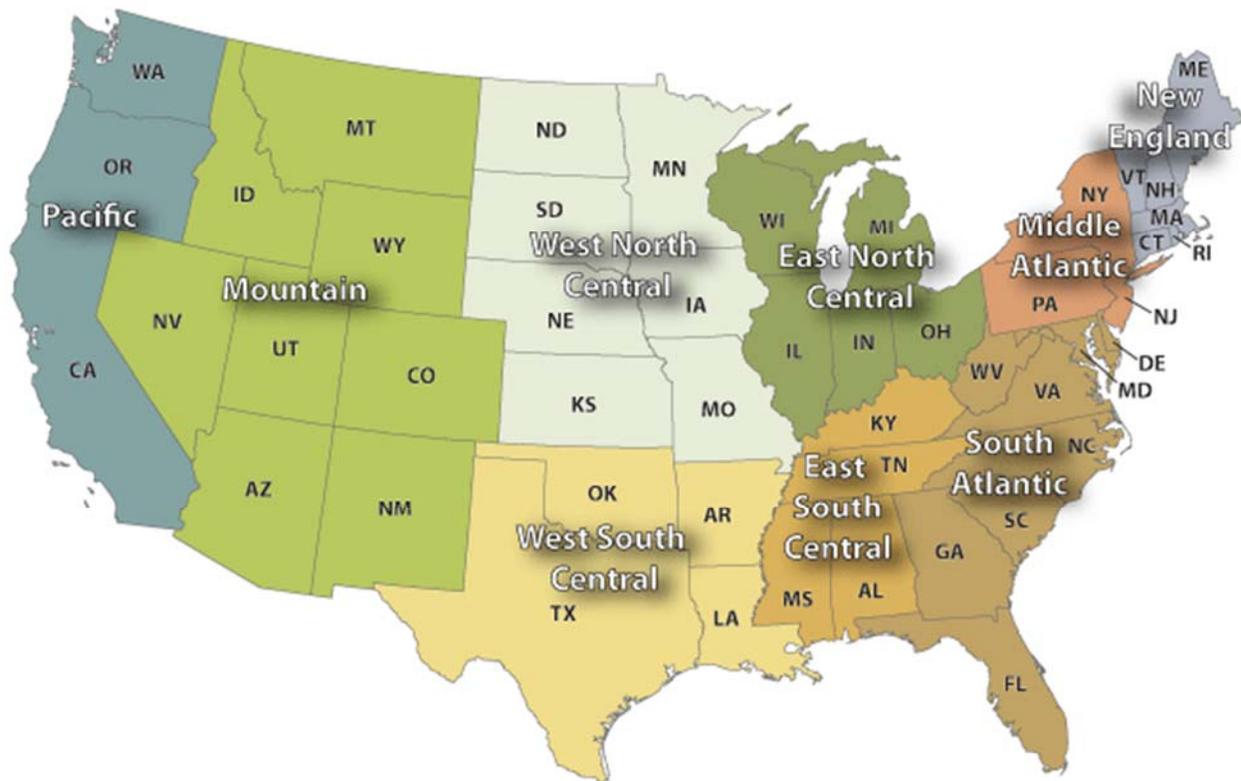


Figure 1 Geographical Boundaries of the U.S. Census Divisions (Source: N.O.A.A.)

The period effects are captured through the use of a few different measures. One measure is the frequency of internet use. Millennials came of age during a period when rapid technological evolution was having a transformative influence on people's lives, both at the workplace and at home. As expected, millennials depict a much higher frequency of internet use than Generation X. Another variable that is used is the frequency of shared service use. The shared service use variable represents the number of times in the prior 30 days that individuals used rideshare services (e.g., Uber, Lyft), carshare services (e.g., ZipCar, Car2Go), or bikeshare services (e.g., Lime, Razor, Bird). For Generation X, this frequency is zero because shared mobility options did not exist in 2001. For millennials, the distribution shows that most use the service rather sparingly, but the variable is worthy of inclusion to capture period effects because the services constitute technology-enabled modal options that millennials could use (thus affecting their activity-travel behavior).

Finally, the period effect is represented by an economic indicator – namely, the average unemployment rate in the metropolitan area where the respondent resided. For each metropolitan area, the unemployment rate was extracted from the Bureau of Labor Statistics database of unemployment rates (Bureau of Labor Statistics, 2019) for 1993 and 2009 and appended to the records to reflect the economic circumstances under which each of the generations transitioned into adulthood. In 1993, the Generation X cohort was 18-22 years old; in 2009, the millennials were 18-22 years old. This is the age at which individuals transition from being minors to adults, and begin to establish independence from their parental home (either by transitioning to college or to the workplace). In addition, 2009 represents a year in which the severe recession was being felt across the country; by including 2009 unemployment rate as a measure of economic circumstances faced by millennials, it is possible to reflect the effects of the severe recession on transportation

choices. In the NHTS data, the location information is suppressed for individuals residing in metropolitan areas of population less than one million. For these cases, the statewide unemployment rate was used as a proxy to reflect the general economic conditions.

4. MODELING METHODOLOGY

The nature of the problem being addressed in this paper is characterized by a high degree of endogeneity. There are a number of inter-related dependent variables; not only are the variables inter-related, but there may be a number of unobserved attributes and traits that affect multiple behavioral dimensions. The prevalence of multiple inter-related dependent variables coupled with the need to account for correlated unobserved attributes that affect them called for the development, specification, and estimation of a simultaneous equations model system that could capture these complex relationships.

