NBER WORKING PAPER SERIES

A NEW RACIAL DISPARITY IN TRAFFIC FATALITIES

Aaron Chalfin
Maxim N. Massenkoff

Working Paper 30636
http://www.nber.org/papers/w30636

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2022

Neither co-author has any source of funding to acknowledge. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

A New Racial Disparity in Traffic Fatalities
Aaron Chalfin and Maxim N. Massenkoff
NBER Working Paper No. 30636
November 2022
JEL No. I0,K0,R49

ABSTRACT

In 2015, for the first time in nearly forty years, the rate of motor vehicle fatalities for Black Americans exceeded that of white Americans. By 2020, the gap in death rates stood at 34%, accounting for approximately 4,000 excess deaths between 2014 and 2020. This disproportionate increase occurred in nearly all states, in rural as well as urban areas, and was shared by drivers of all ages and genders. We consider a variety of potential explanations for the emerging race gap including race-specific changes in time spent driving, the circumstances of driving, the quality of medical care for crash victims, decreases in other types of mortality, changes in policing, and risky driving behaviors such as speeding, driving without a seat belt and driving while intoxicated. We can rule out many of these factors as important contributors to the race gap, but find evidence for two of them. The first is opportunity: Relative to white Americans, Black Americans are spending more time in vehicles than they have in the past. Changes in time spent driving, while modest, likely explain an important share of the emergent race gap. The second is a relative increase in drug use, manifested by a quadrupling of the rate of overdose deaths among Black Americans after 2014. Increased drug use appears to have resulted in a concomitant increase in fatal crashes involving drivers under the influence of drugs. Finally, we consider whether the emerging race gap is explained by the so-called "Ferguson effect," the idea that police officers have pulled back from enforcement activity in recent years. On the one hand, traffic stops made by police officers do appear to have declined after 2014. However, the decline in traffic stops does not appear to be race-specific and there is little evidence of a broad increase in risky driving behaviors like speeding and driving without a seat belt.

Aaron Chalfin
Department of Criminology
University of Pennsylvania
558 McNeil Building
3718 Locust Walk
Philadelphia, PA 19104
and NBER
achalfin@sas.upenn.edu

Maxim N. Massenkoff
Graduate School of Defense Management
Naval Postgraduate School
Monterey, CA 93943
maxim.massenkoff@nps.edu

1 Introduction

Motor vehicle accidents kill approximately 40,000 people annually in the United States and are the second largest cause of preventable deaths after overdoses. While racial disparities between Black and white Americans can be found in virtually every mortality category (Cunningham et al., 2017), mortality from vehicle accidents has, since at least the early 1970s, exhibited strikingly little variation by race, with Black and white Americans experiencing similar mortality risks and following similar trends.

Since 2014, however, race-specific motor vehicle mortality rates have diverged considerably, with the Black rate rising to a higher level than the white rate for the first time since at least the 1970s. Black Americans went from a slightly *lower* risk of traffic fatalities during the 1999-2014 period to a 14% higher mortality risk in 2019 and a 34% higher risk in 2020.[1] Overall, these disparities account for approximately 4,000 additional deaths among Black Americans since 2014. In this paper, we document the emergence of this disparity, noting that it is surprisingly widespread, showing up in nearly every U.S. state, in rural as well as urban locations, and among all age and gender subgroups.

Next, we asses a number of leading hypotheses for the recent race-specific divergence in U.S. vehicle mortality trends. Given the inherent difficulty of studying the "causes of effects" as opposed to the "effects of causes" (Holland, 1986), our methods are primarily descriptive.[2] To the extent that we do not observe race-specific changes in a candidate explanation during the time period in question, we consider that explanation to be an unlikely driver of the emerging race gap.

A relative increase in driving—approximately 5 extra minutes per day—among Black-Americans accounts for a sizable share (between 24% and 87% given sampling variability in

[1]While 2020 was potentially an aberration due to the initial onset of the COVID-19 pandemic and resulting lockdowns, early estimates suggest that crash fatalities, in fact, jumped again in 2021—by around 10% (NHTSA, 2022). As of the writing of this article, the full data for 2021 are not available.

[2]That is, while there are numerous strategies for studying the effects of a treatment of interest, fewer strategies are available to provide a holistic explanation for why the world is the way that it is. This is due the difficulty in discerning between root causes and proximate causes as well as impossibility of finding a unique natural experiment for every potential cause of interest. Similar examples study why crime declined during the 1990s (Blumstein et al., 2000; Levitt, 2004), why U.S. labor force participation rates have fallen over time (Murphy and Topel, 1997; Krueger, 2017).

the available survey data) of the race-specific change in fatalities from traffic accidents. In contrast, we find little role for changes in the circumstances of driving, mobility patterns, local economic activity, the quality of medical care for crash victims, and competing risks from other causes of death. We also consider whether the race gap might be the result of race-specific changes in risky driving behavior, including speeding, driving without a seat belt or a driver's license and driving under the influence of alcohol. The Fatal Accident Reporting System, which we rely on for many of our analyses, records features of the crash that may have contributed to a fatal accident. For most driving behaviors, including those described above, there is little evidence for race-specific changes around the time that Black vehicle fatalities began to rise.

While the data do not suggest a large role for alcohol-related crashes, we do find evidence that driving under the influence of illegal drugs might explain some of the new racial gap in traffic fatalities, based on three related descriptive findings. First, beginning around 2014, there has been a large divergence in overdose deaths between Black and white Americans. While drug overdose fatality rates have more than doubled among white Americans over this time period, they have nearly quadrupled among Black Americans. Given the link between intoxicated driving and car accidents (Penning et al., 2010; Kuypers et al., 2012; Gjerde et al., 2013), a race-specific divergence in traffic fatalities might be expected to follow. Second, data from roadside surveys of drivers and laboratory toxicology reports performed after fatal accidents suggest that a recent race gap has emerged in drugged driving. Finally, region-by-demographic cohorts for whom the increase in drug overdose deaths is the largest are, on average, the same cohorts for whom the increase in vehicle mortality is the largest. Taken as a whole, the data are consistent with an important role for increased drug abuse.

Finally, we consider whether the widening race gap in motor vehicle mortality can be explained by changes in the intensity of policing—the so-called "Ferguson effect" (e.g., Pyrooz et al., 2016). There is empirical support for a causal relationship between police resources and vehicle mortality generally (DeAngelo and Hansen, 2014). But an analysis of national survey data reveals little evidence for a discontinuous change in race-specific police enforcement on U.S. roadways. While drivers were less likely to be pulled over in 2018 compared to 2011, this decrease was fairly uniform across different race groups, and the age-gender groups among which the race gap in traffic enforcement widened the most are not the same age-gender groups that experienced the largest race gap in traffic fatalities. Further, a number of risky or illegal driving behaviors such as speeding, driving under the influence of alcohol and driving without a seatbelt, presumably the key pathways through which policing would affect mortality on the roads, do not seem to have changed in race-specific ways since 2014. While we cannot conclusively rule it out, a law enforcement-led explanation for the new race gap in traffic fatalities requires that decreases in traffic stops were more impactful for Black Americans compared to other groups, and that driving behaviors responded in ways not recorded in the accident data.

The remainder of the paper proceeds as follows. In Section 2, we describe the sources of administrative and survey data we use to test leading theories. Section 3 provides a broad overview of national trends in race-specific vehicle mortality rates during the last two decades. Section 4 provides a qualitative assessment of the evidence for and against each of several leading theories for the emergent mortality gap. Section 5 concludes.

2 Data

We use data from the Fatality Analysis Reporting System (FARS; NHTSA, 2019) to study race-specific trends in traffic fatalities as well as trends in the underlying circumstances of those fatalities. The FARS, with coverage beginning in 1975, is a census of all motor vehicle fatalities in the United States, with data on the cause of the crash, type of vehicles involved, and information about the vehicle's driver. Beginning in 1999, the FARS began collecting information on the race of the decedent (Briggs et al., 2005), although not of people involved in the accident who did not die. We present descriptive data from the FARS in Table 1, separately for the 1999-2013 period in which there was no Black-White race gap in fatalities and the post-2014 period during which the race gap opened up. During the 1999-2013 period, Black Americans accounted for 13% of traffic-related fatalities. During the post-2014 period, this proportion had increased to 16% despite the fact that the Black share of the U.S. population has remained constant (between 12-13%) during the 2000-2020 period. Across the two periods, drivers accounted for 64% of traffic-related fatalities with the remainder made up of passengers or pedestrians/bicycle riders. Notably there has been a rise in the pedestrian share of deaths over time, though this is seen in equal measures among Black and white Americans and therefore has not been a driver of the race gap. With respect to risky driving behaviors, as a percentage of fatal crashes, the trends vary depending on the specific behavior of interest. While the share of fatal crashes in which the decedent was not wearing a seatbelt has fallen from 67% in the pre-period to 59% in the post-period, the share of fatal accidents involving drugs or alcohol has risen from 38% to 43%. Within that category, the alcohol share has remained flat and the drug share has doubled from 5% to 10%.

We supplement the FARS data with CDC data derived from death certificates (CDC, 2021). Since the CDC data are available as far back as 1973, this allows us to extend the series backwards in time to observe longer-run trends. The CDC data also provides an instructive robustness check because while some states inconsistently record race in the FARS data, the CDC data are more consistently recorded. Importantly, the FARS data and the CDC data reveal similar levels and trends. In both datasets, we observe parallel trends in fatalities among Black and white drivers until approximately 2014.

To measure the amount of time that people spend driving, a key proxy for the opportunity for a fatal accident to occur, we use survey data from the American Time Use Survey, a joint product of the U.S. Bureau of Labor Statistics and the U.S. Census Bureau that is designed to study how and where United States residents spend their waking hours. The survey has been administered annually to a nationally representative sample of between 20,000 and 40,000 American households since 2003 and asks respondents to carefully document how they spent their time during a recent day, including the amount of time they spent traveling in a vehicle (US BLS, 2022).[3]

To study the prevalence and nature of interactions between drivers and law enforcement, we turn to the Police Public Contact Survey (US BJS, 2018). The PPCS surveys a nationally representative sub-sample of respondents to the U.S. National Crime Victimization Survey and is typically administered every three years. The survey asks respondents to indicate whether they have had an interaction with a police officer in an official capacity during the

[3] We also supplement the ATUS with data from the National Household Travel Survey which is available for a subset of years.

prior calendar year. If they have, respondents are asked to provide details about the nature and outcome of that interaction and the quality of service that they received. We present descriptive statistics for the PPCS in Table 2. During the study period, approximately 8% of drivers came in contact with the police as a result of a traffic stop, a proportion that has been fairly constant over time with the exception of 2011 where 11% of individuals indicated experiencing a traffic stop. Among drivers who were stopped by the police, there appears to have been a decline in the share of drivers who were ticketed, reflecting a decline in enforcement along the intensive margin of police-citizen contact. Importantly though the decline is seen among both Black and white drivers. We further probe these trends in Section 4 where we disaggregate the data more formally by race.

3 Main Results

We begin by documenting national changes in race-specific motor vehicle fatality rates over time. In Figure 1 we plot traffic deaths relative to their pre-2000 average separately for Black and white Americans. In panel (a), we use FARS data; in panel (b) we use mortality data from the U.S. Centers for Disease Control. Both figures reveal substantively similar patterns: after experiencing similar rates and trends for many years, beginning around 2014, motor vehicle fatalities rose sharply among Black Americans relative to white Americans. Fatality rates for both groups declined from 2007 to 2013. Around 2014, deaths rates increased sharply for both Black and white Americans. However, the increase was much sharper and more sustained for Black Americans. According to CDC data, by 2019, the fatality rate was approximately 14% higher for Black Americans than for white Americans. The gap further widened during the COVID-19 pandemic in 2020.[4] Figure A.1 shows monthly deaths from

[4]The CDC data are useful to test whether race-specific changes in mortality recorded in the FARS are not an artifact of changes in the quality of recording practices. In particular, race is imperfectly recorded in the FARS data and practices vary geographically, with states collating information from police crash reports, death certificates, driver license files, and other sources. Data from the CDC provides a robustness check as these data are based exclusively on the universe of US death certificates, with race more consistently recorded. The same sharp divergence in mortality rates is visible in per capita ("crude rate") series from death certificates, plotted in Figure A.2. For both groups, 2014 marks an increase in motor vehicle accidents (ICD10 codes V01-V99, "Transport accidents"). In this year, the black-white difference in per capita fatalities is positive for the first time since 1973.

the CDC, similarly normalized by each racial group's 1999-2013 average. As in the annual plots, the separation begins around 2014. This more granular time scale shows that from 1999 to 2013, the two series followed strikingly similar trajectories.

Given wide regional variation in many social outcomes within the United States, it is possible that the national trends mask important markers of regional heterogeneity. If so, this could point to changes in state-level policymaking as a potential culprit. Strikingly, the national pattern is mirrored in almost every state in the country (Figure 2), a fact which suggests that the underlying causes are likely to be broad-based rather than driven by shifts in local policies such as the liberalization of marijuana possession and state-specific changes in criminal justice policies or driving enforcement. Likewise, though the relative increase in traffic fatalities is about twice as large in urban counties than in rural counties, the emerging Black-White mortality gap is found in both rural and urban areas and the deviation in trends occurs at the same time in both types of locations (Figure 3).

In Figure 4, we consider how race-specific mortality from motor vehicle accidents has changed according to the age and gender of the decedent.[5] Again, the patterns are broad-based. While the largest gap is found for male drivers, a race-specific mortality gap has emerged during this time period for every age and gender group in the United States with the exception of women over the age of 50. Since men are disproportionately represented among traffic fatalities, they contribute disproportionately to excess mortality after 2014 as well. However, in percentage terms, the increases are similar for men and women.[6]

Finally, we consider whether race-specific changes in vehicle deaths are an artifact of the changing mix of driver, passenger and pedestrian injuries. In Figure A.5, we present FARS fatality data separately for drivers, passengers, single car accidents and pedestrians and cyclists. It is clear from the figures that the Black and white series diverge to a similar

[5]We present the same information disaggregated only by age group in Figure A.3 and only by gender in Figure A.4.

