Fatal Wrong-Way Crashes on Divided Highways, United States, 2014–2023

Wrong-way crashes are relatively rare, but they often result in more severe safety outcomes. This brief reports on the prevalence of fatal wrong-way crashes that occurred on divided highways from 2014 to 2023, along with their associated risk factors, updating and extending previous AAA Foundation for Traffic Safety (AAAFTS) work that examined these crashes. Updated wrong-way crash statistics are provided, previously cited risk factors were examined in reference to the updated data, and potential new risk factors were explored.

From 2014 to 2023, 4164 fatal wrong-way crashes occurred on U.S. divided highways and resulted in a total of 5730 fatalities. While annual traffic fatalities nationwide increased over the study period, fatal wrong-way crashes increased even more, indicating that while these crashes are relatively rare, they are a growing issue. Results show that alcohol-impaired drivers, older drivers, drivers without valid licenses, and drivers of older vehicles have higher risk of fatal wrong-way crashes, consistent with previous research. New insights from the current study include findings that risk of fatal crashes is also increased in rural areas, in dawn/dusk and darkness, among drivers who live far away from the crash location, and among drivers of vehicles registered to other people. This wider and more up to date list of risk factors has implications for countermeasures.

METHOD

This analysis examined wrong-way crashes on divided highways in the United States from 2014 to 2023. Annual numbers of fatal wrong-way crashes and their corresponding fatalities were computed overall and in relation to crash, vehicle, and driver-related factors of interest. Factors that increase or decrease the risk of wrong-way crashes were assessed using models that compared wrong-way drivers with comparison groups of drivers who were driving in the correct direction, and whose actions made no apparent contribution to the crashes.

The wrong-way crash cases examined in the analysis were identified using the Fatality Analysis Reporting System (FARS), which is a dataset compiled by the National Highway Traffic Safety Administration (NHTSA) comprising information about every crash in the United States each year that occurs on a public road and results in the death of a person within 30 days (National Center for Statistics and Analysis, 2025). The scope of cases included those that occurred on Interstate highways, other freeways and expressways, one-way or divided two-way principal arterials, and ramps leading to/from those roads. Cases were classified as a wrong-way crash based on a cited violation or driver factor in the crash report—specifically those where the driver was reported as driving the wrong way on a one-way trafficway, two-way trafficway, or one-way road, or driving on the wrong side of the road generally. “Crossover crashes” were not included as wrong-way crashes. In this analysis, a crash was considered a crossover crash if the FARS vehicle sequence of events variables indicated that the vehicle crossed the centerline or median before the first substantive impact.

Factors Influencing Risk of Wrong-Way Crashes

The previous AAAFTS report highlighted driver age, alcohol impairment, license status, vehicle type and age, and the driver's state of licensure (intended as a proxy for familiarity with the road) as pertinent risk factors for wrong-way drivers (Villavicencio et al., 2021). In this analysis, the following variables were explored as factors that might increase or decrease the risk of wrong-way crashes:

- Driver age
- Driver sex
- Blood alcohol concentration (BAC)
- License status
- Presence and number of passengers
- Vehicle type
- Vehicle ownership
- Vehicle age
- Driver distance from home
- Lighting condition
- Area type (urban or rural)

In this analysis, the approximate distance from the crash location to the driver's home zip code was used as a proxy indicator of driver familiarity. This was estimated using the straight-line distance from the crash location to the centroid of the driver's home zip code. (If the crash occurred within the driver's home zip code, the distance was coded as 0 irrespective of the distance to the centroid.)

BAC levels are not always captured by police reports as not every driver is tested. The NHTSA method of multiple imputation is used to estimate BAC when it is unknown and includes the imputed values in the FARS database (Subramanian & Utter, 1998). The imputation procedure used by NHTSA, while validated to provide accurate national-level estimates overall, does not consider whether the driver was involved in a wrong-way crash. It is important for an imputation model to include any variable that will be used in subsequent analyses to avoid bias when estimating the relationship of the imputed variable (e.g., BAC) and other variables (e.g., wrong-way crash involvement) (White et al., 2011).

To avoid bias in analyses of the role of alcohol in wrong-way crashes, missing BAC values were imputed using a custom imputation model developed for the current study. The model included all variables included in NHTSA's model (Subramanian & Utter, 1998) as well as all variables listed above. The method of predictive mean matching (van Buuren, 2018) was used to capture nonlinear relationships and ensure that imputed BAC values were plausible. Ten imputed datasets were generated and combined for subsequent analysis using the method developed by Rubin (1987). Imputation was performed in R version 4.5.0, and analyses of imputed data were performed using mice (van Buuren & Groothuis-Oudshoorn, 2011) and mitools (Lumley, 2019) libraries.