However, decisions had to be made as to the exact variables that would be used as dependent (endogenous) variables and the variables that would be included in the specification as exogenous variables. While there is no perfect solution to this conundrum, a set of four dependent variables was identified for use in this study. They are: car ownership, frequency of internet use, frequency of shared service use, and vehicle miles of travel as a driver (hereafter, referred to as driver VMT). Car ownership and driver VMT represent two measures of auto use that capture both longer- and shorter-term decisions in this realm. Because the primary topic of interest is the extent to which millennials use the auto mode differently (when compared with Generation X), these two variables were chosen. Frequency of internet use and shared service use constitute period variables that impact out-of-home activity engagement and mode use behavior. At the same time, they are endogenous variables that are influenced by other socio-economic and demographic variables; treating them as exogenous variables would lead to endogeneity biases and inconsistent parameter estimates. The methodology presented in this section constitutes a simultaneous equations modeling approach that connects these four endogenous variables. Because it is not entirely clear as to which socio-economic and demographic variables constitute conscious choices made by the individual, they are all treated as exogenous variables in this study; in reality, at least some of these variables may be viewed as endogenous variables (e.g., driver's license status, employment status, education attainment, household structure). Additional dependent variables were not designated for purposes of computational tractability and ease of calculating effect sizes in explaining differences between Generation X and millennials. In this effort, effect sizes are computed to identify the extent to which the millennial factor contributes to differences in driver VMT between the two generations.

4.1 Joint Model of Activity-Travel Choices

Consider an individual facing a multi-dimensional choice space comprised of one continuous variable (natural logarithm of driver VMT), two ordinal variables (frequency of internet use and frequency of shared service use), and one count variable (car ownership). The formulation for each type of variable is presented first, followed by an explanation of the structure and estimation procedure for the multi-dimensional system.

Let y be the continuous variable (corresponding to the natural logarithm of driver VMT). Let $y = \gamma' s + \varepsilon$ in the usual linear regression fashion, where s is a column vector of exogenous attributes as well as the observed values of other endogenous variables, γ is a column vector of corresponding coefficients, and ε is a normal scalar error term with mean 0 and variance σ_y .

Let there be two ordinal variables. In the empirical context of the current paper, the ordinal variables correspond to the frequency of internet use (three different levels: “rare user”, “infrequent user”, and “frequent user”) and frequency of the use of shared services (two different levels: “never” and “at least once in the last 30 days”). Note that the latter binary variable may be considered an ordinal variable with two categories. Let h be the index for the ordinal variables ($h=1$ for the frequency of internet use and $h=2$ for frequency of shared services use). Let J_h be the number of categories for the h^{th} ordinal outcome, and let the ordinal index for the variable h be j_h ($j_1 = 1, 2, 3$ and $j_2 = 1, 2$) and let a_h be the actual observed chosen ordinal value. Then, for each ordinal variable, an ordered-response probit (ORP) formulation may be written as: $y_h^* = \boldsymbol{\phi}_h' \mathbf{z}_h + \xi_h$, $j_h = a_h$ if $\psi_{h,a_{h-1}} < y_h^* < \psi_{h,a_h}$, where \mathbf{z}_h is a column vector of exogenous attributes (excluding a constant) as well as (possibly) the observed values of other endogenous variables, $\boldsymbol{\phi}_h$ is a column vector of corresponding coefficients, and ξ_h is a standard normal scalar error term. For identification conditions, set $\psi_{h,0} = -\infty, \psi_{h,J_h} = +\infty$, and let $\boldsymbol{\psi}_h = (\psi_{h,1}, \psi_{h,2}, \dots, \psi_{h,J_{h-1}})'$.

Let there be one count variable for an individual. In this study, the count variable corresponds to car ownership (number of vehicles in the household). Let the count index be k ($k = 0, 1, 2, \dots, \infty$) and let r be the actual observed count value for the individual. Then, following the recasting of a count model as a Generalized Ordered Response Probit (GORP) formulation, a generalized version of the negative binomial count model may be written for this individual as (see Bhat et al., 2014):

$$\begin{aligned} \tilde{y}^* &= \tilde{\varepsilon}, \quad \tilde{\psi}_{r-1} < \tilde{y}^* < \tilde{\psi}_r, \\ \tilde{\psi}_r &= \Phi^{-1} \left[\frac{(1-\nu)^\theta}{\Gamma(\theta)} \sum_{t=0}^r \left(\frac{\Gamma(\theta+t)}{t!} (\nu)^t \right) \right] + \tilde{\phi}_r, \quad \nu = \frac{\lambda}{\lambda + \theta}, \quad \text{and } \lambda = e^{\tilde{\gamma}'\mathbf{x}} \end{aligned} \quad (1)$$

where \tilde{y}^* is a latent continuous stochastic propensity variable that maps into the observed count r through the $\tilde{\psi}$ vector (which is a vertically stacked column vector of thresholds $(\tilde{\psi}_{-1}, \tilde{\psi}_0, \tilde{\psi}_1, \tilde{\psi}_2, \dots)'$). $\tilde{\varepsilon}$ is a standard normal random error term. $\tilde{\gamma}$ is a column vector corresponding to the vector \mathbf{x} (including a constant) of exogenous observable covariates. Φ^{-1} in the threshold function is the inverse function of the univariate cumulative standard normal. θ is a parameter that provides flexibility to the count formulation, and is related to the dispersion parameter in a traditional negative binomial model ($\theta > 0$). $\Gamma(\theta)$ is the traditional gamma

function; $\Gamma(\theta) = \int_{\tilde{t}=0}^{\infty} \tilde{t}^{\theta-1} e^{-\tilde{t}} d\tilde{t}$. The threshold terms in the $\tilde{\psi}$ vector satisfy the ordering condition

(i.e., $\tilde{\psi}_{-1} < \tilde{\psi}_0 < \tilde{\psi}_1 < \tilde{\psi}_2 \dots < \infty$) as long as $\tilde{\phi}_{-1} < \tilde{\phi}_0 < \tilde{\phi}_1 < \tilde{\phi}_2 \dots < \infty$. The presence of the $\tilde{\phi}$ terms in the thresholds provides substantial flexibility to accommodate high or low probability masses for specific count outcomes without the need for cumbersome traditional treatments using zero-inflated or related mechanisms in multi-dimensional model systems (see Castro et al., 2012 for a detailed discussion). For identification, set $\tilde{\phi}_{-1} = -\infty$ and $\tilde{\phi}_0 = 0$. In addition, identify a count value e^* ($e^* \in \{0, 1, 2, \dots\}$) above which $\tilde{\phi}_k$ ($k \in \{1, 2, \dots\}$) is held fixed at $\tilde{\phi}_{e^*}$; that is, $\tilde{\phi}_k = \tilde{\phi}_{e^*}$ if $k > e^*$, where the value of e^* can be determined based on empirical testing. Doing so enables the

count model to predict beyond the range available in the estimation sample. For later use, let $\tilde{\phi} = (\tilde{\phi}_1, \tilde{\phi}_2, \dots, \tilde{\phi}_{e^*})'$ ($e^* \times 1$ vector) (assuming $e^* > 0$).

