HHS Public Access
Author manuscript
*Traffic Inj Prev*. Author manuscript; available in PMC 2021 October 12.

Published in final edited form as:
*Traffic Inj Prev*. 2020 October 12; 21(SUP1): S54–S59. doi:10.1080/15389588.2020.1805445.

# Vehicle safety characteristics in vulnerable driver populations

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## Abstract

**Objective:** National data suggest drivers who are younger, older, and have lower socioeconomic status (SES) have heightened crash-related injury rates. Ensuring vulnerable drivers are in the safest vehicles they can afford is a promising approach to reducing crash injuries in these groups. However, we do not know the extent to which these drivers are disproportionately driving less safe vehicles. Our objective was to obtain population-based estimates of the prevalence of important vehicle safety criteria among a statewide population of drivers.

**Methods:** We analyzed data from the NJ Safety and Health Outcomes warehouse, which includes all licensing and crash data from 2010–2017. We borrowed the quasi-induced exposure method's fundamental assumption—that non-responsible drivers in clean (i.e., only one responsible driver) multi-vehicle crashes are reasonably representative of drivers on the road—to estimate statewide prevalence of drivers' vehicle characteristics across four driver age groups (17–20; 21–24; 25–64, and ≥65) and quintiles of census tract median household income (n=983,372). We used NHTSA's Product Information Catalog and Vehicle Listing platform (vPIC) to decode the VIN of each crash-involved vehicle to obtain model year, presence of electronic stability control (ESC), vehicle type, engine horsepower, and presence of front, side, and curtain air bags.

**Results:** The youngest and oldest drivers were more likely than middle-aged drivers to drive vehicles that were older, did not have ESC, and were not equipped with side airbags. Additionally, across all age groups drivers of higher SES were in newer and safer vehicles compared with those of lower SES. For example, young drivers living in lowest-income census tracts drove vehicles that were on average almost twice as old as young drivers living in highest-income tracts (median [IQR]: 11 years [6–14] vs. 6 years [3–11]).

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Supplemental data for this article are available online at https://doi.org/10.1080/15389588.2020.1805445.

**Conclusions:** Vehicle safety is an important component of seminal road safety philosophies that aim to reduce crash fatalities. However, driver groups that are overrepresented in fatal crashes--young drivers, older drivers, and those of lower SES—are also driving the less safe vehicles. Ensuring drivers are in the safest car they can afford should be further explored as an approach to reduce crash-related injuries among vulnerable populations.

**Keywords**

Automobile driving; young drivers; teen drivers; older drivers; traffic accidents; vehicle safety

## INTRODUCTION

Despite advances in road design and vehicle technology, motor vehicle crashes continue to be a leading cause of injury-related death in the US, particularly among the youngest and oldest drivers. For young drivers, Graduated Driver Licensing (GDL) programs remain the most effective approach for reducing crash fatalities. However, the slowed progression in enhancing and recent reversals of state GDL policies are concerning (Williams et al. 2016). Further, risk reduction messaging aimed at young drivers and their parents have produced limited results in changing young drivers' behaviors or further reducing their crash risk (Curry et al. 2015). On the other end of the age spectrum, older drivers (age ≥65) have the highest crash fatality rate of any age group despite having lower overall crash rates than middle-aged drivers (Cicchino and McCartt, 2014; Palumbo et al. 2019). This is likely in part due to increased frailty related to changes in physical health (e.g., muscle mass, bone density and geometry) (Cicchino 2015). Regardless of age, there is additional evidence of a wide and growing socioeconomic disparity in motor vehicle crashes, with individuals of lower socioeconomic status (SES) overrepresented in fatal crashes (Harper et al. 2015). There remains a dearth of knowledge related to the origins of socioeconomic disparities in crash involvement and outcomes (Harper et al. 2015; Girasek and Taylor, 2010). Thus, there is a critical need to understand factors that contribute to these vulnerable populations' increased burden of crash-related injuries in order to identify effective interventions.