Statistical Analysis

To examine factors associated with wrong-way driving, two complementary modeling approaches were employed:

1) Matched Comparison Group

Conditional logistic regression was used to estimate odds ratios for each factor of interest. In this model, wrong-way drivers were compared to other drivers involved in the same crash who were driving in the correct direction (right-way drivers). This method assumes that right-way drivers involved in wrong-way crashes approximate a random sample of all drivers on the road at the time and place of the wrong-way crash and thus theoretically had the opportunity to be wrong-way drivers. Under this assumption, differences in the characteristics of wrong-way drivers versus right-way drivers suggest that those characteristics influence the risk of driving in the wrong direction and causing a fatal crash. Because the comparison is between "matched" drivers involved in the same crash, the impact of factors that differ between drivers in the same crash (e.g., age) can be estimated; however, the impact of factors that do not differ between drivers in the same crash (e.g., time of day) cannot. In the matched analysis, conditional logistic regression was used to estimate odds ratios comparing the odds of being a wrong-way driver versus a right-way driver for each factor of interest.

2) Non-Matched Comparison Group

In this analysis, wrong-way drivers were compared to all other right-way drivers in fatal crashes in the same time frame on divided highways and ramps and who did not appear to have contributed to the occurrence of their crashes. Contribution to crash occurrence was assessed based on the driver-related contributing factors variables in FARS; right-way drivers whose actions contributed to the occurrence of their crashes were excluded. Unlike in the matched analysis, right-way drivers in this analysis included drivers in all fatal crashes on road types within the study scope (including crashes not involving any wrong-way drivers). This approach is based loosely on the theory of quasi-induced exposure (Stamatiadis & Deacon, 1997), wherein drivers involved in crashes, despite having not contributed meaningfully to the occurrence of the crash (sometimes deemed "non-culpable" or "non-responsible" drivers), are assumed to approximate a representative sample of the drivers on the road at the times and places where crashes occur. By using a comparison group that was not restricted to matched drivers in the same crash, the model was able to include a wider set of predictors, including environmental and roadway factors that cannot be examined in a matched analysis, while still approximating the driver population who had the opportunity to be wrong-way drivers. In this analysis, ordinary (unconditional) logistic regression was used to estimate odds ratios comparing the odds of being a wrong-way driver versus right-way driver in relation to each factor of interest.

RESULTS

Prevalence and Trends

Over the study period (2014–2023), the annual number of fatal wrong-way crashes approximately doubled. The total number of fatal crashes nationwide increased over the same period, but wrong-way crash fatalities increased even more, as reflected by the increasing trend in wrong-way crash fatalities as a percentage of total fatalities (see Figure 1).