The jointness across the different types of dependent variables may be specified by writing the mean and covariance matrix of the $[4 \times 1]$ vector $\tilde{y} = (y, y_1^*, y_2^*, \tilde{y}^*)$ as:

$$\text{Mean}(\tilde{y}) = \mathbf{B} = \begin{bmatrix} \overline{y's} \\ \overline{\phi_1' z_1} \\ \overline{\phi_2' z_2} \\ 0 \end{bmatrix} = \begin{bmatrix} \mathbf{B}_1 \\ \mathbf{B}_2 \end{bmatrix} \text{ and } \text{cov}(\tilde{y}) = \mathbf{\Omega} = \begin{bmatrix} \sigma_y & \sigma_{yy_1^*} & \sigma_{yy_2^*} & \sigma_{y\tilde{y}^*} \\ \sigma_{yy_1^*} & 1 & \sigma_{y_1^* y_2^*} & \sigma_{y_1^* \tilde{y}^*} \\ \sigma_{yy_2^*} & \sigma_{y_1^* y_2^*} & 1 & \sigma_{y_2^* \tilde{y}^*} \\ \sigma_{y\tilde{y}^*} & \sigma_{y_1^* \tilde{y}^*} & \sigma_{y_2^* \tilde{y}^*} & 1 \end{bmatrix} = \begin{bmatrix} \sigma_y & \mathbf{\Omega}_{12} \\ \mathbf{\Omega}'_{12} & \mathbf{\Omega}_{22} \end{bmatrix}, \quad (2)$$

where σ_{cd} is the covariance between c and d . All non-fixed elements of the symmetric $\mathbf{\Omega}$ matrix are identifiable. Next, let ω be the collection of parameters to be estimated: $\omega = [\gamma', \phi_1', \phi_2', \psi_1', \psi_2', \theta, \tilde{\phi}', \tilde{\gamma}'; \text{Vech}(\mathbf{\Omega})]'$, where $\text{Vech}(\mathbf{\Omega})$ represents the vector of estimable upper triangle elements of $\mathbf{\Omega}$. Also, let $V = \tilde{y} | y$. Then, the likelihood function for an individual can be written as:

$$L(\omega) = \frac{1}{\sigma_y} \phi\left(\frac{y - \gamma's}{\sigma_y}\right) \times \left(\Pr\left[\tilde{\psi}_{low} \leq V \leq \tilde{\psi}_{up}\right]\right), \quad (3)$$

where the truncated domain for the V vector is determined by the observed outcomes of the ordinal and count variables $[\tilde{\psi}_{low} = (\psi_{a_1-1}, \psi_{a_2-1}, \tilde{\psi}_{r-1})$ and $\tilde{\psi}_{up} = (\psi_{a_1}, \psi_{a_2}, \tilde{\psi}_r)$], and $\phi(\cdot)$ is the univariate standard normal density function. Define $\mathbf{W} = \mathbf{B}_2 + \mathbf{\Omega}'_{12} \left(\frac{y - \gamma's}{\sigma_y}\right)$ [3×1 vector] and

$\mathbf{\Delta} = \mathbf{\Omega}_{22} - \mathbf{\Omega}'_{12} (\sigma_y)^{-1} \mathbf{\Omega}_{12}$ [3×3] matrix. Using the marginal and conditional distribution properties of the multivariate normal distribution, it can be shown that V is distributed multivariate (trivariate in this study) normal with mean \mathbf{W} and covariance matrix $\mathbf{\Delta}$. The likelihood function of Equation (3) may be rewritten as:

$$L(\omega) = \frac{1}{\sigma_y} \phi\left(\frac{y - \gamma's}{\sigma_y}\right) \times \int_{D_v} f_V(\mathbf{v} | \mathbf{W}, \mathbf{\Delta}) d\mathbf{v}, \quad (4)$$

where the integration domain $D_v = \{\mathbf{v} : \tilde{\psi}_{low} \leq \mathbf{v} \leq \tilde{\psi}_{up}\}$ is simply the truncated multivariate region of the V vector determined by the observed ordinal indicator outcomes. $f_V(\mathbf{v} | \mathbf{W}, \mathbf{\Delta})$ is the MVN (trivariate) density function with a mean \mathbf{W} and covariance $\mathbf{\Delta}$, and evaluated at \mathbf{v} . More details about the estimation method can be found in Bhat et al. (2014).

4.2 Quantifying the Relative Contribution of Various Factors to Explaining Driver VMT

This paper attempts to unravel the relative contribution of various factors to explaining differences in driver VMT between millennials and Generation X. A total of five effects are considered in this paper. The first is the *age effect*, which is controlled (eliminated) by considering both generations within the narrow range of 26-30 years old. The second is the *cohort effect* (CE), which reflects

the intrinsic fundamental differences between the generations in terms of their auto usage. This effect is captured by including an indicator for millennials as an explanatory variable in the various equations that comprise the simultaneous equations system. The third is the *socio-economic/demographic effect* (SED), which captures the differences between the generations that can be explained by all of the usual socio-economic and demographic variables used in models of traveler behavior. The fourth is the *period effect* (PE) which reflects the influence of the time period in which millennials and Generation X exercised their activity-travel choices. Although there may be many indicators that describe a period, this study considers unemployment rate, frequency of use of various technology-enabled shared services, and the frequency of internet use (the last two variables being endogenous variables) as descriptors of the period. The fifth is the *geographical effect* (GE) reflecting the notion that there may be spatial variations in activity-travel choices due to the contextual situation in which the choices are made.