One promising complementary approach to reducing crash injuries is ensuring vulnerable drivers are in the safest vehicles they can afford. This is consistent with seminal road safety philosophies, including the Haddon Matrix and the systems approach to road safety, and has been recommended by the Insurance Institute for Highway Safety (IIHS). Importantly, it may be effective regardless of the factors underlying, or magnitude of, a driver's crash risk. In the US, IIHS has published recommendations of "good choice" and "best choice" vehicles in varying price ranges that meet important safety criteria for young drivers (www.iihs.org/ratings/safe-vehicles-for-teens); these criteria include larger, heavier vehicles with lower horsepower engines, electronic stability control, and the best possible safety ratings. The potential for vehicle characteristics to reduce crash fatalities is evidenced by a study of the National Highway Traffic Safety Administration's (NHTSA) FARS and GES data (Fausto and Tefft 2018) that found that crash-involved older drivers in vehicles of model years 2010 and newer were nearly half as likely to be killed compared with older drivers in vehicles of model years 2000–2009. Several survey studies have found that younger drivers are more likely to drive vehicles that are older, smaller, and lack widely available safety features (Eichelberger et al. 2015; Oviedo-Trespalacios and Scott-Parker 2018), heightening their risk of crash-related injury or death (Høye 2019). This pattern has also been documented in lower income populations (Girasek and Taylor, 2010). However, there has yet to be a population-based study that more fully characterizes the safety of vehicles driven by drivers of different ages and income levels and determines the extent to which these vulnerable drivers are disproportionately (compared with middle-aged drivers and drivers of higher income levels) driving less safe vehicles.

Thus, the objective of this study was to obtain population-based estimates of the prevalence of important vehicle safety criteria among the general population of drivers. To this end, we analyzed data from the New Jersey Safety and Health Outcomes (NJ-SHO) warehouse, a unique linked data source that includes traffic safety data for NJ drivers, from 2010–2017. We utilized an expanded application of quasi-induced exposure (QIE) methods established in our prior work (Curry 2017) to compare the presence of specific vehicle characteristics—including model year, type, engine size, and the presence of safety features—for drivers of various age groups and income levels.

# METHODS

## Data Source

The unique NJ-SHO warehouse links data from multiple statewide data sources and includes the full history of driver licensing and police-reported crashes of every NJ driver from 2004 through 2017 (n≈11 million; see Curry et al. 2019 for details). Ninety-six percent of crash-involved NJ drivers matched with a unique licensing record. Vehicle data available in the crash database include make, model, model year, and full Vehicle Identification Number (VIN). Driver-level variables included age and sex. License status at the time of the crash was obtained from licensing data. Using ArcGIS, we geocoded the residential address of each crash-involved driver (from the crash report [primary source] or licensing data [secondary source]) to their census tract; we were able to identify the census tract of 97% of crash-involved drivers. We then obtained the median household income for each NJ census tract from the 2009–2013 American Community Survey 5-year estimates.

## Vehicle Data

We used NHTSA's Product Information Catalog and Vehicle Listing (vPIC) platform to decode the VIN of each crash-involved vehicle (vpic.nhtsa.dot.gov). NHTSA requires vehicle manufacturers to submit data to vPIC on all regulated vehicles for model years 1981 and newer. We utilized a Python script routine to submit the first 11 characters of each crash-involved vehicle's VIN to vPIC to obtain detailed information, including model year, vehicle type (passenger cars, SUVs, other multipurpose passenger vehicles, trucks, and other vehicles), engine horsepower, and the presence of safety features such as front, side, and curtain airbags (all required data fields in vPIC). Overall, we matched the VIN of 89% of crash-involved vehicles with information in the vPIC platform; matching rates increased with each crash year (in 2010: 82%, in 2017: 95%). Data obtained from vPIC included electronic stability control (ESC) status for <1% of vehicles (an optional data field in vPIC); thus we created a proxy variable for presence of ESC from an alternative data source. For model year 2005–2011 vehicles, we linked vehicle make, model, and model year with published lists of vehicles in which ESC was present on standard models (at safercar.gov). For model year 2012 and newer vehicles, ESC was required in vehicles of 10,000 pounds or less per federal safety standards. Gross vehicle weight rating (GVWR) data from vPIC was used to classify vehicle weight. For these vehicle years, GVWR data were available for 20% of passenger cars and 99% of other vehicles; passenger cars were assumed to weigh less than 10,000 pounds when weight was unavailable. Vehicles that were included on the published lists for model years 2005–2011 or met the weight criteria for model years 2012 and newer were classified as having ESC; all other vehicles were classified as not having ESC.

## Application of Quasi-Induced Exposure (QIE) Methods

QIE methods were originally designed as a way to adjust crash analyses for relative driving exposure (Stamatiadis and Deacon, 1997). QIE's fundamental assumption is that non-responsible (i.e., not-at-fault) drivers in clean (i.e., one and only one responsible driver) multi-vehicle crashes are "randomly selected" by responsible drivers from the population of road users at the time and space of the crash and thus are reasonably representative of the road user population. If this assumption is valid, then the vehicle characteristics of these non-responsible crash-involved drivers should also reasonably represent the vehicle characteristics among the general driving population. In a series of prior papers, we conducted formative work to validate this assumption among NJ drivers (Curry et al., 2016), detailed our proposed expansion of using QIE methods to estimate population-level driver characteristics and driving behaviors (Curry 2017), and applied this method to the population of novice drivers in NJ (Curry et al. 2017).