[6]To explore whether the race gap is driven to a large extent by younger drivers, we consider what the race gap would have been had the driving mortality rate for younger Black drivers remained fixed at that of their white counterparts. We present such an analysis in Figure A.6 where we compare the observed race gap to a counterfactual race gap. Even under this restrictive assumption, the post-2014 race gap between Black and white drivers remains large and clear, although younger drivers contribute meaningfully to the gap.

degree and around the same time for all categories of accidents and so the emerging race gap is not an artifact of changes in the mix of accident types. Given that the race gap for drivers and passengers is so similar, it does not appear as though the race gap is driven by accidents involving drivers and passengers of different races.

4 Mechanisms

Having documented a sharp and broad-based divergence in race-specific traffic fatality rates, we next consider a number of candidate explanations. In Section

4.1 Potential Explanations

4.1.1 Time spent driving

We begin by considering whether the emerging race gap in motor vehicle mortality rates might be an artifact of race-specific changes in time spent traveling in a vehicle. If Black Americans are now spending more time driving or traveling in a vehicle than their white counterparts, the emerging race gap might simply be a mechanical artifact of changes in opportunity.[7] To explore this possibility, we turn to the American Time Use Survey which records the number of hours that respondents spent in a vehicle, either as a driver or passenger.[8] We use these data from 2003-2020 and consider whether Black Americans' vehicle travel time increased after 2014.[9] The results, plotted in Figure 5, show that the race gap in time spent in a vehicle declined during the study period. Prior to 2014, the average Black American and white American over the age of 15 spent 57.7 minutes per day and 67.4 minutes per day traveling in a vehicle, respectively. After 2014, this number rose to 60.8 minutes for Black Americans and fell to 66.0 minutes for white Americans. Black Americans thus

[7] In another context, time spent driving has been found to reduce criminal opportunities among young people who were subject to graduated driving laws—see Deza and Litwok (2016).

[8] We count time spent in a car, truck or motorcycle as a driver or passenger ("where" codes 230 and 231) and time spent in a taxi or limousine ("where" code 237) (Flood et al., 2022)

[9] We further note that this analysis also helps address whether economic factors led to different driving patterns. The divergence in fatality rates came in the midst of a substantial ten-year decline in unemployment rates for African American men. From a high of 19% in March 2010, the unemployment rate for Black men age 20 or over declined to 6% in December 2019. (For similarly aged white men, unemployment decreased from 9 to 3% over the same period.) However, person-level register data from Sweden finds that unemployment has no impact on motor vehicle fatalities (Gerdtham and Johannesson, 2003).

spent 4.5 more minutes driving (SE = 1.56 minutes) after 2014 relative to white Americans than they had previously.[10,11]

How much of the emergent race gap this might explain? At first glance, 4.5 additional minutes might seem like a relatively small change. However, in percentage terms the increase is large enough to be meaningful. Relative to their pre-2014 means, during the 2014-2019 period, driving time rose for Black Americans by 5.6% and fell among white Americans by 2.1%, a 7.7% relative increase among Black Americans. If the risk of a fatal accident during the marginal minute spent driving is equal to the risk during the average minute, a 7.7% relative increase in opportunity predicts a 7.7% relative increase in traffic fatalities. Based on our principal estimate, opportunity thus mechanically explains approximately half of the 14% relative increase in traffic fatalities during the 2014-2019 period. Given statistical uncertainty around the point estimate, a 90% confidence interval suggests that changes in opportunity explain between 24% and 87% of the race gap that has opened up since 2014. As this is a large range of potential values, a conservative reading of this result is that opportunity likely accounts for an important share of the race gap even if the precise value is difficult to pin down.

Another way to assess the importance of shifts in opportunity is to hold constant the risk of a fatality per hour spent driving at pre-2014 levels and apply this risk level to the number of hours spent driving after 2014. Prior to 2014, the risk of a fatal accident for a Black driver was approximately 3.5 fatal accidents per 10 million driving hours (see Figure 5). Applying an additional 4.6 minutes of driving time to approximately 32 million Black Americans over the age of 15 means that Black American spent 970 million more hours on the road per year after 2014 than they had previously. Given a risk of 3.5 fatal accidents per 10 million driving hours, this works out to 313 additional fatalities per year. In the observed data, there were an additional 636 Black fatalities per year relative to white fatalities after 2014.

[10] In Figure A.7 we use the National Household Travel Survey (NHTS) to plot the same information. The NHTS is administered irregularly so we use the survey years 2009 and 2017. In these data, it appears as though time spent traveling in a vehicle fell for both Black and white Americans. However, the relative increase for Black Americans, 8%, is similar to our estimate using the American Time Use Survey.

[11] In Table A1 we provide the number of deaths per 100K population as well as per 10 million hours traveled, by race, between 2009 and 2020.

This analysis thus suggests that changes in opportunity might explain $\frac{313}{636} = 49\%$ of the race gap prior to 2020.

4.1.2 Medical care

A number of studies find differential treatment of Black patients in the U.S. healthcare system (Hoffman et al., 2016), with possible impacts on mortality (Greenwood et al., 2020). With respect to traffic fatalities, racial differences in features of emergency care, such as the response time of emergency personnel (Jena et al., 2017) or the quality of physician care upon arrival in a hospital (Champion et al., 1990) could have an impact on a victim's survival. If Black accident victims began receiving less effective medical care beginning in 2014, this could potentially explain the recent racial divergence in death rates.

To address this possibility, we study changes in accidents in which the victims died at the scene of the crash, an attribute that is recorded in the FARS data. Over our sample period of 1999-2019, half of the victims in the FARS data are recorded as dying at the scene. If differences in medical care are an important driver of the recent gap in mortality rates, we would expect to see a smaller racial divergence when we limiting the data to victims who were already deceased. In Figure 6, we plot the same normalized series as in Figure 1 except that we restrict to victims who were dead at the scene. The plots show the same differential increase in Black fatalities beginning around 2014 and escalating thereafter. This analysis suggests race-specific changes in the quality of medical care are unlikely to be a leading driver of the emerging race gap in motor vehicle mortality.

4.1.3 Competing risks

Next, we consider whether changes in race-specific motor vehicle fatalities could be a mechanical artifact of a decrease in other risks among Black Americans relative to white Americans. For example, if relative mortality rates for other causes of death were declining then the increase in traffic fatality deaths could be due to a change in competing risks. In addition to all-cause mortality rates, we also consider incarceration rates which were declining during this time period, especially among Black Americans.

In Figure 7 we present death rates from non-external causes for ten-year age groups using data from CDC WONDER. During our study period, deaths from non-external causes (ICD chapters A-U) decreased slightly for Black Americans relative to white Americans. For instance, the mortality rate for Black Americans age 45-54 decreased by 13%, from 530 to 460 per 100,000. For white Americans in the same age group, the mortality rate decreased by 7%. Could a decline in other cause mortality rates mechanically explain a portion of the increase in vehicle fatalities among Black Americans? To explore this possibility, we plot a counterfactual death rate for Black Americans, holding age-specific mortality rates constant at 2010 levels. This counterfactual is represented by the dashed lines in Figure 7. With the exception of those over the age of 75, who comprise only a very small share of motor vehicle fatalities, the actual and counterfactual trends diverge only slightly. Aggregating across all age groups, the cumulative number of averted deaths, relative to fixing the death rates at 2010 levels, amount to 0.3% of the Black population in 2019. For this share of the population to increase the motor vehicle fatality rate, their risk of such deaths would have to be implausibly large.[12]

A second type of competing risk arises from declining rates of incarceration. As U.S. crime rates declined during the 21st century from its peak during the early 1990s, the U.S. state and federal prison population declined by 28% from 2010 to 2020, with an even larger 37% decrease among Black Americans (Carson, 2021). Could a decline incarceration mechanically increase the relative time at risk among Black Americans, helping to explain the increase in vehicle fatalities? For this to be true, released prisoners would have to be more likely to die in motor vehicle accidents. There is, in fact, evidence to support this. Binswanger et al.

[12]To illustrate, the Black fatality rate in motor vehicle accidents increased from 11.4 per 100,000 in 2014 to 14.3 per 100,000 in 2019. If people in the "averted deaths" group accounted for, say, half of this increase, the death rate for the group would have to be extraordinarily high.

The motor vehicle death rate in 2019 can be written as the weighted average of deaths rates from the two groups:

$$14.3 = 0.003 * Rate_A + 0.997 * Rate_B \tag{1}$$

where $Rate_A$ is the motor vehicle death rate for individuals in the averted deaths group and $Rate_B$ is the rate for everyone else, who constitute 99.7% of the Black population. If the increase would have been half as large without the averted deaths group, $Rate_B$ would be 12.9, half of the actual increase. Then for the equality to hold, $Rate_A$ would have to be over 400. Similarly, if the change accounted for just 10% of the increase, the rate in the averted deaths group would need to be 48 per 100,000, which is still implausibly high.

(2007) find that released inmates in Washington are 3.4 times (95% CI: 2.4-4.8) more likely to die in car accidents than other people.[13]

A simple exercise helps bound the role that released prisoners might play in explaining the emergence of a race gap in traffic fatalities. In 2020, there were 179,000 fewer incarcerated Black Americans as compared to 2010 (Carson, 2021, Table 3). This accounts for 0.44% of the 41.1 million Black Americans living in the United States in 2020. The death rate in 2020 can be written as the weighted average of two death rates, the death rate for the recently released and the rate for everyone else:

$$Rate = EveryoneElseRate * 0.9956 + RecentlyReleasedRate * 0.0044 \tag{2}$$

We condense the changes into one year. Assume that rate for everyone else is 11.4 per 100,000 (the 2014 Black population rate), and in the very next year, this remains constant as 179,000 prisoners are released. Would the *RecentlyReleasedRate* meaningfully increase the population rate? The more pessimistic estimates in Binswanger et al. (2007) suggest a 40 per 100,000 auto fatality rate among the formerly incarcerated, assuming the rate among the released Black population is 3.5 times that of the overall Black population. Given the equation above, this would increase the death rate from 11.44 to 11.57, or by only 0.13 deaths per 100,000. Such an increase would account for just 2 percent of the overall increase from 2014 to 2020, or 4 percent of the increase from 2014 to 2019.

4.1.4 Changes in Driving Circumstances

Another possibility is that there have been race-specific changes in the *circumstances* of driving. To the extent that Black and white drivers are driving at different times or in different places or that they are driving different types of vehicles, such factors could potentially explain the emergence of the race gap in fatalities. For instance, the gap might be caused by economic changes leading to a shift in working hours, or new, more dangerous vehicles.

We address this possibility in Figure 8 where we document race-specific trends in crashes occurring late at night as well as on the weekends, crashes involving a single car, crashes on

[13] Using data in Illinois, Norris et al. (2021) find that the risk of accidental death is 52 per 100,000, which is not meaningfully higher that the US average. But this is a broader category that includes accidental falls, for example.

highways versus local roads, crashes involving a sedan versus a truck and those involving a head-on collision or a rollover crash. While no large changes are apparent and both groups follow largely parallel paths, the Black share of fatal crashes occurring late at night and on the weekend increased slightly after 2014. Such a shift could potentially be consistent with more driving under the influence of alcohol or drugs, a topic we consider in the next section. However, even taking these shifts as exogenous, there is little evidence that this shift in the circumstances of fatal crashes are large enough to explain anything more than a very small proportion of the emerging race gap. We probe this further in Appendix C where we apply a Oaxaca-Blinder decomposition to the FARS data, decomposing the change in the Black share of decedents across the two periods. None of the markers of driving circumstances described above explains the emergence of the Black-White mortality gap after 2014.

4.1.5 Changes in Risky Driving Behavior

Having ruled out a number of mechanical explanations, we next consider whether there have been changes in specific driving behaviors which could potentially explain the emergent race gap. In Figure 9, we plot a number of the most common behavioral factors associated with an increased risk of traffic death. Panels (a)-(c) show that Black decedents are consistently less likely to be wearing a seat belt and more likely to be speeding or driving without a driver's license than white decedents. While these factors potentially predispose Black drivers to be involved in more fatal crashes than white drivers, given that these differences are constant over time and overlap with a period in which there was no driving mortality gap between Black and white drivers, they are unlikely to explain the post-2014 disparity.

With respect to intoxicated driving, the picture is less clear. Alcohol involvement, as recorded in the FARS data, increased among Black drivers relative to white drivers beginning in 2007. However these attributes are based, in part, on the judgment of the first responders at the scene of the crash, and so the data could be be contaminated by racial biases or differences in training among police officers or EMT personnel that change over time. Although data availability is inconsistent across states (Slater et al., 2016), an average of 25% of decedents in the data have their blood tested for alcohol content. In order to consider a more objective measure of alcohol involvement in fatal crashes, in panel (g), we plot the average blood alcohol content (BAC) for Black and white drivers since 1999. The two series track each other closely prior to 2014 and, after 2014, diverge only slightly suggesting that a shift in drunk driving is unlikely to explain a large share of the racial mortality gap that has since emerged. Finally, in order to further address the possibility that even data generated by toxicology reports could be biased in the presence of time-varying selection, panel (d) presents data on the race-specific share of single car crashes, which are predictive of alcohol involvement (Schmidt et al., 1972). The share of single car crashes tends to be slightly higher among Black drivers than white drivers during the study period. However, there is no clear break in 2014. If anything, the race gap has shrunk to a small degree. We regard this as further evidence that changes in drunk driving are not a primary contributor to the post-2014 race gap in traffic fatalities.