To estimate the various effects, one must consider the jointness among the endogenous variables, because of correlations across the underlying propensities for the many choices. Further, some effects, such as the “cohort” effect, influence driver VMT in a direct manner (through appearance as a significant determinant of the logarithm of VMT) as well as an indirect manner through their influence on other endogenous variables (such as on car ownership and frequency of internet use) that then influence driver VMT. To appropriately accommodate such effects as well as recognize the jointness among endogenous variables, first partition the vector s into variables that correspond to socio-economic and demographic characteristics (SED), period effects (PE), geographical effects (GE), and cohort effects (CE). Let $s = (s'_{SED}, s'_{PE}, s'_{GE}, s'_{CE})'$, and correspondingly partition the γ vector into $\gamma = (\gamma'_{SED}, \gamma'_{PE}, \gamma'_{GE}, \gamma'_{CE})'$. The equation for y may be rewritten as:

$$y = \gamma'_{SED} s_{SED} + \gamma'_{PE} s_{PE} + \gamma'_{GE} s_{GE} + \gamma'_{CE} s_{CE} + \varepsilon. \quad (5)$$

As just discussed, the endogenous car ownership variable is included within the vector s_{SED} , and the endogenous “frequency of internet use” and “frequency of shared service use” are included as part of the vector s_{PE} . The mean sum of squared residuals (MSE) of the above regression represents the effect of unobserved factors ($LNVMT_{UF}$).

Next, the observed exogenous (and endogenous) variables in the other endogenous (propensity) equations are also partitioned similarly. With this set-up, there are multiple ways to obtain the relative contributions of each set of variables. In this paper, a simulation procedure that is relatively easy to implement has been adopted. First, realizations are drawn from a multivariate (four-variate) distribution with mean zero and covariance matrix Ω for each sample individual. These provide realizations of the error terms for each individual across the four equations. These realizations are generated once and fixed. Next, the simulation process is started in the recursive fashion of computing effects of the endogenous variables on each other. In the joint model, the recursive effects indicated that car ownership affects propensity of shared service use as well as $\ln(VMT)$. The frequency of internet use (specifically, frequent use) influences the propensity of shared service use. Also, car ownership, frequency of internet use, and frequency of shared service use all affect $\ln(VMT)$.

Given a set of exogenous variables with values, this simulation procedure is straightforward. Start with predicting car ownership deterministically, then frequency of internet use, next frequency of shared service use, and finally VMT (the translation from probabilities to a deterministic prediction for each endogenous variable follows the usual microsimulation process;

the draws from the uniform distribution used for this translation are done once for each individual and each endogenous variable, and then maintained fixed across individual-endogenous combinations in all subsequent simulations). The trick now is to develop a way of partitioning the relative contributions of each set of variables. To explain this, consider the cohort effect. Start with setting the millennial dummy variable to zero for all individuals in the sample, while retaining all sample individuals, and determine the resulting $\ln(\text{VMT})$ variance across individuals. Next, allow the millennial dummy variable to take the actual values, and once again follow the simulation chain to obtain $\ln(\text{VMT})$ and compute the resulting $\ln(\text{VMT})$ variance across individuals. The difference between the two VMT variances provides a magnitude effect of the relative contribution of the cohort effect in explaining $\ln(\text{VMT})$, say LNVMT_{CE} . Similar exercises may be undertaken to obtain $\text{LNVMT}_{\text{SED}}$, LNVMT_{PE} , and LNVMT_{GE} . To quantify the effect of each factor on driver VMT, the fraction of each $\exp(\text{LNVMT})$ contribution as a proportion of the sum of the exponentials of VMTs from each contributing source ($= \exp(\text{LNVMT}_{\text{SED}}) + \exp(\text{LNVMT}_{\text{PE}}) + \exp(\text{LNVMT}_{\text{GE}}) + \exp(\text{LNVMT}_{\text{CE}}) + \exp(\text{LNVMT}_{\text{UF}})$) is computed. These proportions furnish the percent contribution of each factor in explaining driver VMT at the point median VMT estimate.

5. MODEL ESTIMATION RESULTS

This section presents a discussion of model estimation results, focusing on each of the dimensions of interest considered in this paper. The estimation of the joint simultaneous equations model proceeded in a stepwise fashion. First, independent models of each of the dimensions were estimated to identify the variables that are likely to be significant and obtain an initial set of starting values for the estimation of the joint simultaneous equations model system. The specification of the joint model system was finalized based on statistical significance of coefficients and the behavioral intuitiveness of the magnitude and signs of coefficients. Following the discussion of the model estimation results, the effect sizes are presented and discussed.

Model estimation results are presented in Table 2. For ease of discussion, the models will be discussed in the reverse order that they are presented in the Table. Because car ownership and frequency of internet and shared service use appear as explanatory variables in the VMT equation, the discussion essentially follows the logic of the recursive structure of the model system.

5.1 Household Car Ownership

The household car ownership component constitutes a count model. In model estimation, dispersion parameter θ came out to be a large value, and the resulting specification could not be distinguished from the corresponding Poisson-based latent variable specifications. Also, there was no need for additional flexibility terms $\tilde{\phi}_i$ in the specification. The coefficients in Table 2 corresponding to car ownership are embedded within the threshold functions and correspond to the elements of the $\tilde{\gamma}$ vector in Section 4.2. The constant does not have any substantive interpretation. For the other variables, a positive coefficient shifts all thresholds toward the left of the count propensity scale, which has the effect of reducing the probability of zero count. On the other hand, a negative coefficient shifts all thresholds toward the right of the count propensity scale, which has the effect of increasing the probability of zero count.