## Study Population and Variables

From the NJ-SHO warehouse, we identified all licensed NJ drivers who were involved in a police-reported crash involving two or more passenger vehicles (i.e., multi-vehicle crash) from January 2010 to December 2017 (n=2,907,242). A crash is reportable in NJ if it results in an injury or more than $500 in property damage (New Jersey Motor Vehicle Commission 2011). Next, we determined the crash responsibility for each driver. A driver was deemed responsible if they were noted on the crash report to have engaged in ≥1 driver action (e.g., unsafe speed, inattention) that contributed to the crash, regardless of whether a citation was issued (Curry et al. 2013; Jiang and Lyles 2011). In any given crash, officers can determine that any number of crash-involved drivers—including none—were responsible. Using this information, we then identified all non-responsible drivers who were in clean multi-vehicle crashes (n=1,132,186). We excluded 113 drivers whose residential address geocoded to a census tract that did not have median household income data available. Finally, we limited analyses to the 89.2% (n=1,009,256) of drivers in clean multi-vehicle crashes whose VIN data was available in the vPIC database. Drivers were categorized into four driver age groups: young drivers (age 17–20), young adult drivers (age 21–24), middle-aged drivers (age 25–64) and older drivers (age ≥65). In NJ, all newly licensed drivers age ≤21 are licensed under NJ's GDL policy, which includes a one-year intermediate license holding period that limits driving with peer passengers and at night. A flowchart detailing the selection of our study population is shown in the Supplemental Figure.

### Statistical Analysis

Prevalence of a specific vehicle characteristic was estimated as $\mathbf{N_j/N}$, where $\mathbf{N}$ is the total number of non-responsible licensed drivers involved in clean multi-vehicle crashes, and $\mathbf{N_j}$ is the number of these non-responsible licensed drivers who were driving a vehicle with characteristic j at the time of their crash. $\mathbf{N_j}$ was assumed to follow a binomial distribution; corresponding 95% confidence intervals were estimated using exact procedures. Prevalence can be interpreted as trip-level prevalence—that is, the proportion of all driver trips in which the driver's vehicle has the specific characteristic j. We compared trip-level prevalence of vehicle characteristics across the four driver age groups using medians and interquartile ranges (IQR) for continuous variables and proportions for categorical variables. Within each age group, we further compared select vehicle safety characteristics by quintiles of census tract median household income by calculating prevalence ratios (PR) and 95% confidence intervals. Our expectation was that younger and older drivers were more likely to drive less-safe vehicles and that drivers residing in census tracts with lower median income would also be more likely to drive less-safe vehicles. Further, we hypothesized that a positive relationship between income and vehicle safety characteristics would occur for each age group. All analyses were conducted using SAS software, version 9.4 (SAS Institute Inc., Cary, NC, USA).

## RESULTS

### Demographic Characteristics

As shown in Table 1, 7.3% of the total analytic population was young drivers (n=73,311), 8.6% was young adult drivers (n=86,576), 73.9% was middle-aged drivers (n=745,767), and 10.3% was older drivers (n=103,602). Females accounted for 50.1% of all drivers. Forty-seven percent of drivers lived in census tracts in the top two quintiles of annual median household income (≥$80,568); the median census tract-level household income for all drivers was $77,773 (IQR: $57,868, $101,962).

### Vehicle Characteristics by Driver Age

The median vehicle age was 8 years old (IQR: 4–12) for young drivers, 3 years older than for middle-aged drivers (5 years [2–10]; Table 2). Among young drivers, the distribution of vehicle ages for 17- to 18-year-old and 19- to 20-year-old drivers was similar (median: 8 years [4–12]; Supplemental Table 1). The vehicle engines of young drivers had lower median horsepower than middle-aged drivers (166 [140–205] vs. 197 [158–244], respectively). Fewer young drivers than middle-aged drivers drove vehicles with ESC (29.7% vs 45.9%). Almost three-fourths (72.4%) of young drivers drove passenger cars compared with just over half (52.1%) of middle-aged drivers. The horsepower of passenger car engines of young drivers remained lower than of middle-aged drivers (153 [132–185] and 170 [140–210]). Further, although the vast majority of young drivers' passenger cars were equipped with front air bags, they were substantially less likely to have side air bags (49.9%) and curtain air bags (39.8%) than drivers in other age groups (e.g., among middle-aged drivers: 63.8% and 51.4%, respectively; Table 3). The proportions of SUVs that included front, side, and curtain air bags were also lower among young drivers than among middle-aged drivers. Unlike for passenger cars, the prevalence of side and curtain airbags among young adult drivers of SUVs more closely resembled the prevalence observed for young drivers rather than for middle-aged drivers.