Next we turn to driving under the influence of illegal drugs. The opioid epidemic has led to a dramatic rise in the number of drug overdose deaths in the United States during the last decade (Dave et al., 2021; Mattson et al., 2021). While overdose deaths began to rise starting in 2010, the increase has been especially steep since 2014, the same time that the Black-White traffic fatality gap opened up. We explore these trends in Figure A.9, plotting deaths from drug overdoses relative to the 2014 share. In 2019, the white drug overdose rate was twice what it had been in 2014 but the Black rate had nearly tripled (Drake et al., 2020). By 2020, the Black rate had nearly quadrupled. Given the empirical connection between driving under the influence of illegal drugs (Penning et al., 2010; Kuypers et al., 2012; Gjerde et al., 2013), including opioids specifically (Chihuri and Li, 2019; Li and Chihuri, 2019) and car accidents, a race-specific divergence in traffic fatalities might reasonably be expected to follow.

Does the crash data suggest a disproportionate increase in impaired driving due to drug use? There is some evidence to suggest that this may have been the case. Panels (f) and (h) of Figure 9 show that levels of drug involvement for Black and white drivers appear to follow similar trends prior to 2014, whether that is measured using the broader FARS variable (panel f) or toxicology reports (panel h). However, according to the toxicology data, the Black rate began to grow relative to the white rate after 2014, possibly because the opioid epidemic hit Black communities later than it hit white communities. In Figure A.8, we use the toxicology reports from the FARS to plot the race-specific positivity rates for four classes of drugs: Cannabis (panel a), opioids (panel b), stimulants (panel c) and all other drugs (panel d). Crashes in which the driver tested positive for either marijuana or an opioid increased among Black relative to white drivers after 2014. In panel (e), we show the share of decedents who have toxicology data has evolved similarly for Black and white decedents, which provides some assurance that selection into drug testing has not changed meaningfully across races over the period. A similar differential increase is present in auxiliary data from the Voluntary National Roadside Survey of Alcohol and Drug Use by Drivers, a periodic survey of intoxication rates from roadside stops in the United States. The 2007 survey found that 16.8% of Black drivers tested positive for some drug compared to 15.5% of white drivers (Table 89; Lacey et al., 2009a). In the 2013-2014 survey, the figure was 27.7% for Black drivers and 22.5% for whites (Table 14 Kelley-Baker et al., 2017). Thus both sources of data point to an increase in driving under the impairment of drugs among Black Americans relative to white Americans after 2014.[14]

We next show that, at the state level, growth in the Black-white gap in drug deaths is correlated with growth in the Black-white gap in car accidents. Figure 10 is a binned scatterplot showing the change in the racial gap in car accidents (y-axis) vs. the change in the racial gap in drug overdoses (x-axis). We group by state and 5-year periods. In the figure, a "2" on the x-axis would correspond to a state in which the Black-White difference in deaths had increased by 2 deaths per 100,000 since the previous 5-year period. The slope of the trend line drawn through the data is 0.14, indicating that 7 point increase in the Black-White overdose gap predicts a one point increase in the Black-White gap in traffic fatalities. Nationwide, drug overdoses for Black Americans increased by 3 per 100,000 relative to white Americans. Based on the relationship in Figure 10, this would predict growth in the crash gap of 0.42 per 100,000, or about 17% of the overall change in the Black-White vehicle fatalities gap. We probe this result in Appendix C which reports the results of a Oaxaca-Blinder decomposition. The decomposition suggests that drug involvement explains between

[14] Driving under the influence of alcohol has decreased. The share of Black drivers surveyed at night with a blood alcohol content of 0.08 or above was 2.0% in 2007, while for whites it was 2.4% (Table 10; Lacey et al., 2009b). In the 2013-2014 survey, the rate was 1.6% for Black drivers and 1.5% for white drivers (Ramirez et al., 2016).

21% and 26% of the emergent race gap.

Measuring the contribution of drug use is challenging given heterogeneity in the data. On the one hand, the FARS data shows similar trends in drug involvement — and in single car accidents — throughout the last two decade for both races (Figure 9). On the other hand, a series of related descriptive findings point to a potential link between drug use and the emerging mortality gap. First, beginning around 2014, there has been a large divergence in overdose deaths between Black and white Americans. While drug overdose fatality rates have more than doubled among white Americans over this time period, they have nearly quadrupled among Black Americans. Second, among the subsample of deceased drivers who were given toxicology tests, there has been an increase in positive drug test results for Black drivers, a finding which is mirrored in national survey data. An analysis of raw time trends is supported by a more formal Oaxaca-Blinder decomposition which suggests a tightening link between race and drug use, even after adjusting for other factors (Appendix C). Finally, region-by-demographic cohorts for whom the increase in drug overdose deaths is the largest are, on average, the same cohorts for whom the increase in vehicle mortality is the largest. Taken as a whole, the results suggest a meaningful role for drug use in generating he emerging race gap in traffic fatalities.

4.2 Changes in Law Enforcement

A large share of police activity involves the regulation of illegal driving behavior (Paoline and Terrill, 2005; Asher and Horwitz, 2020; Weisburd, 2021), and there is ample evidence that crime is, in general, responsive to changes in policing (Evans and Owens, 2007; Heaton et al., 2016; MacDonald et al., 2016; Chalfin and McCrary, 2018; Braga et al., 2019; Mello, 2019; Weisburst, 2019; Jabri, 2021; Chalfin et al., 2022). It is thus natural to wonder whether changes in law enforcement activity played a role in increased Black mortality on the roads since 2014. In this section, we consider whether law enforcement activity on U.S. roadways changed after 2014, focusing on the number and outcomes of traffic stops made by police officers. As there is no official national data on police stops, and because police-generated data are subject to concerns regarding selection as well as data quality, we use the Police Public Contact Survey (PPCS), a nationally representative survey of individuals living in the United States that is generally released every three years. In the PPCS, respondents are surveyed about the frequency and nature of their contact with the police. The nature of police contact is varied and includes experiences in which the respondent was either the suspect of or a victim in a crime. However, traffic stops are, by far, the leading reason for police contact with approximately 60% of contact between police officers and citizens being initiated on a U.S. roadway.

Consistent with evidence on changes in the intensity of policing during the last decade (Wolfe and Nix, 2016; Shjarback et al., 2017; Premkumar, 2019), the share of PPCS respondents who report that they were stopped by police while driving in the last year fell from 2011 to 2018, the last year for which PPCS survey data are available. We explore these changes in Figure 11, which plots the share of survey respondents who indicate that they were stopped while a police officer while driving during the past year, disaggregated by race, gender and age. We begin with young men, the demographic group that is most likely to be involved in a fatal car accident. Between 2011 and 2018, the share of young Black men reporting a police stop while driving decreased notably, from 17% to 10%. However, a similar decrease is visible for white males in the same age group, from 19% to 14%. The same decline is present in the older age groups too. Black females age 45 and older drop from a 7% to a 3% chance of being pulled over. These are sizeable decreases, with each group seeing its chance of a traffic stop drop by approximately one half.[15] However, there is little evidence in favor of race-specific change in the number of police stops.

Next, since the deterrence value of law enforcement may depend on whether a given stop ultimately led to a punishment, we consider the outcomes of traffic stops. We plot these data in Figure 12, disaggregating by age, race and gender as in the previous figure. Overall, the share of stops that led to a ticket is approximately 50% over the entire study period. Among older drivers there is evidence that the share of stops leading to a ticket has fallen, especially for men. However, for younger male drivers as well as those in the prime age group of 25-44—the largest contributors to traffic fatalities—there is little evidence of a change in police leniency. There is even less evidence of a change that is race-specific. Consistent with

[15] It is worth noting that traffic stops in 2011 were significantly higher than in 2008, so the 10-year difference from 2008 to 2018 is considerably smaller.

prior research, Black drivers appear to be less likely to be the beneficiaries of leniency from police officers (Goncalves and Mello, 2021). However, the trends for Black and white drivers remain parallel during the relevant time period.

Did these declines matter for fatal traffic accidents? We probe this question by asking whether the demographic groups with the largest decline in traffic stops also experienced the largest increases in traffic fatalities. This should be seen as speculative since one could easily worry about reverse causation: an increase in risky driving within a certain group could cause an increase in traffic stops, resulting in a positive correlation. We present the data in Figure 13, which plots the percentage change in motor vehicle deaths (y-axis) against the percentage change in the share of PPCS respondents with a traffic stop (x-axis). Each data point is an age-gender-race group. The relationship is fairly flat, indicated by an R^2 value of 0.05. Demographic groups that were most subject to "de-policing" are not the same groups that experienced the largest rise in motor vehicle fatalities.

Without national administrative data on police proactivity on the road or compelling quasi-experimental variation, we cannot conclusively rule out changes in policing as a driver of the emerging race gap. However, the number and nature of police contacts with Black drivers do not seem to have changed relative to white drivers since 2015, thus narrowing the scope for police contact to a primary driver of the race gap. Likewise, several risky or illegal driving behaviors—including speeding and driving without a seat belt or a driver's license—do not seem to have changed recently in race-specific ways. Thus, if policing explains the new disparity, the increase in deaths is occurring because race-specific effects of policing cause subtle shifts in risk-taking while driving, inducing more drugged driving but not speeding or driving under the influence of alcohol.

5 Discussion

In 2015, for the first time in nearly forty years, the rate of motor vehicle fatalities for Black Americans exceeded that of white Americans. Since then the gap has grown to more than 34% resulting in approximately 4,000 excess deaths during that time period. We document this gap and probe potential causes, finding evidence for two contributing factors. A relative increase in time spent driving likely explains a sizable share of the emergent race gap. There is likewise evidence that drug use may explain another important portion of the change.

While difficult to quantify, we find no evidence for de-policing or the "Ferguson Effect" as a driver of the new gap. A drop in traffic stops over that time period was broad-based, and there is not a clear increase in risky driving behaviors apart from drug use. Still, the increase in motor vehicle deaths coincided with a stark inflection point in homicides, so one possibility is that these developments share a cause related to crime. In Figure A.10(b), we plot the percentage change in traffic deaths against the percentage change in homicide deaths by state-race-cohort. As with the drug overdose plot in panel (a), the relationship is positive, indicating that groups with greater exposure to deaths from homicides also have greater exposure to deaths from traffic fatalities.[16] While these are merely correlations, the data are consistent with the possibility that there has been some general increase in high-risk activities among Black Americans relative to white Americans that began during the middle of the past decade.

This paper documents the emergence of a new and concerning source of racial inequality in a major cause of death, traffic fatalities. We can provide a partial explanation for the emerging gap based on shifts in time spent driving, and suggestive patterns around drug use could indicate that the a recent rise in overdoses has also increased car accidents. But the race gap remains, in part, mysterious. In addition to changes in the quality of driving that might be caused by higher levels of illegal drug use, it is possible that race-specific changes in stress, mental illness or access to healthcare could pay a role. Importantly, these channels could impact the carefulness of drivers without affecting criminal behavior behind the wheel. Such explanations therefore have the potential to explain why we observe an emerging mortality gap despite no large race-specific changes in law enforcement or criminal driving behavior.

[16] A regression table corresponding to this plot can be found in Table A2.

References

Asher, Jeff and Ben Horwitz, "How do the Police actually spend their time?," *The New York Times*, 2020, *19.*

Binswanger, Ingrid A, Marc F Stern, Richard A Deyo, Patrick J Heagerty, Allen Cheadle, Joann G Elmore, and Thomas D Koepsell, "Release from prison—a high risk of death for former inmates," *New England Journal of Medicine*, 2007, *356* (2), 157–165.

Blinder, Alan S, "Wage discrimination: reduced form and structural estimates," *Journal of Human resources*, 1973, pp. 436–455.

Blumstein, Alfred, Joel Wallman, Alfred Blumstein, and David Farrington, *The crime drop in America*, Cambridge University Press New York, 2000.

Braga, Anthony A, Brandon S Turchan, Andrew V Papachristos, and David M Hureau, "Hot spots policing and crime reduction: An update of an ongoing systematic review and meta-analysis," *Journal of Experimental Criminology*, 2019, *15* (3), 289–311.

Briggs, Nathaniel C, Robert S Levine, William P Haliburton, David G Schlundt, Irwin Goldzweig, and Rueben C Warren, "The Fatality Analysis Reporting System as a tool for investigating racial and ethnic determinants of motor vehicle crash fatalities," *Accident Analysis & Prevention*, 2005, *37* (4), 641–649.

Carson, E. Ann, "Prisoners in 2020 - Statistical tables," *Bureau of Justice Statistics*, 2021, *NCJ 302776.* https://bjs.ojp.gov/content/pub/pdf/p20st.pdf.

CDC, "Underlying Cause-of-Death," https://wonder.cdc.gov/mortSQL.html 2021. [Online; accessed 19-July-2021].

Chalfin, Aaron and Justin McCrary, "Are US cities underpoliced? Theory and evidence," *The Review of Economics and Statistics*, 2018, *100* (1), 167–186.

_ , Benjamin Hansen, Emily K Weisburst, and Morgan C Williams Jr, "Police force size and civilian race," *American Economic Review: Insights*, 2022, *4* (2), 139–58.

Champion, Howard R, Wayne S Copes, William J Sacco, Mary M Lawnick, Susan L Keast, and Charles F. Frey, "The Major Trauma Outcome Study: establishing national norms for trauma care," *Journal of Trauma and Acute Care Surgery*, 1990, *30* (11), 1356–1365.

Chihuri, Stanford and Guohua Li, "Use of prescription opioids and initiation of fatal 2-vehicle crashes," *JAMA Network Open*, 2019, *2* (2), e188081–e188081.

Cunningham, Timothy J, Janet B Croft, Yong Liu, Hua Lu, Paul I Eke, and Wayne H Giles, "Vital signs: racial disparities in age-specific mortality among blacks or African Americans—United States, 1999–2015," *Morbidity and Mortality Weekly Report*, 2017, *66* (17), 444.

Dave, Dhaval, Monica Deza, and Brady Horn, "Prescription drug monitoring programs, opioid abuse, and crime," *Southern Economic Journal*, 2021, *87* (3), 808–848.

DeAngelo, Gregory and Benjamin Hansen, "Life and death in the fast lane: Police enforcement and traffic fatalities," *American Economic Journal: Economic Policy*, 2014, *6* (2), 231–57.