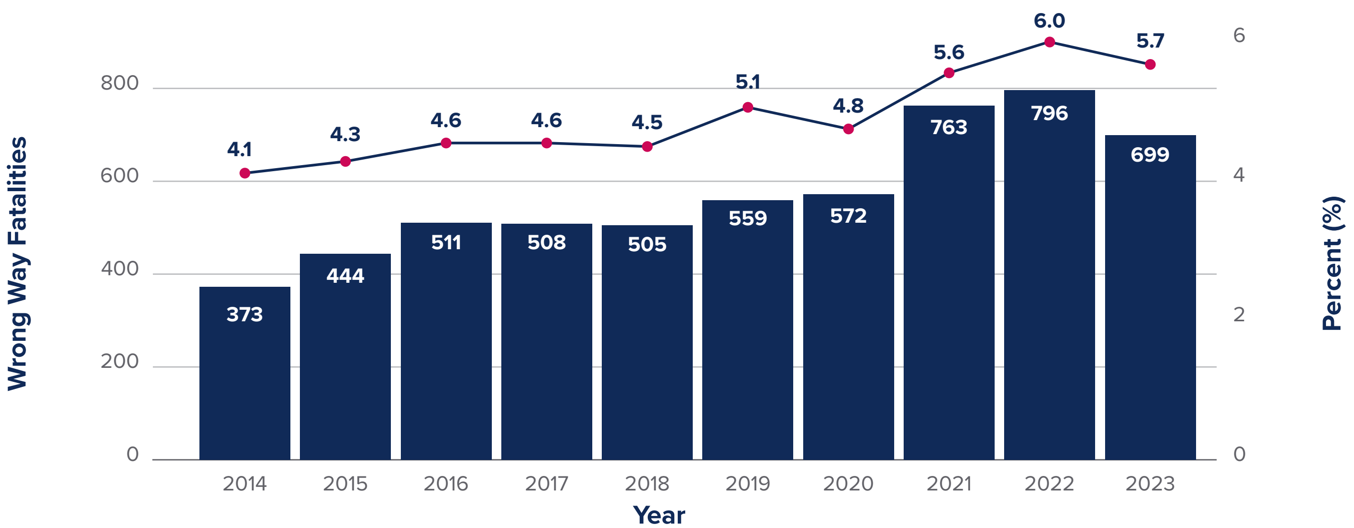

Figure 1: Number of Fatalities Due to Wrong-Way Crashes on Divided Highways and Wrong-Way Crash Fatalities as a Percentage of Total Crash Fatalities on Divided Highways across the United States (2014–2023)

Table 1 summarizes fatal crash trends on divided highways in the United States from 2014 to 2023. Results indicate that, while the total number of fatal crashes on divided highways increased over the study period, wrong-way fatal crashes still showed a gradual upward trend relative to all fatal crashes on these highways. The number of wrong-way crashes rose from 278 in 2014 to 520 in 2023, representing an increase in their share of fatal crashes from 3.4% to 4.6% over the same period. This indicates that although wrong-way crashes remain a small fraction of all fatal crashes on divided highways, their relative contribution has grown steadily over the last decade, highlighting a persistent and potentially increasing safety concern.

State-level statistics, including the total number of wrong-way crash fatalities over the 10-year study period, and wrong-way crash fatalities as a percentage of total crash fatalities on divided highways, are provided in Appendix A.

Factors Influencing Risk of Fatal Wrong-Way Crashes

Table 2 presents the summary of characteristics of wrong-way drivers and the comparison drivers included in both the matched and non-matched analyses, as well as the adjusted odds ratios from the logistic regression models.

Table 1: Fatal Wrong-Way Crashes by Year (2014–2023)

Year	Number of Fatal Crashes			Wrong-Way Fatal Crashes as Percentage of Fatal Crashes on Divided Highways	Total Wrong-Way Crash Fatalities
	Overall Total	Total on Divided Highways	Wrong-Way on Divided Highways		
2014	30,056	8,214	278	3.4%	373
2015	32,538	9,357	333	3.6%	444
2016	34,748	10,151	360	3.5%	511
2017	34,560	10,197	381	3.7%	508
2018	33,919	10,162	367	3.6%	505
2019	33,487	10,052	387	3.8%	559
2020	35,935	10,915	424	3.9%	572
2021	39,785	12,488	548	4.4%	763
2022	39,422	12,090	566	4.7%	796
2023	37,654	11,184	520	4.6%	699

Table 2. Characteristics of Wrong-Way Drivers and Matched and Non-Matched Comparison Drivers on Divided Highways with the Adjusted Odds Ratios from Logistic Regression Models