For the most part, the model component offers behaviorally intuitive results, although some of the coefficients associated with individual characteristics are not immediately explicable. Females exhibit greater propensity to reside in households with fewer vehicles, a finding whose underlying reason is somewhat unclear and merits further investigation. Rather surprising are the findings that individuals with higher levels of education attainment and individuals who are

employed exhibit a greater propensity to reside in households with zero vehicles. It appears that these individuals are equipped and able to use alternative modes of transportation, thus reducing the need for household vehicle ownership – although, once again, the reasons for these findings are somewhat unclear and merit additional examination. Those with a driver’s license are more likely to be in households with greater number of vehicles, while immigrants are more likely to reside in households with no vehicles. Both findings are consistent with expectations and prior research (Klein and Smart, 2017; Yamamoto, 2008).

When it comes to household attributes, all of the indications are consistent with expectations. Individuals in households located in higher density environments are more likely to hold zero vehicles, presumably because density is associated with availability of multiple modes of transportation and easy access to destinations (Jahanshahi and Jin, 2018). Individuals in lower income households are likely to exhibit lower levels of vehicle ownership, as expected, while individuals in households with children exhibit a propensity towards higher levels of vehicle ownership. Similarly, individuals are likely to be in households that exhibit higher levels of vehicle ownership as the number of workers in the household increases. All of these findings are behaviorally intuitive and consistent with expectations. Individuals residing in the Middle Atlantic region are likely to own fewer vehicles, presumably because cities in that region have more modal options and are more compact.

The millennial indicator (reflecting the cohort effect) is positive and statistically significant. The positive indicator does not necessarily mean that millennials exhibit a greater propensity to own more vehicles themselves; it simply means that they are likely to reside in households with a greater number of vehicles (than Generation X individuals at the same age). Given that millennials are residing with their parents at a greater rate than their Generation X counterparts at the same age (Polzin et al., 2014; Pew Research Center, 2019b), it is probable that millennials are essentially reporting vehicle ownership for their parents’ household – comprised of multiple generations of adults residing together. In other words, the millennial effect on car ownership may actually be reflective of the living arrangements rather than a reflection of mobility choices per se.

5.2 Propensity of Internet Use

Frequency of internet use is an ordinal variable with three possible outcomes (rare, infrequent, and frequent usage). The vast majority of millennials fell into the frequent usage category (98.9 percent); the corresponding percentage for Generation X was just 65 percent (see Table 1). As a result, the millennial indicator is positive and statistically significant, clearly indicating that the period in which millennials grew up played a role in shaping their use of technology – and consequently their activity-travel choices (due to the interplay between virtual and physical activity engagement).

TABLE 2 Model Estimation Results for the Joint Model

Type of Dependent Variable		Continuous	Ordinal		Count
Variables		ln (VMT)	Propensity of internet use	Propensity of shared services use	Car ownership
Constant		-7.514 (-27.44)	NA	NA	0.125 (2.65)
<i>Individual characteristics</i>					
Gender	Female	NS	-0.073 (-1.97)	0.116 (3.20)	-0.053 (-3.81)
Educational Attainment (base is high school)	Some college	0.415 (3.92)	0.493 (11.57)	0.205 (2.77)	NS
	Bachelor's degree	0.646 (5.78)	0.896 (17.64)	0.543 (7.64)	-0.070 (-4.35)
	Graduate or professional degree	0.487 (3.82)	0.973 (14.74)	0.674 (9.05)	-0.114 (-5.59)
Student status	Student	0.910 (5.14)	0.410 (4.29)	0.170 (2.06)	NS
Employment status (base is unemployed)	Full-time worker	3.591 (14.94)	0.292 (4.58)	0.217 (2.95)	-0.319 (-7.75)
	Part-time worker	2.276 (7.98)	NS	NS	-0.304 (-8.34)
Homemaker	Homemaker	0.381 (2.42)	0.173 (2.41)	-0.191 (-1.98)	-0.150 (-5.14)
Driver status	Driver's license	5.810 (27.44)	NS	-0.218 (-2.85)	0.516 (14.41)
Immigration status	Not born in the US	-0.454 (-4.06)	-0.124 (-2.29)	NS	-0.094 (-4.16)
Mobility condition	Has medical condition that limits travel	-1.192 (-4.52)	NS	NS	NS
<i>Household characteristics</i>					
Residential Location	Medium density neighborhood	NS	NS	0.281 (5.38)	-0.089 (-5.46)
Choice (base is low density neighborhood)	High density neighborhood	-0.669 (-8.63)	0.163 (4.47)	0.666 (11.56)	-0.165 (-9.88)
Household Income (base is more than US\$ 75K)	Less than US\$ 35K	-0.234 (-2.56)	-0.507 (-9.75)	-0.423 (-7.94)	-0.179 (-8.77)
	Between US\$ 35K and US\$ 75K	NS	-0.216 (-4.47)	-0.478 (-11.52)	-0.065 (-4.11)
Presence of children	Presence of children	0.158 (1.98)	-0.198 (-5.29)	-0.606 (-9.74)	0.066 (4.55)
Number of workers	Number of workers in the household	-0.445 (-7.62)	NS	-0.079 (-2.45)	0.264 (14.74)
Home Ownership	Home Ownership=Own	0.160 (1.99)	NS	NS	NS
Car ownership	Number of vehicles in the household	0.413 (10.30)	NS	-0.154 (-6.78)	NA
<i>Period effects</i>					
Unemployment rate	Unemployment rate	-0.076 (-2.04)	NS	NS	NS
Internet use (base is rare user)	Infrequent user	0.363 (2.21)	NA	NS	NS
	Frequent user	0.363 (2.21)	NA	1.631 (5.09)	NS
Shared services (ride/bike/car) use	Used at least once in last 30 days	-0.683 (-5.89)	NA	NA	NA
<i>Geographic effects</i>					
Middle Atlantic	Middle Atlantic	-0.628 (-6.34)	NS	NS	-0.104 (-5.53)
West South Central	West South Central	0.235 (2.23)	NS	NS	NS
<i>Cohort effects</i>					
Millennial	Millennial	-0.142 (-2.02)	2.133 (29.26)	NA	0.043 (2.83)
<i>Thresholds</i>					
Internet use	Between "rare user" and "infrequent user"	NA	-0.478 (-5.65)	NA	NA
	Between "infrequent" and "frequent" user	NA	0.402 (4.77)	NA	NA
Shared services use	Between "never" and "at least once"	NA	NA	2.567 (7.65)	NA
Variance-covariance matrix of the error terms					
In (VMT)		1.238 (12.67)			
Frequency of internet use		0.107 (2.21)	1.00 (fixed)		
Frequency of shared services use		0.264 (3.93)	0.322 (2.74)	1.00 (fixed)	
Car ownership		0.287 (3.11)	0.00 (fixed)	0.00 (fixed)	1.00 (fixed)
<i>Goodness-of-Fit Measures</i>					
Log likelihood at convergence, $L(\beta) = -69,434.6$ (79 parameters)					
Log likelihood with constants, $L(c) = -98,699.1$; Log likelihood with no constants, $L(0) = -124,783.20$					
Adjusted $\rho^2(c) = 0.2957$; Adjusted $\rho^2(0) = 0.4429$					
$N_{GenX} = 3,478$; $N_{Millennials} = 7,360$; $N_{Total} = 10,838$					