Deza, Monica and Daniel Litwok, "Do nighttime driving restrictions reduce criminal participation among teenagers? evidence from graduated driver licensing," *Journal of Policy Analysis and management*, 2016, *35* (2), 306–332.

Drake, Jasmine, Creaque Charles, Jennifer W Bourgeois, Elycia S Daniel, and Melissa Kwende, "Exploring the impact of the opioid epidemic in Black and Hispanic communities in the United States," *Drug Science, Policy and Law*, 2020, *6*, 2050324520940428.

Evans, William N and Emily G Owens, "COPS and Crime," *Journal of Public Economics*, 2007, *91* (1-2), 181–201.

Flood, Sarah, Liana Sayer, and Daniel Backman, "American Time Use Survey Data Extract Builder: Version 3.1 [dataset]," *College Park, MD: University of Maryland and Minneapolis, MN: IPUMS*, 2022. https://doi.org/10.18128/D060.V3.1.

Fortin, Nicole, Thomas Lemieux, and Sergio Firpo, "Decomposition methods in economics," in "Handbook of labor economics," Vol. 4, Elsevier, 2011, pp. 1–102.

Gerdtham, Ulf-G and Magnus Johannesson, "A note on the effect of unemployment on mortality," *Journal of Health Economics*, 2003, *22* (3), 505–518.

Gjerde, Hallvard, Asbjørg S Christophersen, Per T Normann, and Jørg Mørland, "Associations between substance use among car and van drivers in Norway and fatal injury in road traffic accidents: A case-control study," *Transportation research part F: traffic psychology and behaviour*, 2013, *17*, 134–144.

Goncalves, Felipe and Steven Mello, "A few bad apples? Racial bias in policing," *The American Economic Review*, 2021, *111* (5), 1406–41.

Greenwood, Brad N, Rachel R Hardeman, Laura Huang, and Aaron Sojourner, "Physician–patient racial concordance and disparities in birthing mortality for newborns," *Proceedings of the National Academy of Sciences*, 2020, *117* (35), 21194–21200.

Heaton, Paul, Priscillia Hunt, John MacDonald, and Jessica Saunders, "The short-and long-run effects of private law enforcement: Evidence from university police," *The Journal of Law and Economics*, 2016, *59* (4), 889–912.

Hoffman, Kelly M, Sophie Trawalter, Jordan R Axt, and M Norman Oliver, "Racial bias in pain assessment and treatment recommendations, and false beliefs about biological differences between blacks and whites," *Proceedings of the National Academy of Sciences*, 2016, *113* (16), 4296–4301.

Holland, Paul W, "Statistics and causal inference," *Journal of the American Statistical Association*, 1986, *81* (396), 945–960.

Ingram, Deborah D and Sheila J Franco, *2013 NCHS urban-rural classification scheme for counties*, US Department of Health and Human Services Centers for Disease Control, 2014. https://www.cdc.gov/nchs/data_access/urban_rural.htm.

Jabri, Ranae, "Algorithmic Policing," 2021.

Jann, Ben, "A Stata implementation of the Blinder-Oaxaca decomposition," *Stata journal*, 2008, *8* (4), 453–479.

Jena, Anupam B, N Clay Mann, Leia N Wedlund, and Andrew Olenski, "Delays in emergency care and mortality during major US marathons," *New England Journal of Medicine*, 2017, *376* (15), 1441–1450.

Kelley-Baker, Tara, Amy Berning, Anthony Ramirez, John H Lacey, Katherine Carr, Geetha Waehrer, Christine Moore, Karen Pell, Julie Yao, Richard P Compton et al., "2013–2014 National Roadside Study of alcohol and drug use by drivers: Drug results," Technical Report, United States. Department of Transportation. National Highway Traffic Safety 2017. https://www.nhtsa.gov/sites/nhtsa.gov/files/documents/13013-nrs_drug_092917_v6_tag.pdf.

Kitagawa, Evelyn M, "Components of a difference between two rates," *Journal of the american statistical association*, 1955, *50* (272), 1168–1194.

Krueger, Alan B, "Where have all the workers gone? An inquiry into the decline of the US labor force participation rate," *Brookings papers on economic activity*, 2017, *2017* (2), 1.

Kuypers, Kim, Sara-Ann Legrand, Johannes Gerardus Ramaekers, and Alain Verstraete, "A case-control study estimating accident risk for alcohol, medicines and illegal drugs," *PLOS ONE*, 2012, *7* (8).

Lacey, John H, Tara Kelley-Baker, Debra Furr-Holden, Robert B Voas, Eduardo Romano, Anthony Ramirez, Katharine Brainard, Christine Moore, Pedro Torres, Amy Berning et al., "2007 National roadside survey of alcohol and drug use by drivers: drug results," Technical Report, United States. Department of Transportation. National Highway Traffic Safety 2009. https://rosap.ntl.bts.gov/view/dot/1889.

_ , _ , _ , _ , _ , Pedro Torres, A Scott Tippetts, Anthony Ramirez, Katharine Brainard, Amy Berning et al., "2007 National roadside survey of alcohol and drug use by drivers: alcohol results," Technical Report, United States. National Highway Traffic Safety Administration. Office of … 2009.

Levitt, Steven D, "Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not," *Journal of Economic perspectives*, 2004, *18* (1), 163–190.

Li, Guohua and Stanford Chihuri, "Prescription opioids, alcohol and fatal motor vehicle crashes: a population-based case-control study," *Injury epidemiology*, 2019, *6* (1), 1–8.

MacDonald, John M, Jonathan Klick, and Ben Grunwald, "The effect of private police on crime: evidence from a geographic regression discontinuity design," *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 2016, *179* (3), 831–846.

Mattson, Christine L, Lauren J Tanz, Kelly Quinn, Mbabazi Kariisa, Priyam Patel, and Nicole L Davis, "Trends and geographic patterns in drug and synthetic opioid overdose deaths—United States, 2013–2019," *Morbidity and Mortality Weekly Report*, 2021, *70* (6), 202.

Mello, Steven, "More COPS, less crime," *Journal of Public Economics*, 2019, *172*, 174–200.

Murphy, Kevin M and Robert Topel, "Unemployment and nonemployment," *The American Economic Review*, 1997, *87* (2), 295–300.

NHTSA, "Fatality Analysis Reporting System (FARS) Analytical User's Manual, 1975-2018," *National Center for Statistics and Analysis Report No. DOT HS 812 827*, 2019.

_ , "Early Estimate of Motor Vehicle Traffic Fatalities in 2021," *Traffic Safety Facts*, April 2022.

Norris, Samuel, Matthew Pecenco, and Jeffrey Weaver, "The effect of incarceration on mortality," *Available at SSRN 3644719*, 2021.

Oaxaca, Ronald, "Male-female wage differentials in urban labor markets," *International economic review*, 1973, pp. 693–709.

Paoline, Eugene A and William Terrill, "The impact of police culture on traffic stop searches: An analysis of attitudes and behavior," *Policing: An International Journal of Police Strategies & Management*, 2005, *28* (3), 455–472.

Penning, Renske, Janet L Veldstra, Anne P Daamen, Berend Olivier, and Joris C Verster, "Drugs of abuse, driving and traffic safety," *Current Drug Abuse Reviews*, 2010, *3* (1), 23–32.

Premkumar, Deepak, "Public Scrutiny and Police Effort: Evidence from Arrests and Crime After High-Profile Police Killings," *Available at SSRN 3715223*, 2019.

Pyrooz, David C, Scott H Decker, Scott E Wolfe, and John A Shjarback, "Was there a Ferguson Effect on crime rates in large US cities?," *Journal of criminal justice*, 2016, *46*, 1–8.

Ramirez, Anthony, Amy Berning, Tara Kelley-Baker, John H Lacey, Julie Yao, A Scott Tippetts, Michael Scherer, Katherine Carr, Karen Pell, Richard P Compton et al., "2013–2014 National roadside study of alcohol and drug use by drivers: Alcohol results," Technical Report, United States. Department of Transportation. National Highway Traffic Safety ... 2016.

Schmidt, Chester W, Seymour Perlin, Russell S Fisher, and John W Shaffer, "Characteristics of drivers involved in single-car accidents: A comparative study," *Archives of general psychiatry*, 1972, *27* (6), 800–803.

Shjarback, John A, David C Pyrooz, Scott E Wolfe, and Scott H Decker, "De-policing and crime in the wake of Ferguson: Racialized changes in the quantity and quality of policing among Missouri police departments," *Journal of Criminal Justice*, 2017, *50*, 42–52.

Slater, Megan E, I-Jen P Castle, Barry K Logan, and Ralph W Hingson, "Differences in state drug testing and reporting by driver type in US fatal traffic crashes," *Accident Analysis & Prevention*, 2016, *92*, 122–129.

US BJS, "Police-Public Contact Survey (PPCS)," *US Bureau of Justice Statistics*, 2018. Downloaded from ICPSR, https://doi.org/10.3886/ICPSR37916.v2.

US BLS, "The American Time Use Survey," 2022. Downloaded from https://www.atusdata.org.

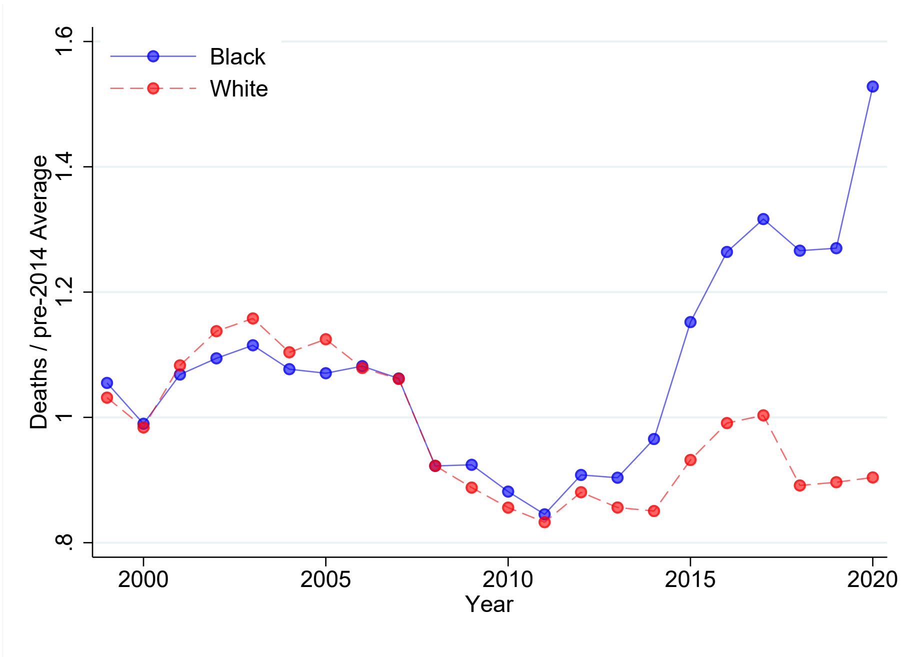
Weisburd, Sarit, "Police presence, rapid response rates, and crime prevention," *The Review of Economics and Statistics*, 2021, *103* (2), 280–293.

Weisburst, Emily K, "Safety in police numbers: Evidence of police effectiveness from federal COPS grant applications," *American Law and Economics Review*, 2019, *21* (1), 81–109.

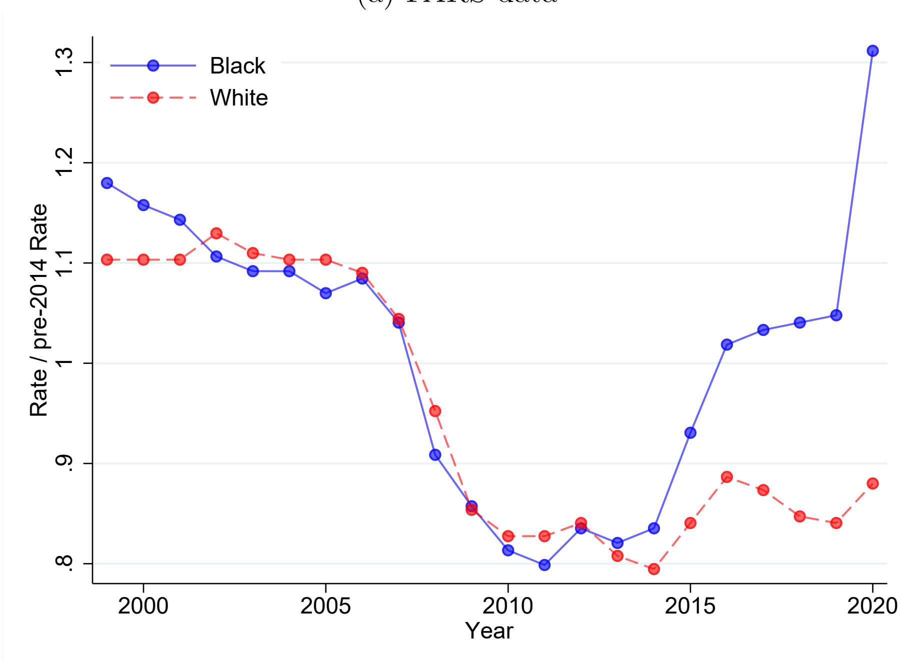
Wolfe, Scott E and Justin Nix, "The alleged "Ferguson Effect" and police willingness to engage in community partnership.," *Law and Human Behavior*, 2016, *40* (1), 1.

Yun, Myeong-Su, "A simple solution to the identification problem in detailed wage decompositions," *Economic inquiry*, 2005, *43* (4), 766–772.

