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A validation of the low mileage bias using naturalistic driving study data

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ABSTRACT

Introduction: This paper evaluated the low mileage bias (LMB) phenomenon for senior drivers using data mined from the Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study. Supporters of the LMB construct postulate that it is only those seniors who drive the lowest annual mileage who are primarily responsible for the increased crash rates traditionally attributed to this population in general. *Method:* The current analysis included 802 participants, all aged 65 or older who were involved in 163 property damage and injury crashes, and deemed to be at-fault in 123 (75%) of those instances. Poisson regression models were used to evaluate the association between annualized mileage driven and crash risk. *Results:* Results show that the crash rate for drivers with lower annualized mileage (i.e., especially for those driving fewer than approximately 3000 miles per year) was significantly higher than that of drivers with higher annualized mileage, and that 25% of the overall sample were low- mileage drivers according to this criterion. Data were also evaluated by gender and meta-age group (i.e., younger-old: 65–74 and older-old: 75–99), and the results were consistent across these sub-groups. *Conclusions:* This study provides strong support for the existence of the LMB. *Practical applications:* These results can help to reshape how transportation safety stakeholders view senior drivers in general and help them to focus their efforts on those seniors most in need of either risk-reducing countermeasures or alternative means of transportation.

1. Introduction

Senior drivers generally have a substantially higher crash rate per mile driven than middle-aged drivers, a rate that is comparable to that of the youngest and least-experienced drivers (Insurance Institute for Highway Safety, 2014; Kua, Korner-Bitensky, Desrosiers, Man-Son-Hing, & Marshall, 2007; Owsley, Ball, Sloane, Roenker, & Bruni, 1991; Ryan, Legge, & Rosman, 1998; Stutts, Martell, & Staplin, 2009). This is a good indication of the driving risk associated with a particular individual on a per mile driven basis, and this paper is primarily focused on this level of risk analysis. However, when measured by the number of crashes per licensed driver, those aged 74+ consistently demonstrate the lowest risk of any of the driving age groups (National Highway Traffic Safety Administration, 2015).

One key factor that may explain this apparent disparity between the two opposing ideas noted above is that seniors tend to drive far fewer miles per year, thus incurring far less exposure. In general, annual mileage trends downward with increasing age after peaking at around age 40 (Santos, McGuckin, Nakamoto, Gray, & Liss, 2011). Janke (1991) postulated that simply examining mileage and crash rate alone may be misleading because it ignores the fact that crash risk does not increase linearly with increased mileage, perhaps because low-mileage drivers are more likely to drive in riskier situations (i.e., congested city traffic with many intersections). Higher-mileage drivers, on the other hand, likely accumulate much of their mileage on controlled-access highways, which are inherently lower risk (i.e., in terms of number of crashes per mile of driving exposure). Janke (1991) also points to the possibility that mental and/or physical health status may be the mediating factor that leads to both the decreased driving distance and the increased crash rate.

Hakamies-Blomqvist, Raitanen, and O'Neill (2002) coined the term *low mileage bias (LMB)* to capture the notion that the general trends showing increased crash rates for seniors are misleading and hypothesized that the seniors driving the lowest annual mileage are primarily responsible for the characteristic upturn in crash rate per mile driven. Hakamies-Blomqvist et al. (2002) based their conclusions on a survey of two age groups of Finnish drivers, 26–40 and 65+. When they divided the data into low, medium, and high annual driving distances (i.e., <3000 km, 3000–14,000 km, and >14,000 km per year, respectively), they found little or no differences in crash rates between the two age groups for those in the medium- or high-mileage categories. Instead, the characteristic increase in crash rate per mile driven for seniors was only demonstrated with respect to the lowest mileage drivers. Like

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Janke (1991), Hakamies-Blomqvist et al. (2002) also recognized that low-mileage drivers may have an increased crash risk due to either the level of risk associated with the types of driving and roadways traveled by this particular group or due to functional impairment in dimensions important for safe driving (e.g., cognition, perception, psycho-motor skill, and physical robustness). Several subsequent studies (Keall & Frith, 2006; Koppel et al., 2005; Langford, Methorst, & Hakamies-Blomqvist, 2006) produced findings that support the LMB hypothesis using survey data from different countries. In particular, Koppel et al. (2005) collected screening and driving performance data as well as LMB-specific data. Their analysis revealed that seniors in the low-mileage bin scored significantly worse on a set of functional assessments and on a relicensing driving examination, which strongly supports driver status as an important factor in the consideration of LMB.