	Wrong-Way Drivers (N = 4,176)	Matched Comparison Group (N = 5,051)			Non-Matched Comparison Group (N = 35,515)		
	%	%	OR	CI	%	OR	CI
Sex							
Male	70.6	71.2	1.0	0.8–1.3	72.2	0.9	0.8–1.1
Female	29.1	28.4	Reference		26.9	Reference	
Age							
Less than 20 years	1.6	2.9	0.8	0.4–1.8	2.2	1.4	0.9–2.2
20–29 years	30.8	26.7	1.0	0.7–1.5	20.8	1.2	0.96–1.4
30–39 years	23.3	21.7	1.2	0.9–1.8	20.3	1.3	1.1–1.6
40–49 years	12.7	18.3	1.0	0.7–1.5	18.3	1.1	0.9–1.4
50–59 years	9.0	15.2	Reference		18.5	Reference	
60–69 years	8.3	9.4	2.0	1.3–3.1	11.5	2.1	1.7–2.7
70–79 years	6.5	2.5	6.8	4.1–11.3	4.5	5.5	4.2–7.2
80+ years	6.5	1.1	20.3	10.9–37.8	2.3	21.3	16.0–28.4
Blood Alcohol Concentration [g/dl]							
0	20.2	77.5	Reference		86.2	Reference	
0.01–0.079	9.2	17.7	6.4	3.9–10.2	11.4	7.4	5.9–9.2
0.08–0.12	10.6	2.6	18.6	9.9–34.9	1.1	16.3	12.6–21.1
Greater than 0.12	59.9	2.2	83.1	53.8–128.3	1.4	72.2	61.3–85.1
License Status							
Valid	76.3	90.4	Reference		91.1	Reference	
Expired/revoked/suspended	14.0	4.6	2.4	1.6–3.5	3.6	3.0	2.4–3.7
Not licensed	8.3	3.5	2.3	1.5–3.7	3.0	2.4	1.8–3.0
Additional Occupants							
None	86.4	63.7	Reference		66.5	Reference	
1 passenger	10.1	22.3	0.3	0.2–0.4	20.8	0.3	0.2–0.3
2 passengers	2.0	6.8	0.2	0.1–0.4	6.2	0.2	0.1–0.3
3+ passengers	1.4	7.3	0.2	0.1–0.3	6.5	0.2	0.1–0.2
Vehicle Type							
Passenger cars	57.9	44.1	Reference		35.7	Reference	
Light truck/vans	38.2	38.1	0.7	0.6–0.9	36.2	0.7	0.6–0.9
Large truck/buses	1.5	15.9	0.1	0.1–0.2	19.9	0.1	0.07–0.14
Motorcycles	2.2	1.6	0.6	0.3–1.2	7.2	0.1	0.1–0.2
Registered Owner of Vehicle							
Driver = Owner	62.5	52.0	Reference		52.4	Reference	
Unregistered	2.2	1.3	1.1	0.4–2.6	1.4	0.9	0.6–1.4
Other private owner	29.9	26.5	1.2	0.9–1.5	22.6	1.2	1.03–1.4
Business/govt.	3.4	17.8	0.6	0.4–1.03	21.0	0.6	0.4–0.8
Rental	0.8	1.6	1.4	0.6–3.7	1.4	1.1	0.6–1.9
Stolen vehicle	0.6	0.1	35.8	4.7–272.2	0.03	70.0	26.3–186.5
Unknown	0.6	0.7	0.8	0.1–8.2	1.2	0.8	0.2–2.4
Vehicle Age							
5 years or less	23.1	37.1	Reference		36.4	Reference	
6–10 years	25.3	26.4	1.5	1.1–2.0	26.0	1.1	0.96–1.3
11–15 years	24.8	19.7	1.6	1.3–2.2	19.1	1.4	1.2–1.6
16–20 years	17.7	11.8	1.7	1.2–2.3	12.2	1.4	1.2–1.7
Greater than 20 years	9.1	5.0	2.0	1.3–3.2	6.4	1.5	1.1–1.9
Distance from Home Zip							
Less than 10 miles	39.6	33.1	Reference		38.6	Reference	
10–25 miles	28.2	24.6	1.0	0.8–1.4	22.1	1.4	1.2–1.6
25–50 miles	11.3	11.3	1.0	0.7–1.5	10.4	1.4	1.2–1.7
50–100 miles	6.4	8.4	1.2	0.8–1.8	7.1	1.5	1.2–2.0
100–250 miles	5.5	9.0	1.3	0.8–2.1	7.7	1.6	1.2–2.0
Greater than 250 miles	7.1	11.4	1.1	0.7–1.8	11.0	1.8	1.4–2.3
Lighting Condition							
Daylight	16.4	Not estimable in matched analysis			51.8	Reference	
Dark	80.7				44.1	2.4	1.9–3.1
Dawn/dusk	2.8				4.0	2.0	1.4–2.8
Area Type							
Urban	65.4	Not estimable in matched analysis			71.6	Reference	
Rural	34.6				28.4	1.8	1.6–2.1

Driver Factors

The results indicated that male drivers made up higher proportions of both wrong-way and comparison drivers across analyses. Though, in both the matched and non-matched analyses, the odds of being a wrong-way driver did not differ significantly by sex. When examining age, drivers aged 20–39 years represented more than half of all wrong-way drivers, slightly higher than their corresponding shares of the two comparison groups of right-way drivers, but they did not significantly differ in odds. In contrast, while older adults aged 70 and older comprised a much smaller share of wrong-way drivers, they were vastly over-represented relative to their corresponding proportions of right-way drivers. Drivers aged 60 and above showed significantly higher odds of being wrong-way drivers, particularly those aged 70–79 years and greater than 80 years in both the matched and non-matched analysis.