Figure 1: Race-Specific Trends in U.S. Motor Vehicle Fatalities, FARS and CDC data



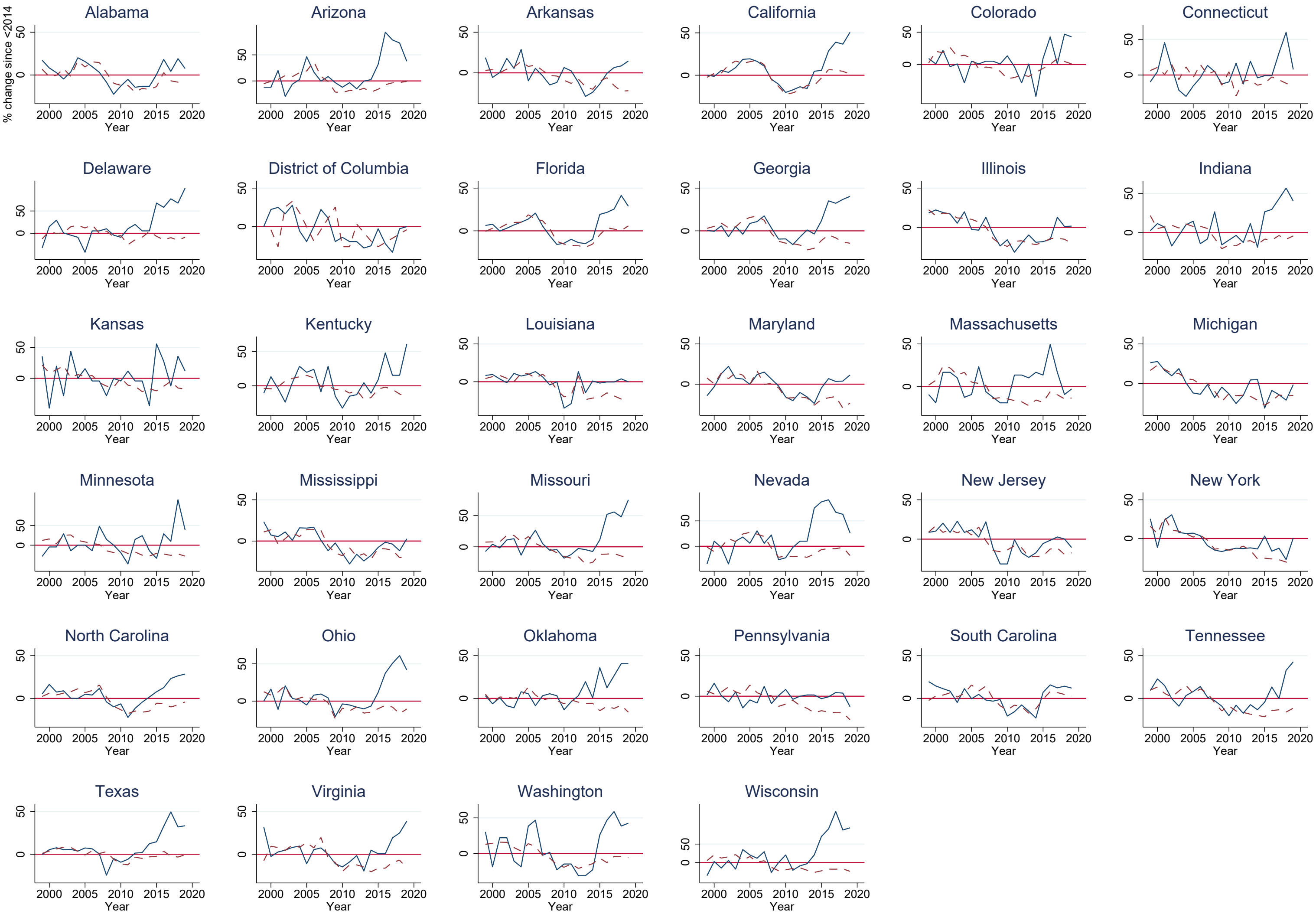
(a) FARS data



(b) CDC Data

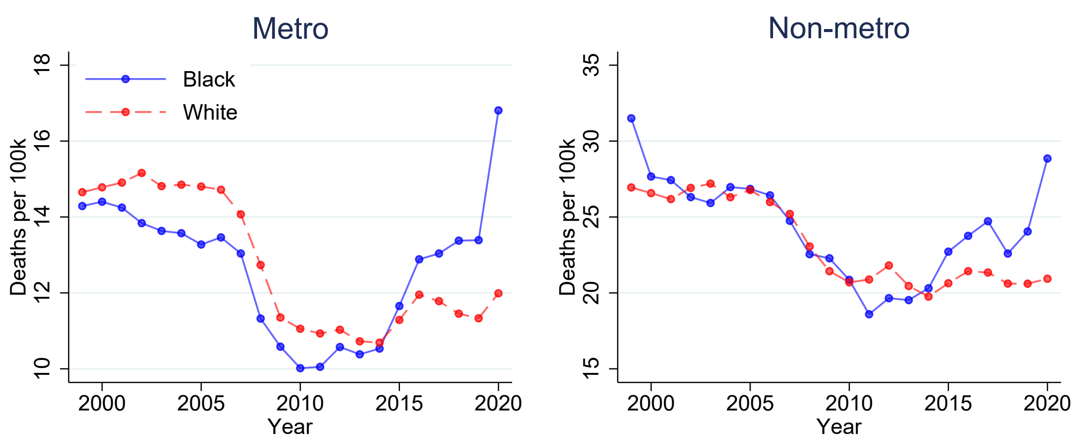
Notes: This figure shows a normalized annual count of fatalities from motor vehicle accidents using FARS data (panel a) and CDC data (panel b) and splitting by race. Each series is divided by its average in the years 1999-2013.

Figure 2: Race-Specific Traffic Fatality Trends by State, CDC data



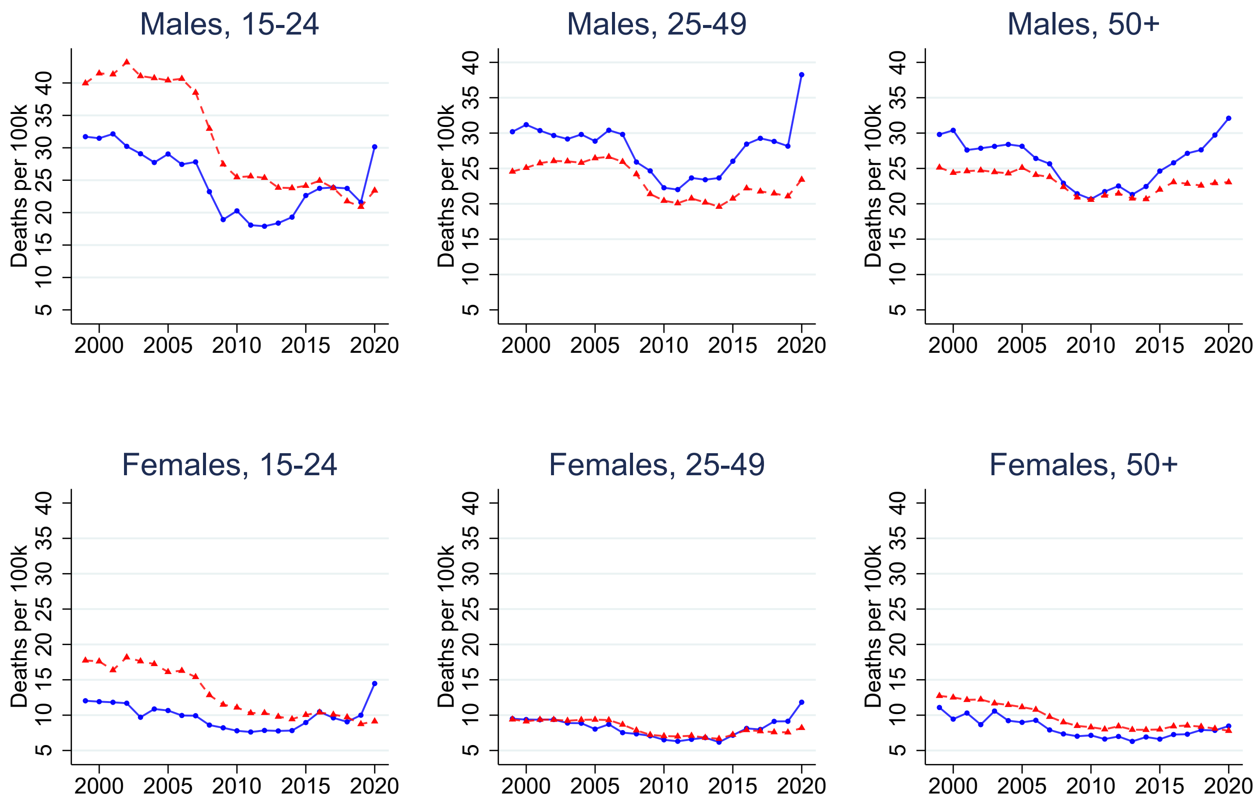
Notes: In all plots, the solid blue line gives Black motor vehicle fatalities and the dashed red line gives white motor vehicle fatalities. The series are normalized to give the percent change in fatalities compared to the own-race average count of yearly fatalities from 1999-2013. The horizontal line marks a 0% change from the 1999-2013 average. For example, the Washington plot shows that in 2017, Black motor vehicle fatalities in the state were 59% higher than the 1999-2013 average. For whites in Washington, motor vehicle fatalities were 4% lower than the 1999-2013 average. Source is CDC WONDER Underlying Cause of Death data, 1999-2019.

Figure 3: Race-Specific Traffic Fatality Rates, Urban vs. Rural Deaths, CDC data



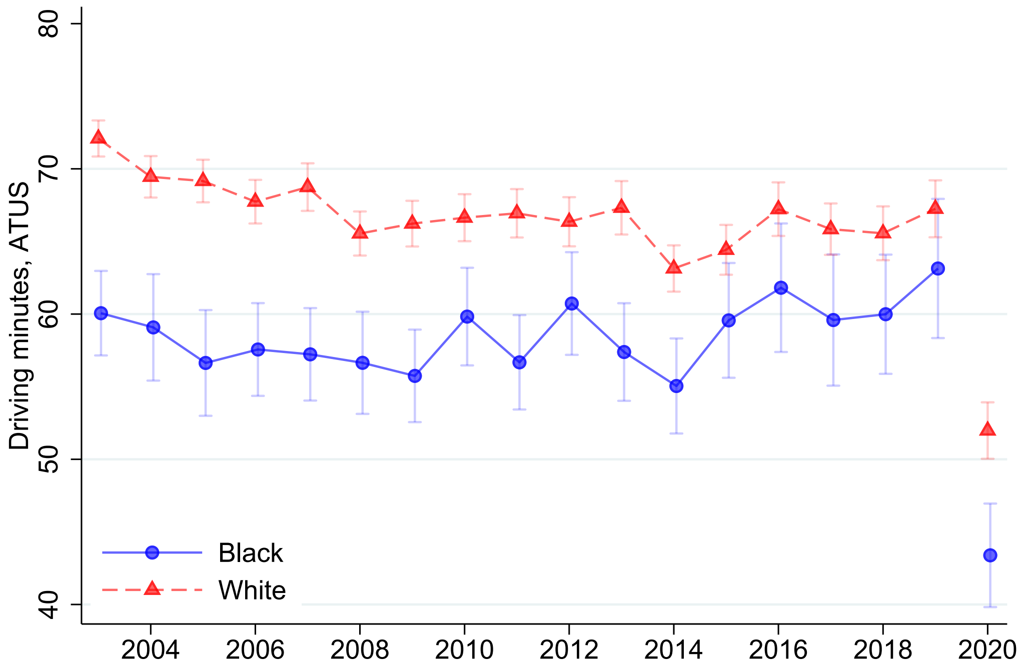
Notes: This figure shows the annual crude (per capita) fatality rate from motor vehicle accidents using CDC Underlying Cause of Death data restricted to transport accidents. We split by race and the 2013 NCHS urban-rural classification scheme for counties (Ingram and Franco, 2014). Metropolitan areas are defined as Large Central Metro, Large Fringe Metro, Medium Metro, and Small Metro. Non-metro areas are defined as Micropolitan and NonCore.

Figure 4: Race-Specific Traffic Fatality Rates, By Age and Gender



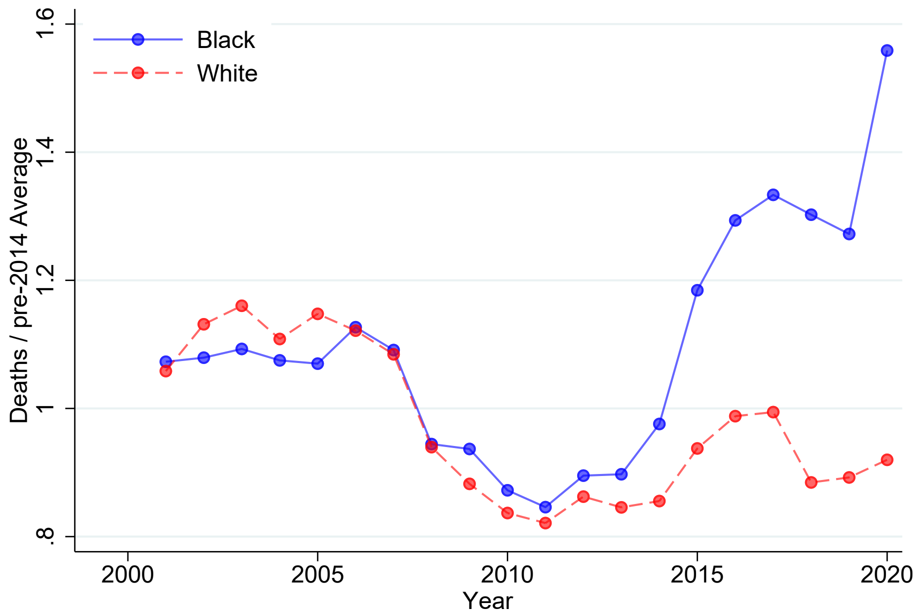
Notes: This figure shows race-specific traffic fatality rates split by age and gender. Data source is CDC WONDER.