Overall, older drivers drove vehicles that were slightly older than middle-aged driver vehicles (median: 6 years [2–10]); however, median vehicle age was highest among the oldest driver group (65–74: 6 years [2–10]; 74–85: 7 years [3–11]; ≥85: 8 years [4–13]; Supplemental Table 1). Older drivers were less likely to be driving a vehicle with ESC and more likely to drive a passenger car. The prevalence of passenger cars of older drivers with front, side, and curtain air bags was slightly less than for passenger cars of middle-aged drivers, while the prevalence of all three air bag types in SUVs of older drivers was the highest among all age groups. However, there were notable differences among older drivers groups in that oldest drivers—likeliest the most frail and vulnerable of older driver groups—were substantially less likely to be driving passenger cars or SUVs equipped with side and curtain air bags (Supplemental Table 1).

### Vehicle Characteristics by Driver Age and Census-Tract Income

The relationship between vehicle characteristics and driver age differed by the median household income of the driver's census tract. Among young drivers, those living in census tracts with the lowest quintile of median household income drove vehicles that were on average almost twice as old as drivers living in the highest income tracts (median: 11 years [6–14] vs. 6 years [3–11]; Figure 1; Supplemental Table 2). This pattern—oldest vehicles in the lowest income areas to newest vehicles in the highest income areas—was observed for all age groups. In addition, although virtually all (94%) of NJ drivers' passenger cars had front air bags (regardless of age group and socioeconomic status), passenger cars of drivers in the lowest income areas were less likely to have side and curtain air bags than those of drivers in the highest income areas. As shown in Figure 2 and Supplemental Table 3, this pattern was also observed for all age groups. For instance, compared with young drivers in the lowest-income areas, young drivers in the highest-income areas were 53% more likely to have cars with side airbags (59.9% and 39.2%, respectively; PR: 1.53 [1.47–1.58]). Passenger cars of older drivers living in the highest-income areas were 35% more likely to have side airbags than cars of drivers in the lowest-income areas (68.6% and 50.6%, respectively; PR: 1.35 [1.32–1.39]).

## DISCUSSION

Using QIE methods, we conducted the first analysis describing safety characteristics of the vehicle fleet among a statewide population of drivers. Our findings indicate that compared with drivers of other ages, the youngest and oldest drivers were more likely to drive vehicles that were older and not equipped with side airbags. Further, those living in lower-income areas were much less likely to be driving safe vehicles, a pattern that was particularly strong among the youngest drivers. Collectively, these patterns highlight an important discrepancy in that our nation's most vulnerable drivers—young drivers, older drivers, and those with lower socioeconomic status—are driving vehicles that are less able to mitigate injury in a crash.

Potential reasons why these populations are less likely to drive safer vehicles have not been thoroughly explored. Several prior studies suggest this might be a result of economic cost (e.g., costs associated with higher insurance rates, higher price of newer vehicles, fixed-income among older adults) and social norms (e.g., giving teens hand-me-down vehicles) (Hellinga et al. 2007; Eichelberger et al. 2015; Koppel et al. 2013). Further, surveys of older drivers and parents buying a vehicle for their teenage driver reveal that they tend to overestimate the level of protection of the vehicle's safety features and underestimate the relative importance of these features compared to other determinants for vehicle choice (Hellinga et al. 2007; Koppel et al. 2013). Importantly, the IIHS "good choice" and "best choice" recommendation lists illustrate that drivers can purchase inexpensive used vehicles with prices that range from $2000 to less than $20,000 (with median price of $6,700 and $8,600, respectively), meaning that safety is not exclusively tied to more expensive or new vehicles. Future work should be conducted to better understand drivers' and parents' perspectives related to vehicle safety, which can then lead to improved messaging regarding the importance of vehicle safety in protecting drivers from crash injuries.