BAC levels were found to be starkly different among wrong-way and right-way drivers. In both the matched and non-matched analysis, most right-way drivers had zero BAC levels whereas nearly 70% of wrong-way drivers had BAC levels above 0.08 g/dL (the per se legal limit in all U.S. states except Utah, whose BAC limit is 0.05 g/dL). The two logistic regression models show a strong association between BAC levels and wrong-way driving. In the matched analysis, drivers with BAC levels of 0.08–0.12 had nearly 20 times higher odds of being wrong-way drivers, and those with BAC above 0.12 had over 80 times higher odds compared to drivers with BAC of 0. The non-matched analysis produced similar results. These findings highlight that high alcohol impairment is the most major risk factor for wrong-way crashes.

Wrong-way drivers were also much more likely to be unlicensed or have an invalid license compared to right-way drivers. In the matched analysis, 14% of wrong-way drivers had an expired, revoked, or suspended license, and 8.3% were not licensed, while only 4.6% and 3.5% of right-way drivers fell into these categories. These differences translated into significantly higher odds of wrong-way involvement, with odds ratios of 2.4 for expired/revoked/suspended licenses and 2.3 for drivers without a license. The non-matched analysis showed a similar pattern.

Drivers who were more than 250 miles from their home zip code had 1.8 times the odds of being the wrong-way driver compared to drivers within 10 miles of their home zip code in the non-matched analysis. In the matched analysis, however, the association was weaker and not statistically significant. This was a rare case in which the results of the matched and non-matched analysis differed meaningfully.

Vehicle Factors

Vehicle occupancy also differed sharply between groups. Wrong-way drivers were predominantly driving alone, with 86% having no passengers, whereas only about 64% of matched right-way drivers and 67% of non-matched right-way drivers were driving without passengers. The logistic regression models indicated that the presence of passengers was strongly protective against wrong-way driving. In both matched and non-matched analyses, having at least one passenger was associated with markedly lower odds of being a wrong-way driver, and having multiple passengers decreased the odds of a wrong-way crash even further. The odds of being a wrong-way driver decreased with an increase in the number of occupants, suggesting that having other occupants in the vehicle can have a protective effect.

Wrong-way drivers mostly drove passenger cars with 58% of wrong-way drivers involved in wrong-way crashes driving a passenger car compared to 44% and 36% of drivers in the matched and non-matched comparison groups. Light trucks and vans accounted for a similar share of wrong-way and right-way drivers, but the odds ratios indicate they were less likely than passenger car drivers to be wrong-way drivers (matched and non-matched odds ratio of 0.7). Large trucks and buses were much less likely to be a wrong-way driver. These drivers represented a substantial portion of right-way drivers (16% in the matched analysis and 20% in the non-matched analysis) but only 1.5% of wrong-way drivers, indicating they are more likely to be a victim in wrong-way crashes. Motorcycles were relatively uncommon among wrong-way drivers, and the non- matched analysis suggested a lower likelihood of wrong-way crash involvement.

Wrong-way crashes tended to involve older vehicles, with nearly half of the vehicles being more than 10 years old. In contrast, right-way vehicles were generally newer, with about 37% being less than 5 years old. The odds of wrong-way involvement increased steadily with vehicle age, as vehicles over 20 years old were about 1.5 to 2 times as likely to be involved in a wrong-way crash.

Most wrong-way drivers were driving their own vehicle compared to both the matched and non-matched right-way drivers. Wrong-way drivers were disproportionately represented among stolen vehicles, which, although rare (0.6%), carried extremely high odds of wrong-way involvement (matched odds ratio of 35.8, non- matched odds ratio of 70.0). Drivers of vehicles registered to other private owners made up nearly one third of wrong-way drivers and had significantly elevated odds of wrong-way involvement in the non-matched model (the odds ratio in the matched analysis was the same but was not statistically significant). Other categories such as unregistered, rental, and unknown ownership showed small differences and largely non significant odds ratios.

Roadway and Environmental Factors

When comparing the environmental characteristics of wrong-way drivers' crashes to the characteristics of drivers in the non-matched sample, wrong-way crashes were more likely to occur in dark lighting conditions and in rural areas. Almost 81% of wrong-way fatal crashes occurred in dark lighting conditions, whereas the majority of right-way drivers in the non-matched sample crashed in daylight. After adjusting for other factors, odds of a wrong-way crash approximately doubled in dawn/dusk lighting conditions and more than doubled in darkness. The odds of being a wrong-way driver in a fatal crash were 1.8 times higher in rural areas on divided highways than for urban areas.