Figure 5: Race-Specific Trends in Time in a Vehicle, ATUS Data



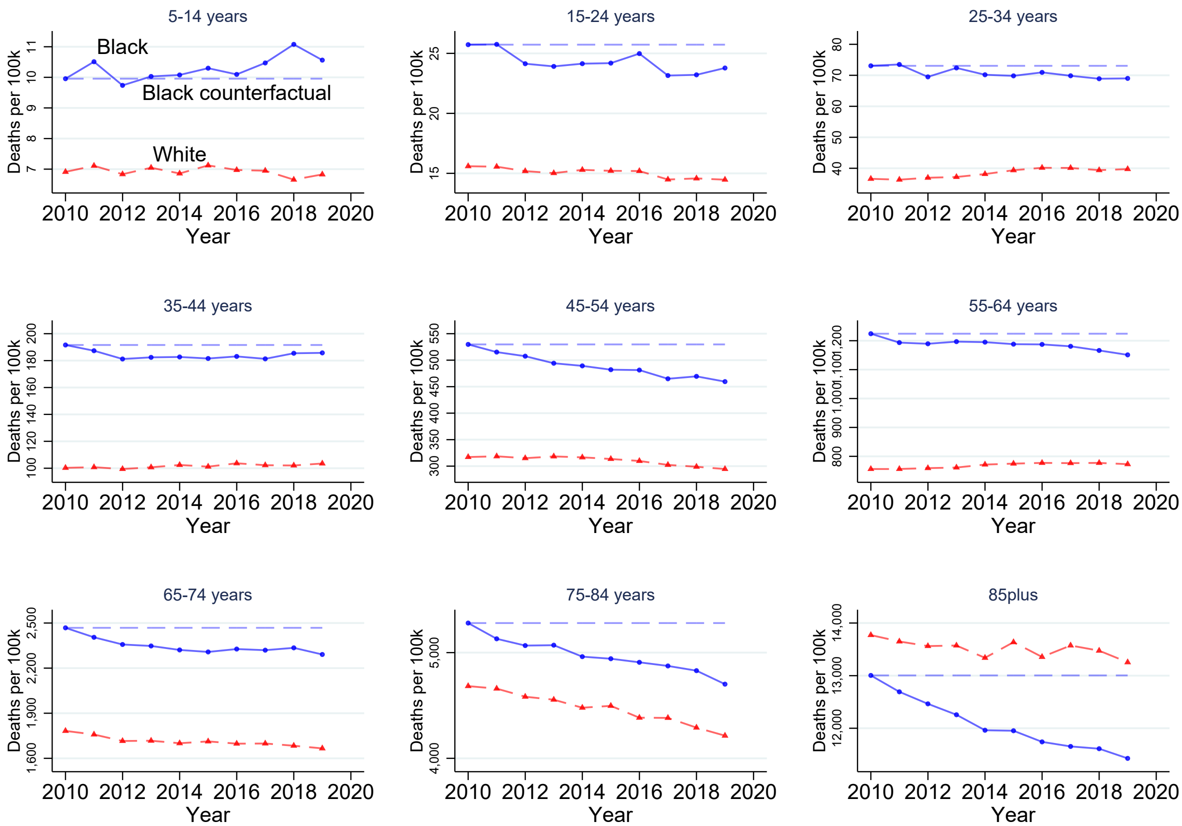
Notes: This figure shows average daily time spent in a vehicle split by race. Source is the American Time Use Survey using 2006 weights. Counts time spent in a car, truck, motorcycle, taxi, or limousine as either a driver or passenger using the "where" variable. Whiskers show the 95% convidence intervals. Due to COVID, ATUS data were not collected from March 18, 2020 to May 9, 2020, so the 2020 average is not representative of the year.

Figure 6: Race-Specific Trends in Dead on Arrival Motor Vehicle Fatalities, FARS Data



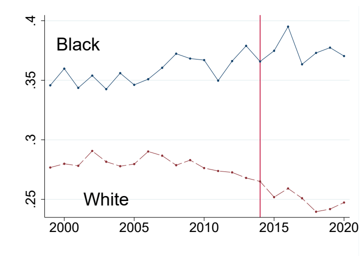
Notes: This shows the same series as Figure 1 except restricting to motor vehicle fatalities where the decedent was recorded as dead on arrival. Each series is divided by its average in the years 1999-2013. Source is FARS data.

Figure 7: Race-Specific Changes in Non-External Death Rates, CDC Data

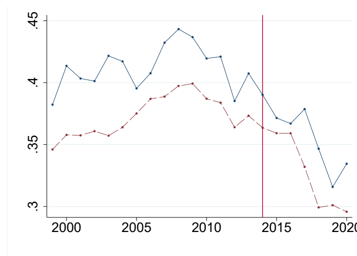


Notes: This figure shows changes in non-external death rates in ten-year age bands, split by race. The dashed line gives a counterfactual where the Black death rate is fixed at its 2010 level. Data source is CDC WONDER.

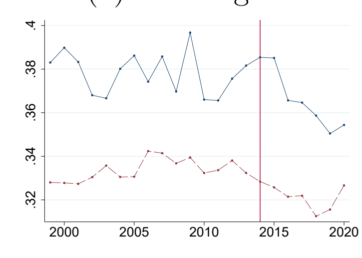
Figure 8: Race-Specific Changes in Situational Factors, FARS Data



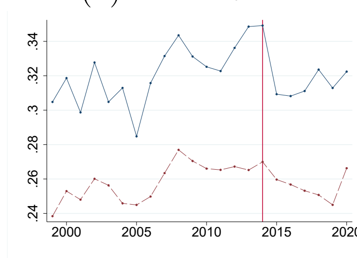
(a) Late night



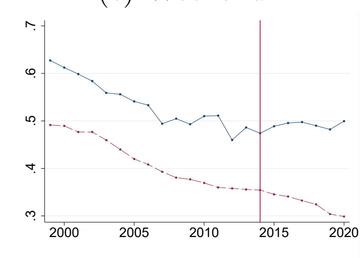
(b) Local Road



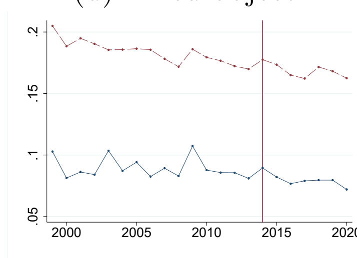
(c) Weekend



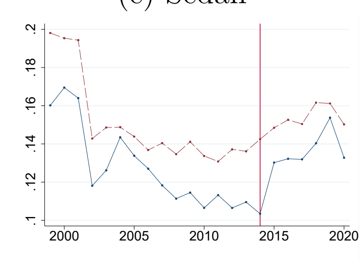
(d) Fixed object



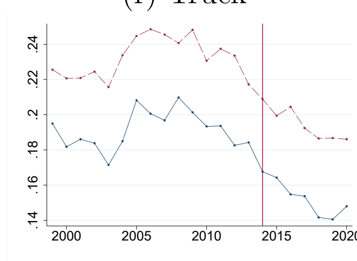
(e) Sedan



(f) Truck



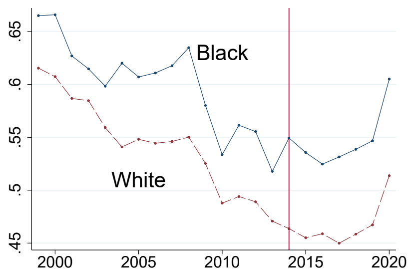
(g) Head-on collision



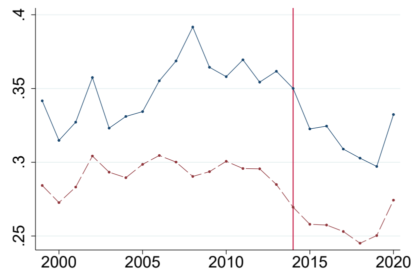
(h) Rollover

Notes: This figure shows changes in situational factors in fatal car accidents split by race. Source is the FARS data. The vertical line marks 2014.

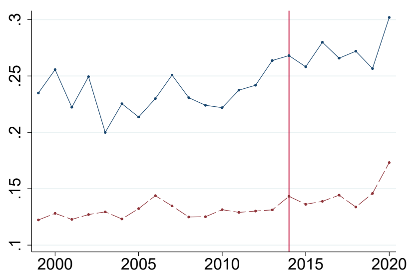
Figure 9: Race-Specific Changes Risky Driving Behaviors, FARS Data



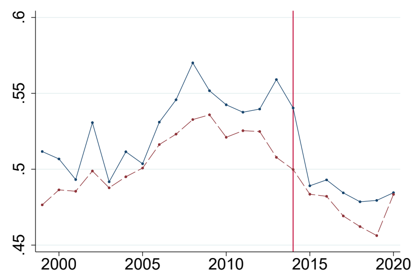
(a) No seatbelt



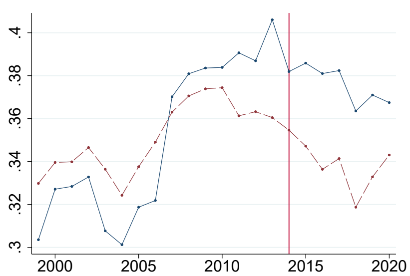
(b) Speeding



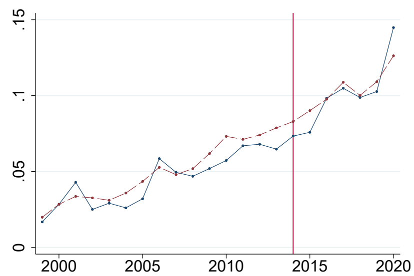
(c) No driver's license



(d) Single car



(e) Alcohol involvement



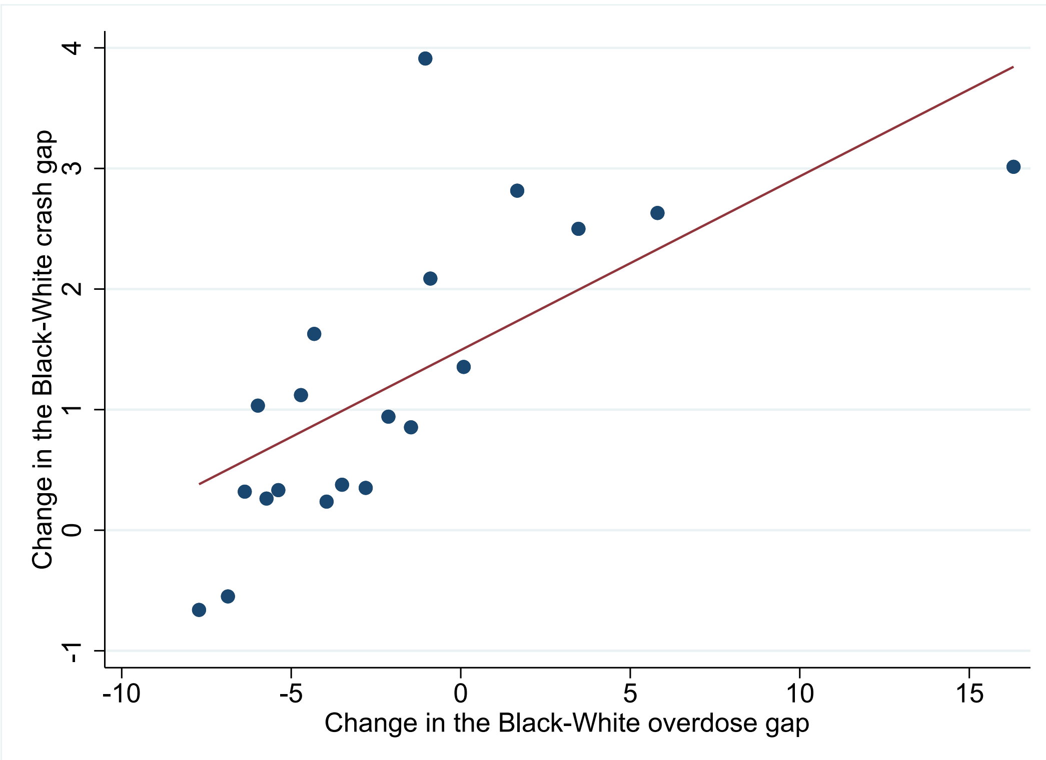
(f) Drug involvement

(g) Blood alcohol content

(h) Positive drug test

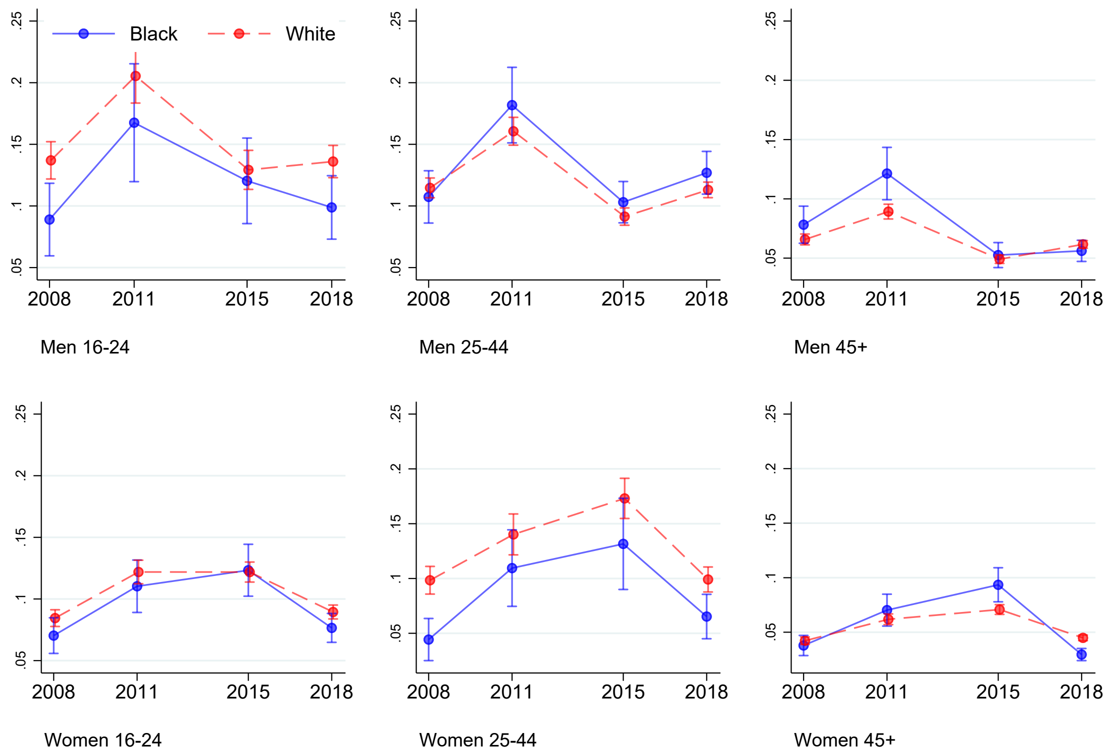
Notes: This figure shows changes in risky driving measures in fatal car accidents split by race. Source is the FARS data. The red vertical line marks 2014.