For all of these vulnerable groups, optimizing the safety of a driver's vehicle may be a promising complementary approach to reducing crash-related injuries. Among young drivers, behavioral change strategies have largely been unsuccessful in reducing crash outcomes (Curry et al., 2015). Further, although studies assessing the relationship between SES and crash-related injuries are scarce, based on a wide and growing socioeconomic disparity in US fatal crash rates there is indication that there may be a particularly high-risk subgroup of young drivers (Harper et al. 2015). In addition, our finding of a much lower prevalence of vehicle safety characteristic among vehicles driven by drivers those who are 85 years of age or older—e.g., only one-half of their cars are equipped with side airbags compared with almost two-thirds of cars of middle-aged drivers—is concerning. Although several strategies for reducing crash involvement among older drivers exist (e.g., individualized behind-the-wheel training, self-regulation; Ball et al. 2010), previous findings that older drivers have lower rates of crash involvement but higher rates of fatal crash involvement emphasize the need to focus future efforts in protecting crash-involved older drivers from severe injury (Palumbo et al. 2019; Cicchino 2015). Notably, improved vehicle safety may be effective in reducing injuries regardless of the extent to which these drivers engage in specific safe or high-risk driving behaviors, and may be particularly important given that certain populations are at higher risk for reasons largely beyond our ability to influence (e.g., inexperience of young novice drivers, declining faculties of older drivers).

Primary strengths of this study include our expansion of quasi-induced exposure methods to estimate population prevalence of driving conditions—in this case driving a vehicle with specific safety characteristics. Importantly, this method enables us to estimate the prevalence of behaviors and situations among the *general driving population*. Thus, we are able to overcome weaknesses of prior studies, which have measured these constructs either through survey studies (with all their many attendant shortcomings) or among *all* crash-involved drivers, which is rarely, if ever, a good indicator of population prevalence. An important limitation of this study, which mirrors already-identified weaknesses in QIE-based studies, is that drivers of different ages may have different likelihoods of being a non-responsible driver in a clean multi-vehicle crash. Inherent in QIE's fundamental assumption is that non-responsible drivers are "randomly" selected; however, some groups may be less likely to be selected (e.g., defensive drivers). Our prior validation work among NJ drivers and the majority of other studies that aimed to validate this primary assumption have indicated that the assumption reasonably holds (Curry et al., 2016; Jiang et al. 2014). In addition, prevalence estimates are weighted toward groups that have relatively more presence on the road and towards vehicles driven in places where clean multi-vehicle crashes occur; additional limitations for using QIE to estimate prevalence of driving situations can be found in Curry 2017. Limitations on vehicle safety data include incomplete data available from the crash report and vPIC platform. As shown in the Supplemental Figure, 11% of crash-involved vehicles did not have a VIN recorded on the crash report that matched data in the vPIC platform. We were able to retrieve higher proportions of VIN-matched vehicle data with each crash year over the study period, thus the amount of available vehicle data increased over time. Some of the data available through the vPIC platform is provided voluntarily by the manufacturer, and as a result data on certain important vehicle safety features were not included in the VIN data we obtained for this study. For example, data on GVWR is not required for passenger cars and thus was only available for 55% of all vehicles and only 20% of passenger vehicles. We therefore did not include vehicle weight in this analysis due to the large amount of missing data. Additionally, our proxy indicator for presence of ESC (not required in vPIC) may have underestimated the proportion of vehicles with ESC, particularly among older vehicles with ESC but not included on the published lists from 2005–2011. Finally, we analyzed data from one US state. There are likely differences in the distributions of important factors (e.g., urbanicity, vehicle buying practices) across US jurisdictions that may limit generalizability.

Vehicle safety is an important component of seminal road safety philosophies. However, driver groups that have been found to be overrepresented in fatal crashes—young drivers, older drivers, and those of lower SES—are driving less safe vehicles. Thus, ensuring drivers are in the safest car they can afford should be further explored as a complementary approach to reduce crash-related injuries for vulnerable populations. As demonstrated by the IIHS's recommendation list, vehicle safety is not exclusively tied to more expensive or new vehicles.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

## ACKNOWLEDGMENTS

The authors would like to thank Christina Labows, BA and Melissa Pfeiffer, MPH for their assistance in preparing this manuscript and Jalaj Maheshwari, MS for his help extracting data from the vPIC platform and thoughtful suggestions. We also thank the NJ Department of Transportation, NJ Motor Vehicle Commission, and NJ Office of Information Technology for their assistance in providing data. This work was supported by the Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD) Award Numbers R21HD092850 and my R21HD098276 (PI: Curry). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. The sponsor had no role in the: design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; or decision to submit the manuscript for publication. Drs. Curry and Metzger had full access to all of the data in the study and take responsibility for the integrity of the data and accuracy of data analysis. None of the authors have a conflict of interest or financial disclosure to report.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the NJ Motor Vehicle Commission and Department of Transportation. Restrictions apply to the availability of these data, which were used under a Memorandum of Agreement for this study. New Jersey crash data are available at https://www.state.nj.us/transportation/refdata/accident/.