Others have called into question the mostly subjective methods used to establish and support LMB (Staplin, Gish, & Joyce, 2008). Examining data from the National Household Travel Survey (NHTS), Staplin and his colleagues argued that the use of self-reported mileage and crash data are potentially far less accurate than would be hoped for, and, worse, that the specific direction of the expected bias in these estimates may be largely responsible for the findings that support the existence of LMB (Staplin et al., 2008). In response, Langford, Koppel, McCarthy, and Srinivasan (2008) performed additional calculations using NHTS data that supported LMB, but at a somewhat reduced level. The authors of both articles agreed on the need for more-objective data sources, for both mileage driven and crash involvement rates, to help refine our understanding of this important issue. If LMB were to be supported by such an objective set of data, the understanding of this phenomenon may help to better focus future efforts aimed at enhancing roadway safety and mobility for seniors.

The purpose of this study was to address the need, as noted above, to apply more objective sources of data to the exploration of the LMB construct.

2. Materials and methods

2.1. SHRP 2 naturalistic driving study data

The analysis in this paper was based on aggregated mileage and crash data mined from the Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS) database (Dingus et al., 2015). A total of 802 participants were screened for inclusion in the current analysis based on three criteria: (a) age 65+; (b) the presence of complete trip and crash records; and (c) a minimum of 6 months of driving participation (to provide a sufficiently long sample of each individual's driving habits). As the LMB construct has been chiefly put forth as a way to explain senior driver behaviors and crash rates, we chose to evaluate only senior drivers (i.e., those 65 and older; Guo et al., in press) in this analysis. This data analysis was approved by the Virginia Tech Institutional Review Board (IRB).

This study included only the most serious three levels of crash severity, levels I to III based on the SHRP 2 classification. Level I crashes are those involving airbag deployment, personal injury, rollover, high delta-V, or any required vehicle towing; Level II crashes are other police-reportable crashes (i.e., with sufficient property damage to warrant reporting); and Level III crashes are relatively minor crashes with another object. Level IV crashes, the lowest in severity (e.g., curb strikes), were excluded. Analyses were conducted for both overall crashes and at-fault crashes only. The annualized mileage of each participant was derived by dividing the actual total mileage driven by the participant by the number of years the participant was in the study. For instance, if a participant drove 20,000 miles during his 2.0 years of participation in the study, the participant's annualized mileage would be 10,000 miles per year.

2.2. Statistical analysis

Poisson regression and its derivative negative binomial regression are state-of-practice approaches for analyzing crash count data (Chen, Fang, Guo, & Hanowski, 2016; Fitch et al., 2013; Guo & Fang, 2013; Guo, Fang, & Antin, 2014; Ouimet et al., 2014). Preliminary analysis showed that the overall crashes and at-fault crashes satisfied the variance assumption of Poisson regression well and that over-dispersion was not present (Pearson chi-square/degree-of-freedom is 1.1–1.2). Therefore, a standard Poisson regression model was used to link a driver's annualized mileage with the observed crash rate, adjusted by driver age and gender.

The number of crashes was assumed to follow a Poisson distribution,

$$Y_i \sim \text{Poisson}(E_i\lambda_i),$$

where $E(Y_i) = Var(Y_i) = E_i\lambda_i$; Y_i is the number of overall crashes or at-fault crashes for driver i; λ_i is the expected crash rate (the expected number of crashes per 1 million miles driven) for driver i; the exposure E_i is measured by miles driven (per million miles).