Figure 10: Racial Gap in Crash Fatalities vs. Overdoses



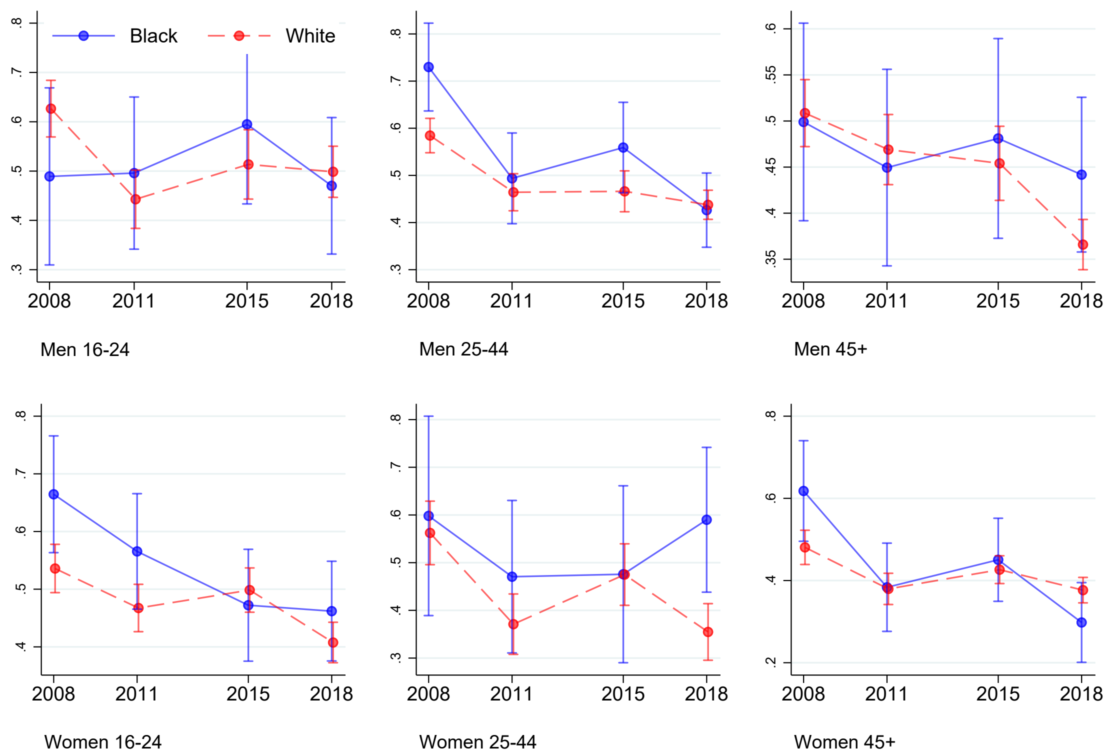
Notes: This a binned scatterplot showing the change in the gap in transport deaths rates against the change in the gap in overdose death rates, with 5-year periods within states as the unit of observation. For example, an observation with a 5 on the x-axis would be a state in a certain five-year period where the Black-White gap in deaths rates grew by 5 per 100,000. The slope of the trendline is 0.14, suggesting that a 7 percentage point increase in the overdose gap predicts a 1 percentage point increase in the crash gap.

Figure 11: Race-Specific Shares of American Drivers Stopped by Police While Driving, PPCS Data



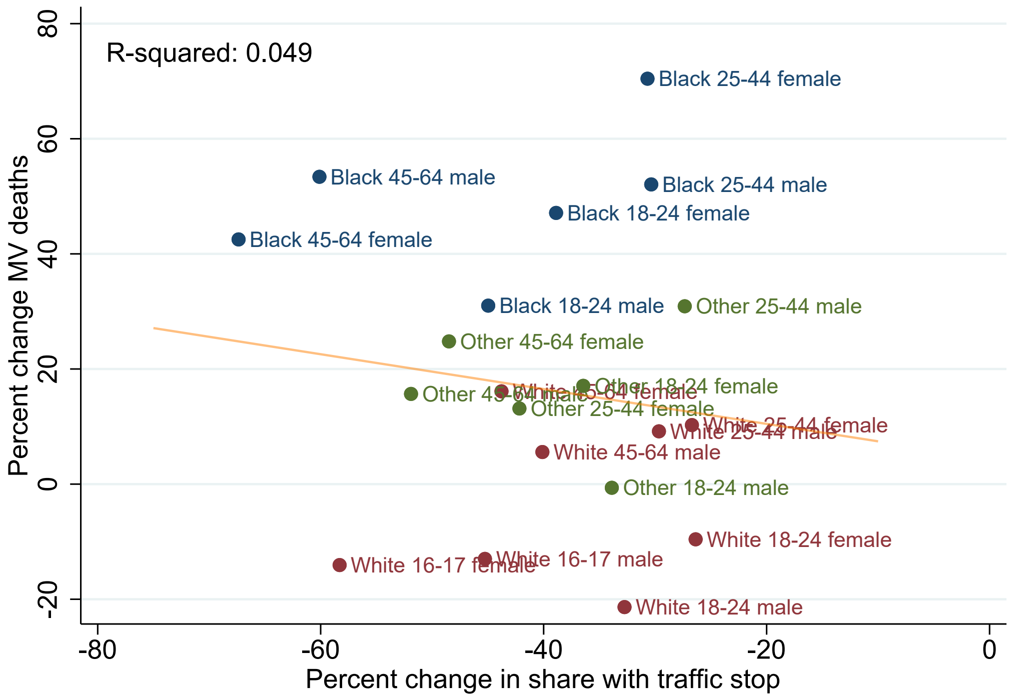
Notes: This figure shows the share of people pulled over by police while driving, split by age, race, and gender. It combines data from the 2008, 2011, 2015, and 2018 Police Public Contact Survey. The indicator for being stopped while driving is constructed using V14A and V14B (2008 survey), V13 (2011 and 2015 surveys), and V23T (2018 survey).

Figure 12: Race-Specific Shares of American Drivers Who Were Ticketed During a Traffic Stop



Notes: This figure shows the share of drivers in traffic stops where were given a ticket, split by age, race, and gender. It combines data from the 2008, 2011, 2015, and 2018 Police Public Contact Survey. The ticket measure is given by V36 in 2008 and V249 in 2011, 2015, and 2018. In all cases, we restrict to people who report being the driver in the focal traffic stop.

Figure 13: Change in deaths vs. Change in Traffic Stops, by Demographic Group



Notes: This figure shows the percent change in motor vehicle deaths from FARS 2011 to 2018 in the y-axis and the percent change in the share of people reporting having been stopped by the police in a car over the same years, from the BJS's Police Public Contact Survey. People are grouped into age (16-17, 18-24, 15-44, 45-64, 65+) by race (Black, white, Other) by sex bins for 30 groups total. The age 16-17 group is omitted in some cases due to small samples in the police public contact survey. Both variables are residualized against time spent driving for the given demographic cell, calculated using the American Time Use Survey. The r-squared reported is from a regression of the percent change in fatalities on the percent change in share with a traffic stop and the percent change in driving. Colors coincide with race.

Table 1: Descriptive Statistics, FARS Data

	(1) 1999-2013	(2) 2014-2020
Demographics		
White	0.83	0.79
Black	0.13	0.16
Age	40.96	44.06
	(20.91)	(20.55)
Male	0.69	0.71
Person type		
Driver	0.64	0.64
Passenger	0.22	0.17
Pedestrian or cyclist	0.14	0.18
Vehicle		
Sedan	0.40	0.30
Truck	0.14	0.12
Utility Vehicle	0.10	0.12
Motorcycle	0.11	0.14
Crash attributes		
Late Night	0.30	0.29
Single Car	0.56	0.55
Blood Alcohol Content	9.25	8.67
	(10.88)	(10.92)
Weekend	0.35	0.33
Fixed Object	0.22	0.21
Head-on	0.12	0.12
Rollover	0.20	0.16
No License	0.13	0.14
No Seatbelt	0.58	0.45
Drunk Driving	0.33	0.33
Speeding	0.26	0.22
Drug involvement	0.05	0.10
Geography		
West	0.22	0.21
South	0.48	0.51
Midwest	0.22	0.20
Northeast	0.08	0.08
Urban	0.42	0.52
N	509,397	230,573

Notes: Includes all decedents in FARS with non-missing race over the years 1999 to 2020. This restriction removes 100,536 people from the original FARS data, which includes 840,506 decedents in total. Standard deviations shown in parentheses for continuous variables.

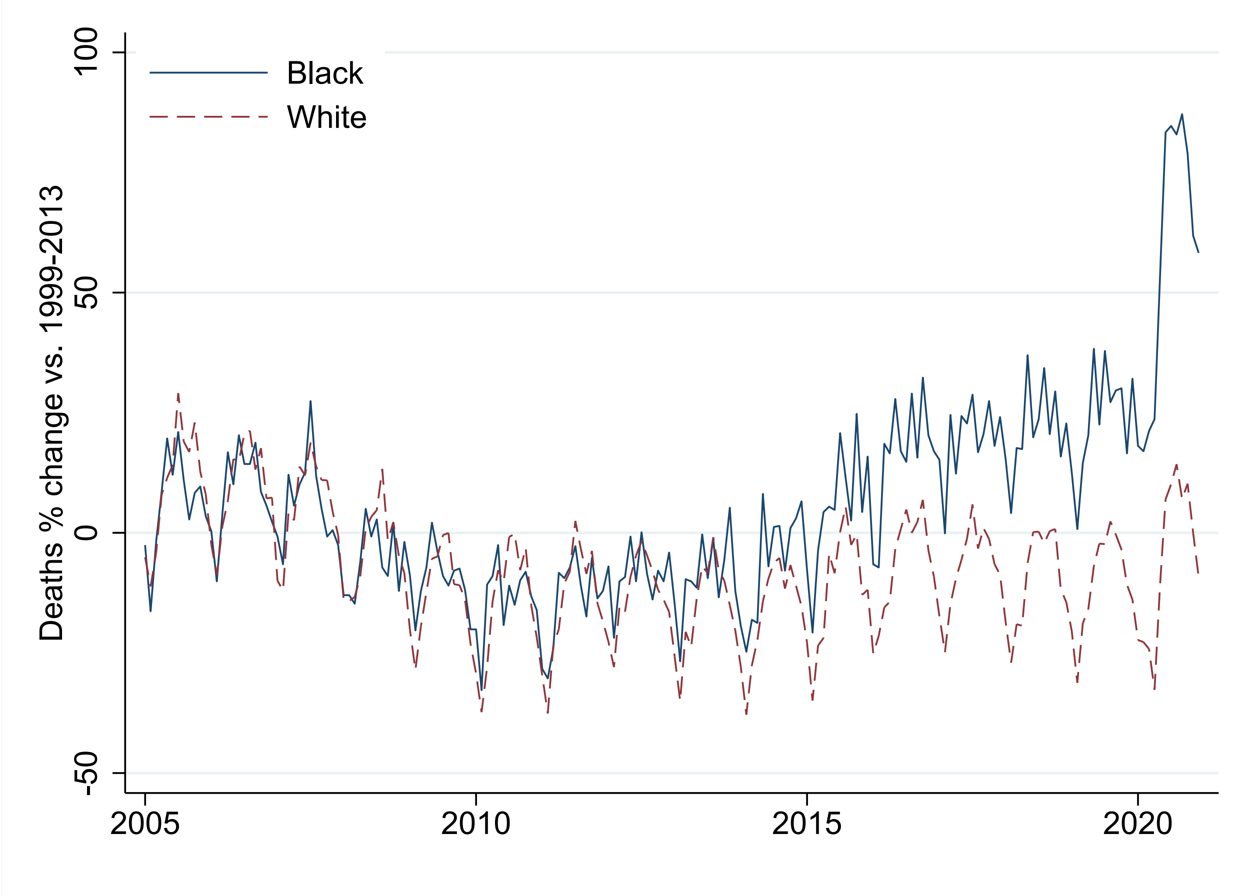
Table 2: Descriptive Statistics, PPCS Data

	(1) 2008	(2) 2011	(3) 2015	(4) 2018
Demographics				
Age	44.87	45.42	46.10	37.64
	(18.27)	(18.35)	(18.68)	(12.99)
Male	0.49	0.49	0.52	0.48
	(0.50)	(0.50)	(0.50)	(0.50)
Black	0.11	0.12	0.12	0.12
	(0.32)	(0.32)	(0.33)	(0.32)
White	0.71	0.69	0.65	0.63
	(0.45)	(0.46)	(0.48)	(0.48)
Police interactions				
Driver in traffic stop	0.07	0.11	0.08	0.07
	(0.26)	(0.31)	(0.28)	(0.26)
if Black	0.07	0.12	0.10	0.07
	(0.25)	(0.32)	(0.29)	(0.25)
if White	0.08	0.11	0.08	0.08
	(0.27)	(0.31)	(0.28)	(0.26)
Given ticket if in traffic stop	0.57	0.46	0.49	0.44
	(0.50)	(0.50)	(0.50)	(0.50)
if Black	0.62	0.48	0.50	0.44
	(0.49)	(0.50)	(0.50)	(0.50)
if White	0.55	0.44	0.47	0.41
	(0.50)	(0.50)	(0.50)	(0.49)
N	57,978	49,246	70,959	104,324

Notes: Source is the 2008, 2011, 2015, and 2018 Police Public Contact Surveys. The white and Black racial categories condition on non-Hispanic.