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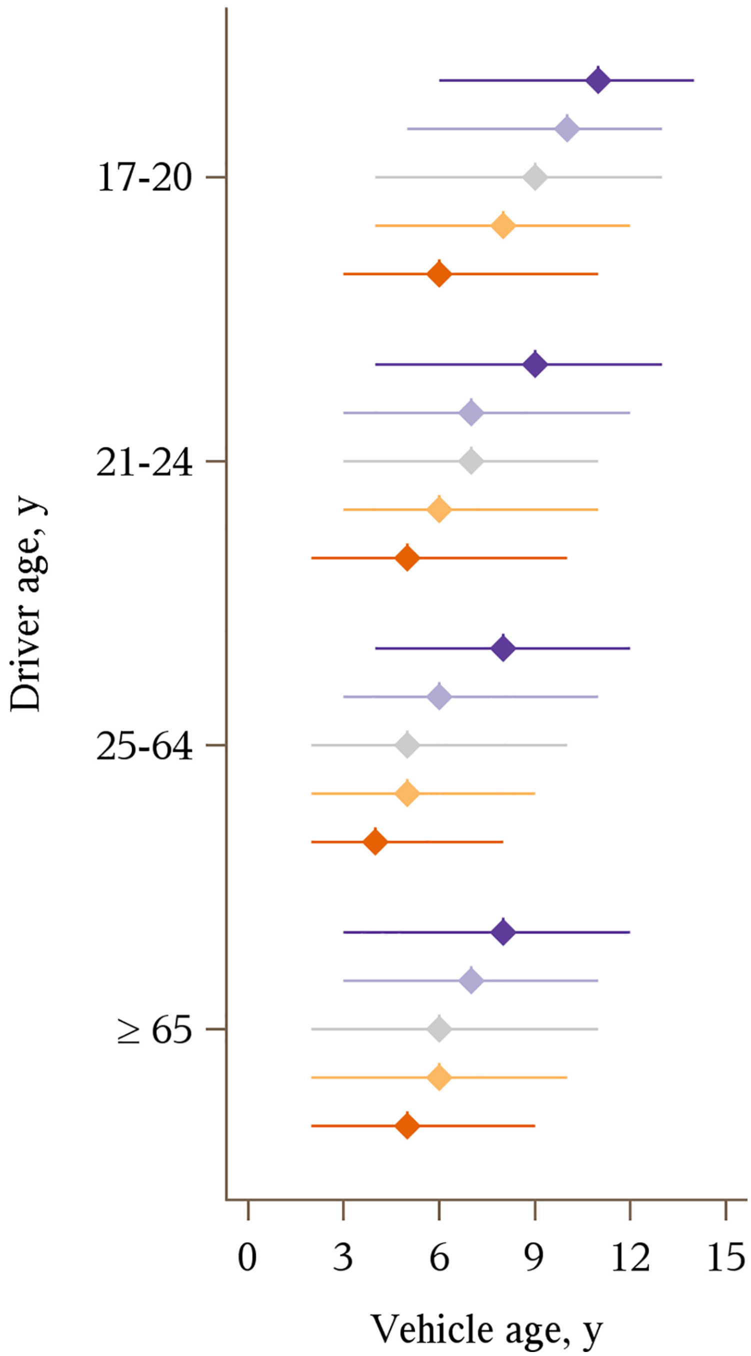


**Figure 1.**

Median (IQR) of vehicle age (years), by driver age group and quintile of median household income of driver's residential census tract. Dark purple (top): 1st quintile; light purple: 2nd quintile; gray: 3rd quintile; light orange: 4th quintile; dark orange (bottom): 5th quintile.