A log-link function was used to link the expected crash rate λ_i (per 1 million miles driven) with three covariates: log-transformed annualized mileage, driver age group, and gender. That is $\log(\lambda_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}$, where $X_{1i} = \log\left\{\frac{\text{total mileage (in miles)}_i}{\text{timespan (in years) betwen first and last trip}_i}\right\}$ is log-transformed annualized mileage for driver i; age group variable $X_{2i} = 1$ if driver i was between 75 and 99 years old at the time of enrollment in the study, 0 if between 64 and 74 years old; gender variable $X_{3i} = 1$ if driver i is female and 0 if male; β_0–β_3 are regression coefficients. Crash rate ratio with respect to a covariate is calculated by taking the exponential of the corresponding regression coefficient. Natural logarithmic transformation is a widely used practice to account for the right-skewness of mileage data. Driver age and gender were used to adjust for demographic-related variations in crash risk.

The age factor was consolidated into the two meta-age groups indicated above in order to (a) coincide with generally observed overall

Table 1
Distributions of safety outcomes and annualized mileage by age group.

Driver age	Number of drivers	% Male	Overall crashes	At-fault crashes	Total miles driven	Driver's annualized mileage (miles per year)			
						Mean	s.d.	Min	Max
65–69	195	50.8	32	23	1,936,430	7061	4934	421	28,435
70–74	162	51.9	23	15	1,605,109	7205	5017	18	28,967
75–79	239	54.8	36	28	1,835,993	5757	4058	62	25,191
80–84	141	50.4	59	45	1,179,706	5453	3640	863	25,256
85–89	56	62.5	11	10	289,581	4152	2643	406	10,668
90–94	7	71.4	2	2	23,815	3703	1779	733	5871
95–99	2	50.0	0	0	3311	1811	198	1672	1951
Total	**802**	**53.1**	**163**	**123**	**6,873,944**	**6173**	**4428**	**18**	**28,967**

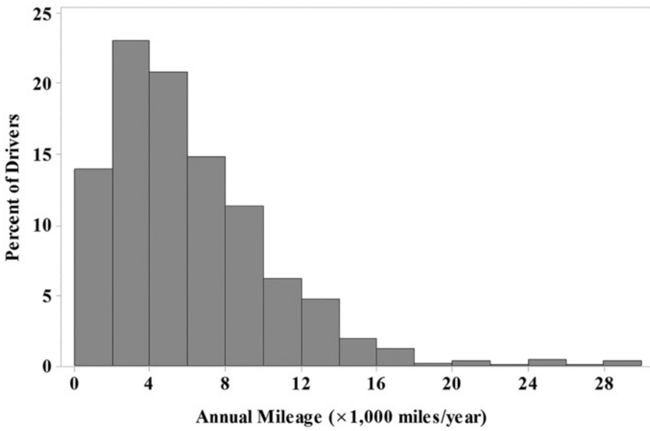

Fig. 1. Overall distribution of annualized mileage.

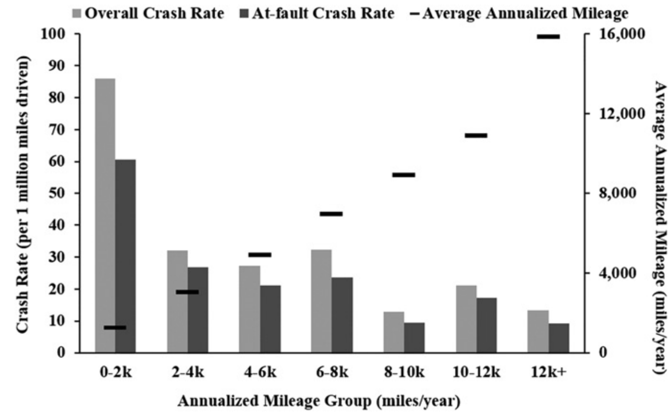

Fig. 2. Observed crash rate and average annualized mileage by annualized mileage group.

crash rates (i.e., the tendency to see a sharp increase in crash rate at around age 75 (Stutts et al., 2009)), and (b) ensure each age stratum had sufficient sample size for the intended analyses. Preliminary analyses indicate that there was no significant interaction effect among these three covariates, hence a main effects model was used.