Note: NA = Not Applicable; NS = Not Significant

All other variables provide interpretations that are consistent with expectations. Females depict a lower propensity for internet use, consistent with findings reported in the literature (Rowntree, 2018). Students, those with higher education attainment, and those who are employed report higher propensities for internet use; this finding is consistent with expectations in that these individuals are likely to be more technologically savvy and have a need to use the internet more often to fulfill their work and school activities (Mohammad et al., 2019; Mei et al., 2016). Homemakers depict a greater proclivity to use the internet, but immigrants show a lower proclivity to do so. Prior studies have reported the presence of a digital divide for minority groups, and this finding is consistent with that notion (Tsetsi and Rains, 2017; Gonzales, 2017). Among household attributes, those residing in dense urban areas display higher propensities to use the internet, presumably because they are more tech-savvy and can take advantage of urban services by doing so. Lower income individuals exhibit a lower proclivity for frequent internet use, as do individuals in households with children. The finding related to income is reflective of the digital poverty experienced by lower income individuals (Rideout and Katz, 2016; Katz et al., 2017), while the second finding related to influence of children may be a consequence of time constraints and household obligations faced by individuals in households with children (Bernardo et al., 2015).

5.3 Propensity of Shared Service Use

Frequency of shared use is treated as a binary dependent variable. The variable is uniformly zero for Generation X, and hence the millennial indicator does not enter the equation. Students, those with a higher education status, and those who are employed are more likely to use shared services; these findings are consistent with those reported in the literature and suggest that educated and employed individuals are likely to have the tools and tech-savviness to use these services (and this may explain, to some degree, the negative effects of these variables on car ownership) (Alemi et al., 2018; Clewlow and Mishra, 2017). Females are also more likely to use shared services, suggesting that young females (26-30 years old) are embracing these new modes of transportation more so than their male counterparts. Those with a driver's license are less likely to use shared mobility services, presumably because they are able to operate their own personal vehicles.

Among household attributes, individuals residing in households in denser urban areas are more likely to use shared services – a finding also reported by others (Clewlow and Mishra, 2017; Conway et al., 2018). Individuals in lower income households exhibit a lower propensity to use shared mobility services, presumably due to monetary constraints and the digital divide that comes with income disparities (Clewlow and Laberteaux, 2016). Individuals in households with children or multiple workers are also less likely to use these services; these households are likely to own personal vehicles, thus decreasing the proclivity to use these services. As expected, higher levels of vehicle ownership are associated with lower levels of shared service use, a finding consistent with that reported in the literature (Heno and Marshall, 2018; Conway et al., 2018). Technology-oriented individuals, indicated in the model by frequency of internet usage, are more inclined to use shared mobility services, presumably because the services require the use of mobile technologies and apps to access them.

5.4 Driver Vehicle Miles of Travel (VMT)

The key dependent variable of interest in this paper is the driver VMT (VMT as a passenger is not included due to the desire to focus on VMT undertaken as a driver). As expected, students, those with a higher education level, and those who are employed report higher levels of driver VMT relative to the base groups; these findings are consistent with the classical notion that these groups

generally exhibit higher levels of mobility (Stern, 1993). Homemakers report a higher level of driver VMT, presumably because they shoulder a greater burden of household responsibilities and chauffeur children to and from school and other activities (Chen and McKnight, 2007). Those with a driver's license also report higher levels of driver VMT for obvious reasons. Immigrants and those with a medical condition that limits mobility report fewer vehicle miles of travel as a driver; these findings are all consistent with expectations and reported previously in the literature (Tal and Handy, 2010; Bakker and van Hal, 2007).

Household attributes depict patterns of influence consistent with expectations and behaviors reported in the literature. Those residing in higher density areas report lower driver VMT, consistent with the notion that higher density environments are conducive to multimodal use and lower trip distances to access opportunities (Singh et al., 2018; Zhou and Kockelman, 2008). Lower income is associated with lower levels of driver VMT. Individuals in households with children report higher driver VMT (similar to Ye et al., 2018), presumably due to higher level of activity engagement that comes with having children in the home. Home ownership is associated with a higher level of driver VMT as is vehicle ownership. These findings are consistent with expectations and evidence in the literature (Polzin et al., 2014). Among period effect variables, a higher unemployment rate is associated with lower driving VMT, consistent with the notion that travel decreases in a time of recession (Garikapati et al., 2016; McMullen and Eckstein, 2012; Milioti et al., 2015). Internet use is positively associated with VMT as a driver, a finding similar to that reported by others who have documented the existence of a complementary relationship between virtual/online activity and physical in-person activity engagement outside the home (Mokhtarian, 2002). On the other hand, use of shared mobility services contributes negatively to driver VMT as expected; individuals who use shared mobility services would not drive as much as those who do not use such services. Those in the more compact areas of the Middle Atlantic region drive fewer VMT, while those in the more sprawled and auto-oriented areas of the West South Central region drive more VMT.