DISCUSSION

This research provides updated statistics on the prevalence of fatal wrong-way crashes on divided highways as well as factors that influence risk. Over the 10-year period of study, the annual number of fatal wrong-way crashes approximately doubled. While total traffic fatalities nationwide also increased over the same period, the increase in fatal wrong-way crashes was significantly larger.

The current analysis was consistent with the previous AAAFTS research (Villavicencio et al., 2021) in identifying alcohol-impaired drivers, older drivers, drivers without valid licenses, and drivers in older vehicles as being at higher risk of being a wrong-way driver in a fatal crash. Also consistent with that study, drivers carrying passengers and drivers of large trucks and buses were found to have lower risk of being wrong-way drivers in fatal crashes.

The current analysis also identified additional environmental and driver risk factors. Risk of fatal wrong-way crashes was higher in dark and dawn/dusk conditions than in daylight conditions, and higher in rural locations than in urban locations. Vehicles that were identified as stolen stood out dramatically in odds of involving a wrong-way driver in a fatal crash compared to vehicles being operated by their registered owner. Even outside of stolen vehicles, drivers of vehicles registered to another private owner (e.g., borrowed vehicles) had slightly higher odds of being wrong-way drivers.

Previous literature supports several of these findings. The National Transportation Safety Board (NTSB, 2012) had previously identified older drivers and alcohol-impaired drivers as being at especially great risk for wrong-way crashes. Others have found associations with driver licensure status (Song et al., 2024), vehicle age (Das et al., 2018), and darker lighting conditions (Abbaszadeh et al., 2024; Das et al., 2018; Song et al., 2024). Similarly, others have noted a reduced likelihood of wrong-way crashes when there are one or more passengers in the vehicle (Savolainen et al., 2018; Song et al., 2024).

Some of the findings of the current study, however, conflict or appear to conflict with results previously reported by others. Several previous studies have reported that the majority of wrong-way crashes occur in urban areas (Avelar et al., 2023; Das et al., 2018; Savolainen et al., 2018). While the current study finds that while the majority of fatal wrong-way crashes do occur in urban areas, they account for a higher percentage of all fatal crashes on divided highways in rural areas than in urban areas. In addition, Villavicencio et al (2021) found that drivers licensed in a different state had significantly lower odds of being wrong-way drivers than drivers licensed in the same state. In the current study, drivers who were further from their home zip code had significantly higher odds of being wrong-way drivers in the non-matched analysis (but not in the matched analysis). The discrepancy with the previous study is likely attributable to adjustment for vehicle type and passenger presence in the current study, as both factors were independently associated with both distance from home and risk of wrong-way crashes (odds ratios reported in the previous study were unadjusted). The difference in results between the non-matched versus matched analysis may be due to the strict matching of wrong-way drivers to right-way drivers in the same crash in the matched analysis. If wrong-way drivers tend to crash soon after entering the highway, then wrong-way drivers who had just entered the highway would often be matched to right-way drivers sampled predominantly from through-traffic, thus potentially confounding the relationship with distance from home. By comparing wrong-way drivers to all right-way drivers on similar roads, the non-matched analysis mitigates this potential source of confounding. Moreover, the result that drivers further from home have increased risk of becoming wrong-way drivers is plausible. While certainly not a perfect proxy, a driver's distance from home is likely correlated with their likelihood of being familiar with their environment, and drivers unfamiliar with their environment may be more likely to enter the highway in the wrong direction. One study found that local drivers were more likely to be involved in fatal wrong-way crashes in urban areas, but non-local drivers were more likely to be involved in fatal wrong-way crashes in rural areas (Abbaszadeh et al., 2024).

Spatial trends were also consistent with established causes of wrong-way events. Although many wrong-way crashes occurred close to the driver's home, the likelihood of being the wrong-way driver increased as the crash occurred farther from home. Prior studies have linked long-distance driving with fatigue (Ting et al., 2008), which increases the risk of wrong-way driving. Research on driver cognition also shows that wayfinding on unfamiliar routes increases mental workload (Bryden et al., 2023), and higher cognitive load reduces the driver's ability to process signage (Du et al., 2022) and detect wrong-way indicators in time to correct their path, which may lead to wrong-way driving. Other investigations have also highlighted potential risk factors related to roadway features, which were not explored in this analysis. These include roadway geometry (Song et al., 2024; Chang et al., 2025; Abbaszadeh et al., 2024; Savolainen et al., 2018), degraded or insufficient roadway markings (Abbaszadeh et al., 2024; National Academies of Sciences, Engineering, and Medicine [National Academies], 2023b), ramp configurations (Federal Highway Administration [FHWA], 2024; National Academies, 2023a; NTSB, 2012), and certain kinds of interchange designs, most notably partial cloverleafs (Chang et al., 2024; Chang et al., 2025; Savolainen et al., 2018; NTSB, 2012). Future work could continue to incorporate these considerations in analyses to better understand the factors that contribute to these types of crashes.