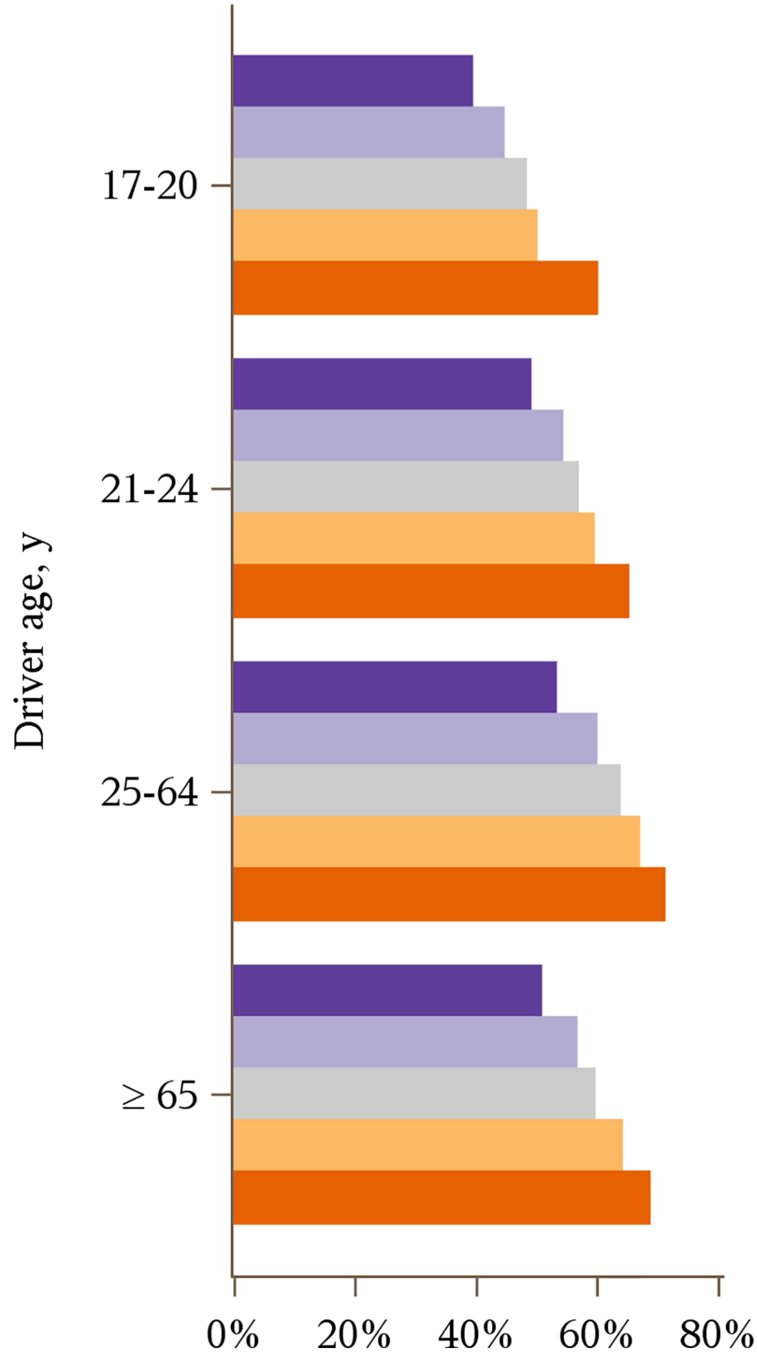


**Figure 2.**

Proportion of passenger cars with side airbags, by driver age group and quintile of Census tract-level median household income. Dark purple (top): 1st quintile; light purple: 2nd quintile; gray: 3rd quintile; light orange: 4th quintile; dark orange (bottom): 5th quintile.

**Table 1.**

Demographic characteristics of analytic study population of NJ drivers, 2010–2017.

| | Young drivers Age 17–20 (N=73,311) | Young adult drivers Age 21–24 (N=86,576) | Middle-aged drivers Age 25–64 (N=745,767) | Older drivers Age ≥65 (N=103,602) | All drivers (N=1,009,256) |
|---|---|---|---|---|---|
| Sex, percent (95% CI) | | | | | |
| Female | 51.0 (50.6, 51.3) | 52.3 (52.0, 52.7) | 50.4 (50.3, 50.5) | 45.1 (44.8, 45.4) | 50.1 (50.0, 50.2) |
| Male | 49.0 (48.7, 49.4) | 47.7 (47.3, 48.0) | 49.6 (49.5, 49.7) | 54.9 (54.6, 55.2) | 49.9 (49.8, 50.0) |
| Quintile of Census tract-level median household income, $, percent (95% CI) | | | | | |
| Q1: < $46,099 | 9.7 ( 9.5, 9.9) | 15.8 (15.5, 16.0) | 12.5 (12.4, 12.6) | 12.2 (12.0, 12.4) | 12.5 (12.5, 12.6) |
| Q2: $46,099 - $63,468 | 16.6 (16.4, 16.9) | 19.9 (19.6, 20.2) | 18.5 (18.4, 18.6) | 17.6 (17.4, 17.9) | 18.4 (18.3, 18.5) |
| Q3: $63,469 - $80,567 | 22.2 (21.9, 22.5) | 22.0 (21.7, 22.3) | 22.1 (22.0, 22.2) | 21.8 (21.6, 22.1) | 22.1 (22.0, 22.2) |
| Q4: $80,568 - $103,020 | 24.2 (23.9, 24.5) | 21.8 (21.5, 22.0) | 22.9 (22.8, 23.0) | 23.5 (23.2, 23.7) | 23.0 (22.9, 23.1) |
| Q5: ≥ $103,021 | 27.2 (26.9, 27.6) | 20.6 (20.4, 20.9) | 24.0 (23.9, 24.1) | 24.9 (24.6, 25.2) | 24.0 (23.9, 24.1) |