The key variable of interest is the millennial (cohort) indicator. This indicator depicts a negative coefficient in the driver VMT equation, clearly indicating that – even after including all other explanatory factors in the model and accounting for endogeneity – millennials drive less VMT than their observationally equivalent Generation X counterparts. This finding suggests that, all other things being equal, millennials drive fewer VMT than Generation X and they are therefore significantly different than the preceding generation when it comes to auto use. Given that the millennials indicator is also significant in the car ownership and internet use equations, and that both of these endogenous variables in turn enter the VMT equation as significant explanatory variables, the millennials indicator also has an indirect relationship on driver VMT through these mediating variables. Millennials use the internet more frequently, and those who use the internet more frequently drive more; thus the indirect effect of millennials on driver VMT (through the internet use frequency variable) is positive. The indirect effect through vehicle ownership is less clear; because vehicle ownership is a household attribute and likely reflecting overall household vehicle ownership (and not necessarily individual-level millennial vehicle ownership), it is difficult to isolate the indirect millennial effect that is mediated through vehicle ownership.

5.5 Error Correlations and Goodness-of-Fit

The joint simultaneous equations model system accounts for correlated unobserved attributes that may simultaneously affect multiple endogenous variables of interest. These correlated unobserved attributes manifest themselves in the form of error correlations across the dimensions being

considered. The variance-covariance matrix of the error terms is shown as a block just above the goodness-of-fit measures. A number of error covariances are found to be statistically significant (as expected). The error term corresponding to frequency of internet use is positively correlated with the error term corresponding to driver VMT; in other words, unobserved attributes that contribute to a higher frequency of internet use also contribute to a higher driver VMT. It is possible that individuals who use the internet more frequently are more active individuals who are variety-seeking in nature; these unobserved traits not only contribute to frequent internet use but also more driver VMT as the individuals seek a variety of pursuits outside the home. Similarly, frequency of shared services use and vehicle ownership both show positive error correlations with driver VMT. Once again, it appears that individuals who enjoy active lifestyles characterized by higher levels of shared mobility service usage and car ownership are also likely to engage in higher driver VMT. Another error correlation that is significant is that between frequency of shared mobility service use and frequency of internet use. It is likely that technology savviness positively impacts both of these endogenous variables, leading to the positive outcome. The presence of significant error correlations corroborates the appropriateness of using a joint simultaneous equations modeling approach for exploring inter-relationships among the choice dimensions considered in this paper.

The goodness-of-fit measures are provided at the end of Table 2. The measures are all consistent with expectations, with the model exhibiting a significantly better performance in fitting the data than the null model or the constants-only model. The adjusted ρ^2 value of nearly 0.3 (with respect to the constants only model) is quite in line with what might be expected for a simultaneous equations model with mixed endogenous variables that is estimated on a large sample disaggregate survey data set. Such data sets are inevitably characterized by a high degree of randomness in behaviors that cannot be fully explained by observed covariates.

5.6 Size and Nature of the “Millennial (Cohort) Effect” Relative to Other Effects

The contribution of each effect in explaining differences in driver VMT between millennials and Generation X was calculated using the approach described in Section 4.2. The computations yield estimates of the total net effects of various factors in explaining individual driver VMT. Based on the computations, the following results were obtained:

- A very large portion of the variance in driver VMT remains unexplained even after including all of the covariates and accounting for endogeneity through the use of a simultaneous equations model specification. The unexplained portion of driver VMT variance accounts for 73.6 percent of the total variance. Thus, only 26.4 percent of the variance in driver VMT is actually explained by the various effects.
- Socio-economic and demographic (SED) characteristics account for the vast majority of the explained variance in driver VMT. The SED effect is estimated to be 25.9 percent of the total driver VMT variance; given that the total explained variance is just 26.4 percent of the total variance, the fact that SED accounts for 25.9 percent suggests that socio-economic and demographic characteristics are the key factors that contribute to differences in driver VMT (and possibly other travel characteristics as well).
- The remaining effects are tiny. The period effect (PE) explains 0.21 percent, the geographical effect (GE) explains 0.12 percent, and the cohort (millennial) effect (CE) explains just 0.16 percent of the variation in driver VMT. In other words, the millennial (cohort) effect is statistically significant (as seen in the model estimation results) and yet very small in size.

These results are not all that unexpected. When a simple single-equation linear regression model of ln VMT was estimated using all variables in the data set as explanatory factors, the best fit model yielded an R^2 value of just 0.296 (note that this model included the whole suite of explanatory variables available, regardless of intuitiveness, and so we characterize this as the explanatory variable dump or EVD model; also, this EVD model had a much lower R -bar squared value than the implied R -bar squared model from our joint model). Again, even in this EVD model, the millennial indicator turned statistically insignificant – further confirming that its effect is rather small and inconsequential. The bottom line is that millennials differ (fundamentally) from Generation X by a tiny amount, at least once millennials reach an age-mature lifecycle stage, and it is unlikely that this small difference will contribute to any substantial shifts in the transportation ecosystem. On the other hand, rapidly evolving technologies and shared mobility services, automated transportation systems, and other technological innovations are likely to engender greater shifts in transportation behaviors than the mere transition from one generation to the next. It should be emphasized again here that the results of this study are obtained in the context of a comparison between two generations when they were both 26-30 years of age. Previous studies have examined travel behavior of millennials when they were younger (e.g., McDonald, 2015). At an earlier stage in age, millennials were perhaps indeed substantially more different from Generation X (during teenage years, for example). What this study has found is that age-mature millennials (well into adulthood) are not all that different than their equivalent age-mature Generation X peers. Having said that, the large unexplained portion suggests that much remains to be learned about the factors that contribute to driver VMT.