Implications for Countermeasures

Driver-based

The primary contributors to wrong-way driving begin at the driver level. Alcohol impairment, older age, and driving a stolen vehicle were very prominent risk factors. Stopping drunk driving at the source is a way to meaningfully counteract these types of crashes; however, driving under the influence (DUI) is a larger traffic safety issue. Some recommendations have been made for increased education and penalties for DUI in the context of state-led wrong-way studies (Carter et al., 2018; California Department of Transportation, 2016; Finley et al., 2014), but there are many organizations with broader guidance on efforts for combatting impaired driving (Kirley et al., 2023; Governors Highway Safety Association, 2025; Insurance Institute for Highway Safety, 2025). AAAFTS also has research in progress to investigate best ways to prevent impaired driving.[1,2] Additionally, increased driver education, especially with a focus on navigating complex interchanges and how to course correct in instances of error, could benefit older drivers and drivers of all ages.

Vehicle-based

Vehicle-based countermeasures are still directed at stopping the wrong-way driver, either by stopping them from driving or by providing direct messaging within their vehicle. Alcohol interlock devices and in-vehicle detection systems can prevent impaired drivers from starting or operating a vehicle (Zhou & Rouholamin, 2014; Finley et al., 2014; NTSB, 2012). For impaired or confused drivers, personalized app-based warnings issued to drivers through their smartphones (typically via a navigation app) may offer promise, serving as an additional alert and indication of active error to wrong-way drivers and providing warnings to right-way drivers in the vicinity (Bosch, 2025; Texas Department of Transportation, 2024; Athey Creek Consultants, 2016).

Roadway-based

The literature provides strong support suggesting that making infrastructure changes can aid drivers in preventing wrong-way crashes, particularly those who are confused or unfamiliar with a given area. There are multiple recommendations related to signage. Static or "passive" countermeasures include using larger signage (FHWA, 2024; National Academies, 2023a; National Academies, 2023b; Chang et al., 2024; Chang et al., 2025; Savolainen et al., 2018; NTSB, 2012), increasing the amount of signage (National Academies, 2023a; National Academies, 2023b; Chang et al., 2024; Carter et al., 2018; NTSB, 2012), and placement of low mounted signage (National Academies, 2023a; Chang et al., 2024; Savolainen et al., 2018; NTSB, 2012). Additions to signage that can help increase visibility, such as retroflective materials and additional lighting, are also recommended (National Academies, 2023a; National Academies, 2023b; Chang et al., 2024; Chang et al., 2025; NTSB, 2012).

More active signage recommendations are intended to gain driver attention when a wrong-way event has been detected. These include blank-out signs, which are triggered by a wrong-way event (FHWA, 2024; Abbaszadeh et al., 2024) and signs with dynamic light enhancements, such as flashing LED borders, red rectangular rapid flashing beacons, and wigwag flashing beacons (National Academies, 2023a; National Academies, 2023b; Savolainen et al., 2018)

[1] https://aaafoundation.org/driving-while-impaired-individual-social-and-contextual-factors-that-impact-drivers-decisions
[2] https://aaafoundation.org/attitudes-towards-impaired-driving-countermeasures

Treatments to the roadway itself are also recommended. Pavement markings such as in-lane arrows, bidirectional pavement marking, longitudinal lines, stop lines, and enhanced delineation can help reinforce directional guidance, and may be particularly useful for unfamiliar drivers (National Academies, 2023a; Savolainen et al., 2018; NTSB, 2012) . Implementations that further alert a wrong-way driver, like directional rumble strips, show promise for impaired drivers (National Academies, 2023b).