3. Results

3.1. Safety outcomes

The 802 participants were involved in 163 overall crashes (18 Level I crashes, 22 Level II crashes, and 123 Level III crashes) and 123 at-fault crashes (75% of the overall crashes, including 12 Level I crashes, 10 Level II crashes, 101 Level III crashes). Participants drove 6,873,944 miles during the study. The distributions of safety outcomes and annualized mileage across the age groups are shown in Table 1.

Average annualized mileage per participant was 6173 miles per year. In general, drivers in the older age groups demonstrated lower annualized mileage, but the within-group variation is large. The distribution of annualized mileages is shown in Fig. 1. The right-skewed shape justified the use of log transformation on annualized mileage data.

The distributions of safety outcomes and mileage across the annualized mileage groups are shown in Table 2. We binned the annualized mileage into groups with 2000 mile intervals for demonstration purpose. The observed crash rate and average annualized mileage by annualized mileage group are shown in Fig. 2. Results clearly show that both the overall crash rate and at-fault crash rate decrease as average annualized mileage increases.

3.2. Poisson regression results

The results of the Poisson regression are shown in Table 3. Model fit was checked using the ratio of Pearson chi-square to its degree-of-freedom (SAS® GENMOD procedure). The ratios for overall crashes (1.21) and at-fault crashes (1.11) are both close to 1, suggesting good model fit. The log-transformed annualized mileage is significantly associated with both overall crash rate and at-fault crash rate. Crash rate ratio is 0.59 for overall crash and 0.63 for at-fault crash. This implies that if Driver A drives *M* miles per year and Driver B drives 2.718 M miles per year, then Driver B will have an expected overall crash rate 41% lower than that of Driver A and an expected at-fault crash rate 37% lower than Driver A. Driver age and gender also have significant impacts on crash risk. Drivers in the older-old meta-age group (75–99) have an expected 80% higher overall crash rate and 110% higher expected at-fault crash rate than drivers in the younger-old meta-age group (65–74). Female drivers have marginally significant 36% higher expected overall crash rate (p-value = 0.0575) and 59% higher at-fault crash rate than male drivers. The fitted curves for different age and gender groups by Poisson regression are shown in Fig. 3. Both overall crash rate and at-fault crash rate dramatically increase for

Table 3
Poisson regression results.

Regression coefficient	Estimate	Standard error	Crash rate ratio (95% CL)	*p*-Value
Overall crashes				
Intercept	7.31	1.05	–	<0.0001
Log(annualized mileage)	−0.52	0.12	0.59 (0.47, 0.74)	<0.0001
Age group (75–99 vs. 65–74)	0.59	0.17	1.80 (1.29, 2.51)	0.0005
Gender (female vs. male)	0.30	0.16	1.36 (0.99, 1.86)	0.0575
At-fault crashes				
Intercept	6.33	1.23	–	<0.0001
Log(annualized mileage)	−0.46	0.13	0.63 (0.48, 0.82)	0.0006
Age group (75–99 vs. 65–74)	0.74	0.20	2.10 (1.42, 3.11)	0.0002
Gender (female vs. male)	0.46	0.18	1.59 (1.10, 2.28)	0.0127

Table 2
Distribution of safety outcomes and mileage by annualized mileage group.

Annualized mileage group	Number of drivers	% Male	% Drivers age 65–74	Mean annualized mileage	% Of driver sample	Total overall crash	Total at-fault crash	Total miles driven
0–2 k mi	112	44.6	39.3	1259	14%	17	12	198,028
2–4 k mi	185	40.0	37.3	3039	23%	24	20	747,773
4–6 k mi	167	49.1	35.3	4929	21%	31	24	1,132,133
6–8 k mi	119	62.2	47.9	6959	15%	37	27	1,142,300
8–10 k mi	91	67.0	49.5	8936	11%	15	11	1,167,389
10–12 k mi	50	70.0	64.0	10,905	6%	16	13	754,596
12 k + mi	78	64.1	65.4	15,872	10%	23	16	1,731,725
Total	**802**	**53.1**	**44.5**	**6173**	**100%**	**163**	**123**	**6,873,944**