6. DISCUSSION AND CONCLUSIONS

Over the past decade, considerable attention has been paid to the activity-travel choices of millennials, primarily because they appeared to depict patterns of behavior that differed from those of predecessor generations. Because they exhibited lower levels of driver's license holding, car ownership, and car use on the one hand, and higher prevalence of alternative mode use and urban residential location choice on the other, it was postulated that the millennial generation would and could bring about a seismic shift in the mobility space – one that would see communities and cities move towards a more sustainable transportation ecosystem. The question remained, however, whether millennials would continue to depict more sustainable travel behaviors over time (as they aged) or would simply revert to the patterns of behavior seen among prior generations. If millennials were fundamentally different (in attitudes, values, and lifestyle preferences) than previous generations, then perhaps the differences in behavior were real and would prove to be lasting and permanent in nature. On the other hand, if the differences were not attributable to the cohort effect, but were simply due to the many other factors that influence travel choices, then the differences depicted by millennials may not survive the test of time.

Although there has been considerable research on millennial travel behavior, most studies have not been able to systematically isolate and quantify the millennial (cohort) effect in explaining differences in activity-travel choices. As there are many confounding factors that may contribute to changes in activity-travel choices across generations, estimation of effect sizes is not straightforward and requires data that would allow for a controlled comparison and analysis of multiple generations. This paper attempts to shed light on the “millennial difference”, i.e., the true cohort effect that contributes to differences seen among age-mature millennials (relative to age-mature Generation X individuals) with respect to activity-travel behaviors. The analysis utilizes data from the 2001 and 2017 National Household Travel Surveys in the United States to compare

Generation X and millennials when they were both 26-30 years of age. By selecting subsamples within a narrow age band, the analysis eliminates and controls for the age effect.

A simultaneous equations model system is estimated to relate multiple dependent variables while recognizing the presence of endogeneity and the presence of correlated unobserved variables that simultaneously affect multiple choice outcomes. The model system considered four endogenous outcomes – car ownership, frequency of internet use, frequency of shared mobility service use, and driver vehicle miles of travel (VMT). A millennial cohort indicator was entered as an explanatory variable into equations for multiple endogenous variables; it was found that the indicator was significant in explaining household vehicle ownership, frequency of internet use, and driver vehicle miles of travel – with millennials depicting lower levels of driver VMT and higher levels of internet use. In the context of explaining the variance in driver VMT, the model system allowed the computation of a number of effect sizes including the socio-economic/demographic effect, the geographic effect, the period effect, and the cohort (millennial) effect. The period effect accounted for the differences in economic conditions and technology landscape between the two time points, thus recognizing that millennials came of age in a different era that saw one of the worst economic recessions and the emergence of the internet and mobile connectivity as powerful tools for communication and activity fulfillment.

Results of the model estimation effort show that driver VMT is largely unexplained even after including a number of explanatory factors. Nearly 74 percent of the total variance in driver VMT remains unexplained. Within the explained variance, the vast majority is explained by socio-economic/demographic variables; all other factors and effects explain just tiny fractions of the variance in driver VMT. The millennial effect is statistically significant, but miniscule in effect size explaining just about 0.16 percent of the total driver VMT variance. In other words, millennials appear to be largely different from Generation X in driver VMT – not because they are fundamentally different in attitudes, values, and lifestyle preferences – but because they differ in socio-economic/demographic characteristics and the technologies available to them (e.g., internet, smartphones and apps, and shared mobility services).

In the interest of computational simplicity and in the absence of an alternative theoretical basis, all socio-economic and demographic variables were treated as exogenous variables in this study. In reality, a few socio-economic and demographic choices may be endogenous in nature, with millennials fundamentally different from Generation X when it comes to employment, education, and household structure preferences. However, there is no way to determine whether differences in socio-economic characteristics (between the two generations) are due to the millennial effect or due to other contextual factors such as period effects (that capture economic and technological conditions under which lifestyle and lifecycle choices are being made). This can be ascertained by treating selected socio-demographic variables as endogenous variables, but the dimensionality of the simultaneous equations model system would explode, rendering model estimation computationally challenging.

Even if socio-economic and demographic choices were treated as endogenous variables, it is not likely that the millennial effect would be all that larger in size (than what has been depicted in this paper). Many socio-economic and demographic choices are a consequence of the situational context in which people find themselves; as such, the millennial effect would contribute only partially to explaining socio-demographic choices. Even if it were assumed that the millennial effect accounts for one-half of the socio-demographic effect (which is an extremely unlikely scenario), the net millennial effect in explaining VMT as a driver would not be higher than about 13 percent. What is actually more surprising is that the period effect is so small in size. It is more

likely that socio-economic/demographic differences (effects) are an outcome of the period effects (i.e., severe recession, shift to knowledge economy, and emergence of internet of things); hence, if socio-economic variables were treated as endogenous, it is more likely that the size of the period effect would increase while the size of the millennial effect remained largely unchanged.

This work suggests that millennials are not all that different from Generation X, once all other confounding factors are controlled (at least when comparing age-mature individuals in the 26-30 years range). Thus, hopes that millennials will bring about a transformational shift in the transportation landscape are unlikely to come to fruition. Phenomena that are likely to bring about such shifts include the internet of things, ubiquitous connectivity, mobile technologies, emerging (shared) mobility services, automated and driverless transportation systems, and economic factors (costs of services and economic conditions). This is not to say that changes in lifestyle preferences and values will not play a role in advancing changes in activity-travel behaviors; it is just that these factors are likely to play a much smaller direct role than the technological, environmental, and economic forces that shape behaviors as well as attitudes, values, and preferences in the first place. In fact, what this study has shown is that the unexplained portion of variance in driver VMT is very large and remains largely unexplored. Future research efforts should aim to unravel the causal factors that account for this large unexplained portion.

A key limitation of this study is that the data sets did not include built environment attributes that are likely to be very significant determinants of driver VMT. At least some of the unexplained portion is likely attributable to built environment attributes not included in the study data. Although this is an important limitation, the inclusion of such attributes is unlikely to change the study conclusions because the millennial effect measured here is probably capturing some of the built environment effects arising from residential location choice decisions. If built environment attributes were included explicitly, not only would the unexplained variance decrease, but the millennial effect would likely decrease as well. It would be of value in future research to explore the consequences of including built environment variables on the size of the millennial effect.

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