System-based

Arizona, California, Colorado, Connecticut, Florida, Iowa, Michigan, Missouri, Nevada, Ohio, Texas, Rhode Island, Wisconsin, and Washington State Departments of Transportation have all piloted or implemented multi-faceted approaches to preventing wrong-way driving (Washington State Department of Transportation, 2025; National Academies, 2023b; Kitch & Geoly, 2023; TAPCO, 2021). These integrated approaches can go above and beyond what infrastructure alone can accomplish. In addition to more preventative road design features, they operate in tandem with detection systems that can issue alerts to wrong-way drivers, right-way drivers, traffic management centers, and/or highway patrols and police to aid in real-time response and incident management. Several of these initiatives, including in Arizona, Texas, and Florida, report successful increases in drivers self-correcting potential wrong-way events (FHWA, 2022; Finley et al., 2024).

Limitations and Data Considerations

This analysis was subject to several limitations. First, as it was based on FARS data, it is similarly subject to any of the limitations associated with the reported elements within. Wrong-way cases were identified to the best ability of the research team by the available variables suggesting a fatal wrong-way crash occurred, but it is possible that other wrong-way crashes have not been identified using these parameters. Second, in the absence of data that could give a more exact comparison, estimation of factors influencing relative risk was based on proxy groups (right-way drivers in the same crash and/or other crashes). Results from both yielded fairly similar results; however, future research could explore additional methods for informing these estimations. Finally, driver impairment from substances other than alcohol were not included in the current analysis due to concerns about data quality (Berning & Smither, 2014); however, given the strong association of alcohol-impairment with wrong-way crashes, other forms of impairment not examined in this study may contribute to wrong-way crashes as well.

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ABOUT THE AAA FOUNDATION FOR TRAFFIC SAFETY

The AAA Foundation for Traffic Safety is a 501(c)(3) nonprofit, publicly supported charitable research and education organization. It was founded in 1947 by the American Automobile Association to conduct research to address growing highway safety issues. The organization's mission is to identify traffic safety problems, foster research that seeks solutions, and disseminate information and educational materials. AAA Foundation funding comes from voluntary, tax-deductible contributions from motor clubs associated with the American Automobile Association and the Canadian Automobile Association, individual AAA club members, insurance companies and other individuals or groups.

SUGGESTED CITATION

Haroon, S. M., Yang., YM., Tefft, B. C., & McDonough, J. (2026). *Fatal Wrong-Way Crashes on Divided Highways, United States, 2014-2023* (Research Brief). Washington, D.C.: AAA Foundation for Traffic Safety.

Appendix A. Fatal Wrong-Way Crashes by State (2014–2023)

State	Wrong-Way Fatalities	Total Fatalities (Divided Highways)	Wrong-Way Fatalities/ Total Highway Fatalities
Alabama	155	2663	5.8%
Alaska	3	165	1.8%
Arizona	159	3333	4.8%
Arkansas	77	1187	6.5%
California	532	14174	3.8%
Colorado	104	2559	4.1%
Connecticut	74	894	8.3%
Delaware	15	511	2.9%
District of Columbia	2	57	3.5%
Florida	406	13741	3.0%
Georgia	253	4546	5.6%
Hawaii	3	259	1.2%
Idaho	21	527	4.0%
Illinois	172	2882	6.0%
Indiana	105	2007	5.2%
Iowa	58	884	6.6%
Kansas	59	882	6.7%
Kentucky	61	1634	3.7%
Louisiana	89	2462	3.6%
Maine	5	141	3.6%
Maryland	80	2308	3.5%
Massachusetts	73	1185	6.2%
Michigan	136	1999	6.8%
Minnesota	59	798	7.4%
Mississippi	139	2228	6.2%
Missouri	192	2667	7.2%
Montana	31	415	7.5%
Nebraska	20	606	3.3%
Nevada	82	1116	7.4%
New Hampshire	4	214	1.9%
New Jersey	75	2281	3.3%
New Mexico	58	1847	3.1%
New York	122	2637	4.6%
North Carolina	156	3525	4.4%
North Dakota	8	270	3.0%
Ohio	173	2335	7.4%
Oklahoma	144	1830	7.9%
Oregon	48	607	7.9%
Pennsylvania	160	2647	6.0%
Rhode Island	11	195	5.6%
South Carolina	94	2667	3.5%
South Dakota	22	248	8.9%
Tennessee	143	2990	4.8%
Texas	894	14154	6.3%
Utah	57	876	6.5%
Vermont	3	86	3.5%
Virginia	114	3094	3.7%
Washington	118	1278	9.2%
West Virginia	32	688	4.7%
Wisconsin	96	1369	7.0%
Wyoming	15	369	4.1%