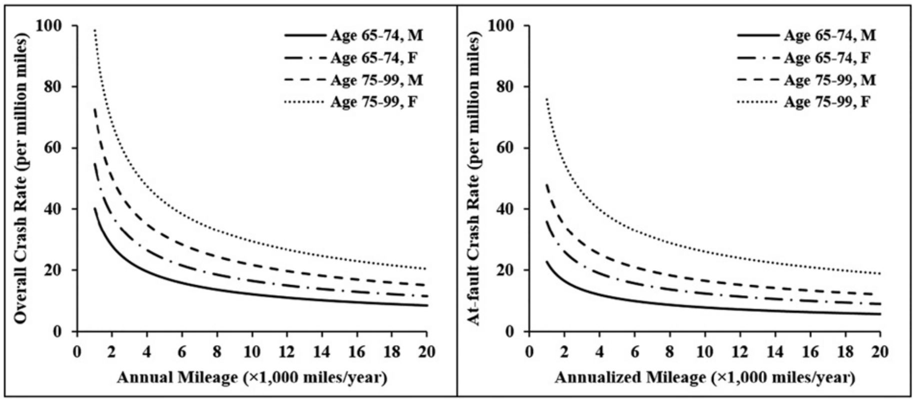

Fig. 3. Fitted overall and at-fault crash rate by annualized mileage.

the low mileage drivers (i.e., those who drive approximately 3000 or fewer miles per year).

The percentages of drivers with low annualized mileage (<3000 miles/year) by age and gender groups are shown in Table 4. About 25% of all 802 participants demonstrate very low annualized mileage. The percentage increases with age, and the percentage is consistently higher for female drivers than for male drivers. These results strongly agreed with our findings in regression analysis that lower annualized mileage, higher driver age, and being a female driver are associated with higher crash risk.

4. Discussion

The results clearly demonstrate that LMB is evident in the SHRP 2 data set. Based solely on objectively collected crash and mileage data, outcomes of the current analysis strongly support the findings of Hakamies-Blomqvist et al. (2002) and other subsequent researchers who have claimed that it is those seniors driving the relatively lowest annualized mileage who are primarily responsible for the increased crash rates traditionally associated with senior drivers in general. The fitted curves in Fig. 3 show a gentle monotonic increase in crash rate with decreasing annualized mileage until annualized mileage dips below approximately 3000 miles per year, at which point we see a much more dramatic increase in crash rate for both overall as well as at-fault crashes only. The observed crash rate by annualized mileage group in Fig. 2 demonstrate a monotonically increasing crash rate with decreasing annualized mileage. As study participants were deemed to be at-fault in almost 75% of the crashes, it is not surprising that the patterns demonstrated are nearly identical between the overall crashes and at-fault crashes in Figs. 2 and 3.

Curves were plotted respectively for each gender by two age groups (younger-old: 65–74 and older-old: 75–99). The general pattern noted above was demonstrated in each of these four curves (i.e., the dramatic increase in predicted crash rate when annualized mileage dips below approximately 3000 miles per year). Predicted crash rates for the older old group were consistently higher across the range of annualized mileage than that of the younger old group, regardless of gender. Also, the predicted crash rates for females were consistently higher than that for males across the range of annualized mileage, regardless of meta-age group membership (i.e., younger-old vs. older-old). On the surface, the difference between the two meta-age groups is in the direction one might expect, as the older-old group may have generally more functional impairments than the younger-old, though examining their functional status was beyond the scope of the current analysis.

There has been some research to support the gender differences seen in the current analyses. Baker, Falb, Voas, and Lacey (2003) analyzed FARS data and found that the proportion of older female drivers involved in fatal crashes was consistently greater than that for older male drivers from 1982 to 2001. And Stutts et al. (2009) found a slight increase in fatal involvement crash ratios for women versus men in the 60–79 age range. However, they also found no substantive difference in this metric between men and women aged 80+.