**Table 2.**

Characteristics of vehicles of crash-involved NJ drivers, by age group, 2010–2017.

| | Young drivers (N=73,311) | Young adult drivers (N=86,576) | Middle-aged drivers (N=745,767) | Older drivers (N=103,602) | All drivers (N=1,009,256) |
|---|---|---|---|---|---|
| Vehicle age, y, median (IQR) | 8 (4, 12) | 7 (3, 11) | 5 (2, 10) | 6 (2, 10) | 6 (2, 10) |
| Engine horsepower, median (IQR) | 166 (140, 205) | 166 (140, 201) | 197 (158, 244) | 185 (154, 239) | 185 (150, 240) |
| Presence of ESC, prevalence (95% CI) | 29.7 (29.4, 30.1) | 35.4 (35.1, 35.7) | 45.9 (45.8, 46.1) | 41.8 (41.5, 42.1) | 43.4 (43.3, 43.5) |
| Vehicle type, prevalence (95% CI) | | | | | |
| Passenger car | 72.4 (72.0, 72.7) | 74.4 (74.1, 74.7) | 52.1 (52.0, 52.2) | 64.5 (64.2, 64.8) | 56.8 (56.7, 56.9) |
| SUV | 15.0 (14.8, 15.3) | 11.7 (11.5, 11.9) | 20.4 (20.3, 20.5) | 14.3 (14.1, 14.6) | 18.7 (18.6, 18.7) |
| Other multipurpose passenger vehicle (MPV) | 7.9 ( 7.7, 8.1) | 7.4 ( 7.3, 7.6) | 17.5 (17.4, 17.6) | 13.9 (13.7, 14.1) | 15.5 (15.5, 15.6) |
| Truck | 4.1 ( 3.9, 4.2) | 4.6 ( 4.4, 4.7) | 7.7 ( 7.6, 7.7) | 5.9 ( 5.7, 6.0) | 7.0 ( 6.9, 7.0) |
| Other | 0.7 ( 0.6, 0.7) | 1.9 ( 1.8, 2.0) | 2.3 ( 2.3, 2.3) | 1.4 ( 1.3, 1.4) | 2.1 ( 2.0, 2.1) |

**Table 3.**

Prevalence (95% CI) of airbag types in passenger cars and SUVs of crash-involved NJ drivers, by age group, 2010–2017.

| | Young drivers | Young adult drivers | Middle-aged drivers | Older drivers | All drivers |
|---|---|---|---|---|---|
| Driving passenger cars… | N=53,046 | N=64,440 | N=388,760 | N=66,854 | N=573,100 |
| Front air bags | 95.6 (95.4, 95.7) | 96.3 (96.2, 96.5) | 96.8 (96.7, 96.8) | 96.5 (96.4, 96.7) | 96.6 (96.5, 96.6) |
| Side air bags | 49.9 (49.5, 50.4) | 57.1 (56.7, 57.5) | 63.8 (63.7, 64.0) | 61.2 (60.8, 61.6) | 61.5 (61.4, 61.6) |
| Curtain air bags | 39.8 (39.4, 40.2) | 47.6 (47.2, 48.0) | 51.4 (51.3, 51.6) | 47.3 (46.9, 47.7) | 49.5 (49.3, 49.6) |
| Driving SUVs… | N=11,008 | N=10,100 | N=152,300 | N=14,854 | N=188,262 |
| Front air bags | 57.0 (56.1, 58.0) | 59.6 (58.6, 60.6) | 63.2 (63.0, 63.5) | 64.6 (63.9, 65.4) | 62.8 (62.6, 63.0) |
| Side air bags | 34.0 (33.1, 34.9) | 38.8 (37.9, 39.8) | 51.7 (51.5, 52.0) | 54.7 (53.9, 55.5) | 50.2 (50.0, 50.4) |
| Curtain air bags | 13.7 (13.0, 14.3) | 15.0 (14.4, 15.8) | 25.5 (25.2, 25.7) | 28.6 (27.9, 29.3) | 24.5 (24.3, 24.6) |