These findings lead to two basic questions. First, why would driving fewer miles per year be associated with an increased crash rate? As noted above, Janke (1991) pointed to two possible underlying factors (which may themselves be interrelated): (a) senior drivers who avoid highway travel may be unwittingly exposing themselves to higher-risk urban driving scenarios on a per mile basis compared with the relatively safer (albeit much higher speed) controlled-access highway system, and (b) it may be that functional impairment profiles are mediating factors for both the reduced mileage and the increased crash rate. That is, senior drivers with poor overall fitness to drive tend both to drive less based on self-imposed restrictions, and to have a higher crash risk per mile driven. Therefore, drivers with poor fitness would drive less but with higher risk per mile, exactly the LMB phenomenon. Limited support is available with regard to the road-type selection alternative noted above. However, with respect to the fitness to drive alternative, much of the research literature suggests a strong relationship between a driver's functional capabilities and driving behavior and risk (Ball et al., 1998; Guo, Fang, & Antin, 2015; Owsley et al., 1998; Stutts, Stewart, & Martell, 1998). Stutts et al. (1998) administered a battery of cognitive tests to 3238 seniors, aged 65 and above. They found that the lowest scorers were 1.5 times more likely to be in a motor-vehicle crash than the highest scorers. Owsley et al. (1998) evaluated 294 drivers aged 55–87. They found that those with a 40% or greater reduction in useful field of view (UFOV) scores, an indication of visual sensory functioning in several dimensions, were more than twice as likely to experience a motor-vehicle crash during the subsequent 3 years. Ball et al. (1998) found that individuals with visual and/or cognitive

Table 4
Number and percent of drivers with low annualized mileage (<3000 miles/year).

Age group	Female		Male		Total	
	n	Percent	n	Percent	n	Percent
65–69	23	24%	18	18%	41	21%
70–74	17	22%	14	17%	31	19%
75–79	33	31%	26	20%	59	25%
80–84	29	41%	15	21%	44	31%
85–89	10	48%	11	31%	21	38%
90–94	1	50%	2	40%	3	43%
95–99	1	100%	1	100%	2	100%
Total	**114**	**30%**	**87**	**20%**	**201**	**25%**

functional impairments reported more driving avoidance or driving self-restriction than those without.

The second question is how prevalent are low-mileage drivers within the senior population? The current analysis suggests that U.S. seniors who drive less than 3000 miles per year would be considered low-mileage drivers, and such individuals comprise approximately 20% to 50% of the samples among most of the different age and gender groups in the current analysis (Table 4).

This study is limited by the degree to which the seniors sampled may or may not be representative of senior drivers in general. However, the SHRP 2 sample includes several hundred seniors sampled from diverse geographical areas demonstrating fairly broad ranges of annualized mileage driven. Some may surmise that it is primarily those seniors who are relatively the most fit and confident who will volunteer to participate in a naturalistic driving study. If this in fact were the case in the SHRP 2 NDS, then we may expect there to be an even higher proportion of low-mileage drivers on U.S. roads than was found in the currently analyzed sample (25% across the overall age spectrum sampled).

5. Conclusion

The LMB hypothesis, strongly supported by the results of this study, helps to better focus the attention of all stakeholders concerned with senior driver safety (e.g., policy-makers, departments of motor vehicles, researchers, personal physicians, family members, passengers, and senior drivers themselves) on those individuals most in need of further clinical assessment or the implementation of safety-enhancing countermeasures (i.e., individuals demonstrating low annualized mileage). One might conclude from these findings that simply encouraging low mileage seniors to drive more would reduce their crash rate. However, it is unlikely that the association demonstrated in this study would work in that "reverse" direction, especially if overall fitness to drive is the true mediating factor leading both to the reduced mileage and increased crash rate per mile driven. On the other hand, well-designed interventions will help to keep the most-capable seniors driving longer and more safely where possible, and will also help to guide those in need toward alternative means of staying mobile and independent.

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