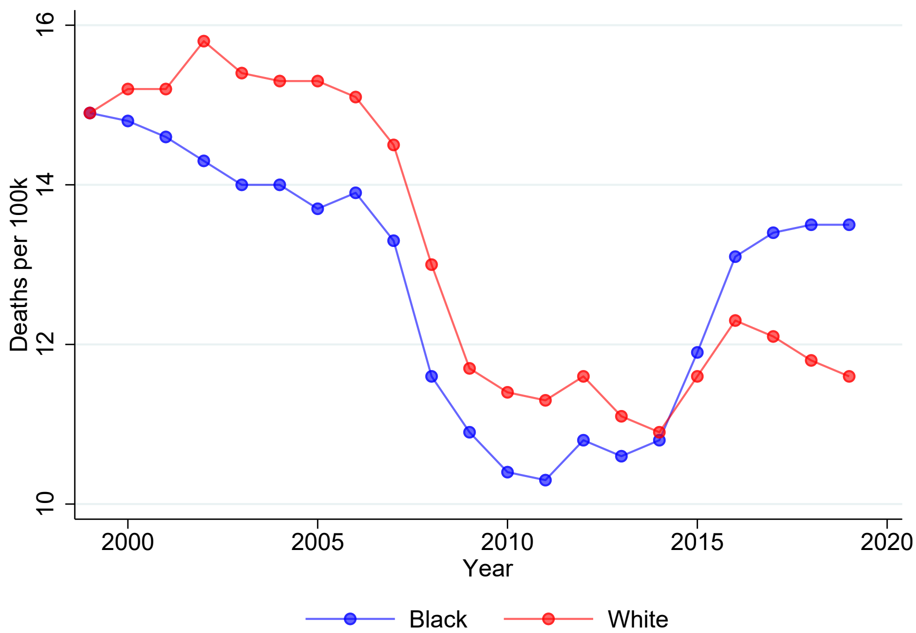
A Appendix

Figure A.1: Normalized Monthly Traffic Fatalities, CDC Data

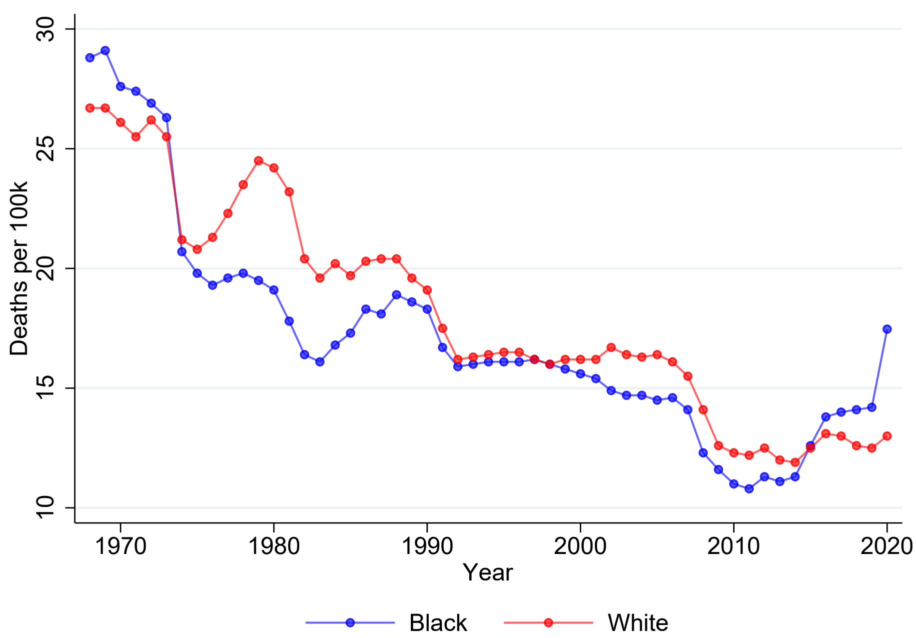


Notes: This figure shows monthly traffic fatalities split by race. Each series give the percent change in the number of deaths that month relative to the average from 1999-2013. Source is monthly data from CDC WONDER.

Figure A.2: Race-Specific Trends in Motor Vehicle Fatalities (Levels), CDC data



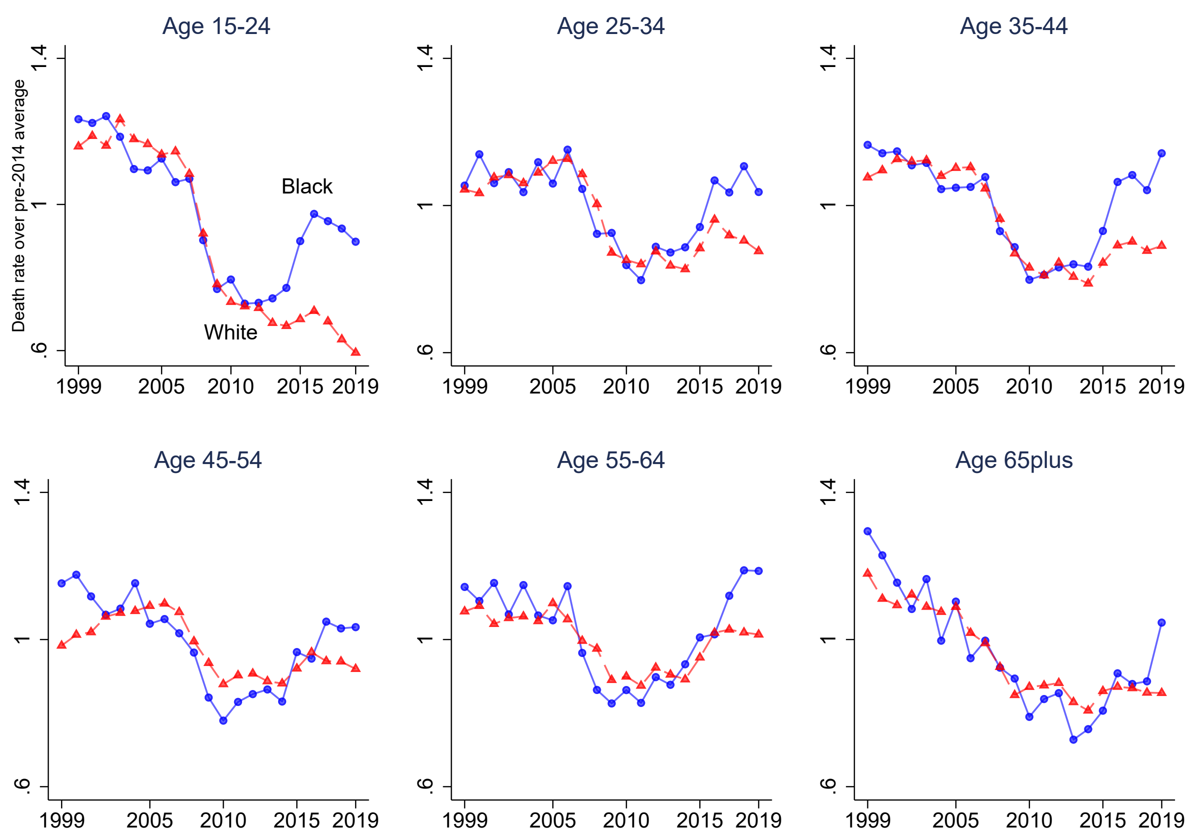
(a) 1999-2020



(a) 1968-2020

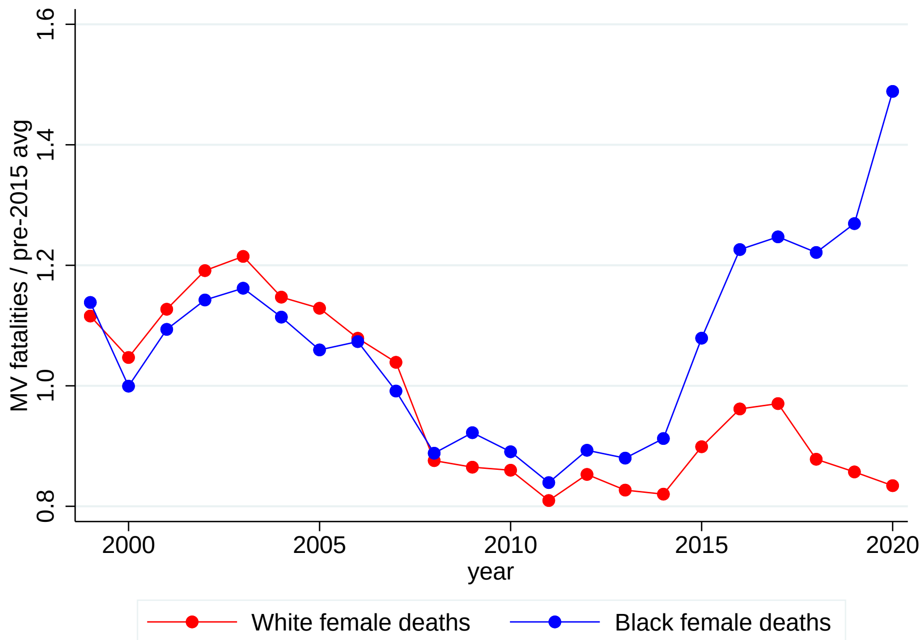
Notes: This figure shows the annual per capita fatalities using CDC WONDER data.

Figure A.3: Race-Specific Trends in Motor Vehicle Fatalities by Age Group, CDC Data

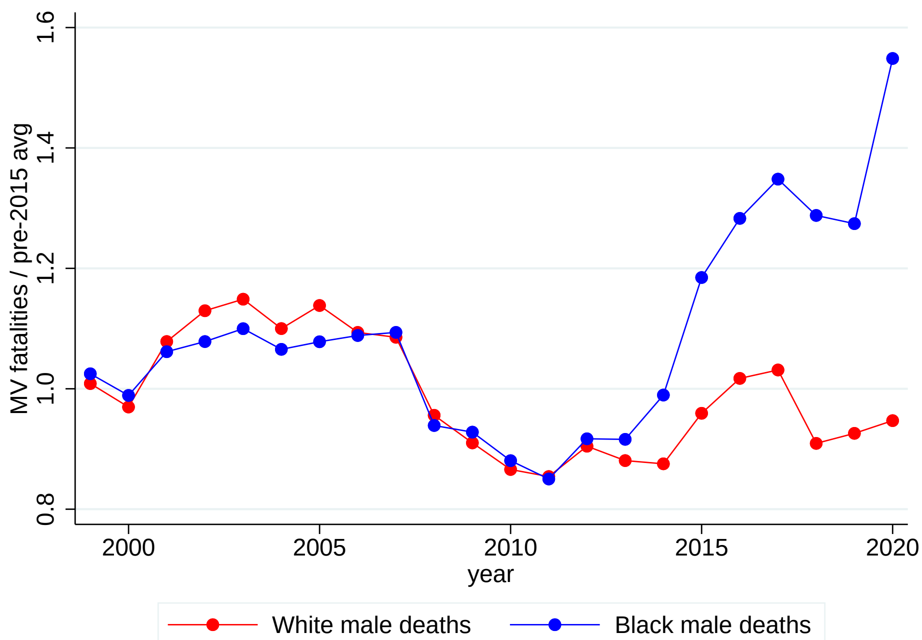


Notes: This figure shows race-specific motor vehicle fatalities split by age. Source is CDC WONDER.

Figure A.4: Race-Specific Trends in Motor Vehicle Fatalities by Gender, CDC Data



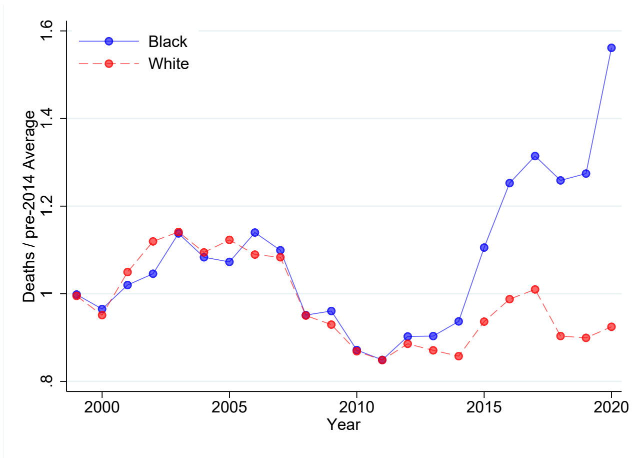
(a) Females



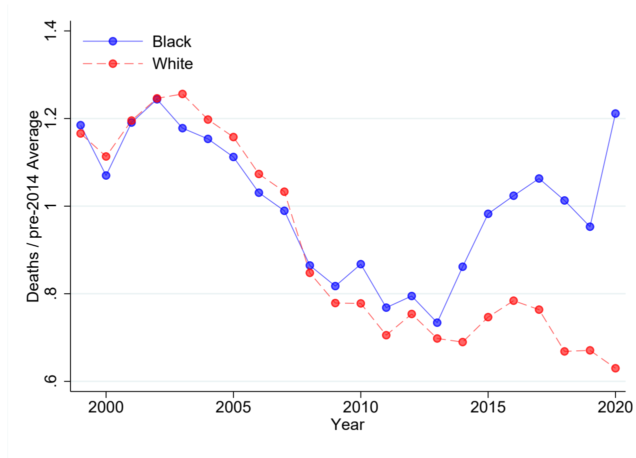
(b) Males

Notes: This figure shows race-specific motor vehicle fatalities split by gender. Source is CDC WONDER.

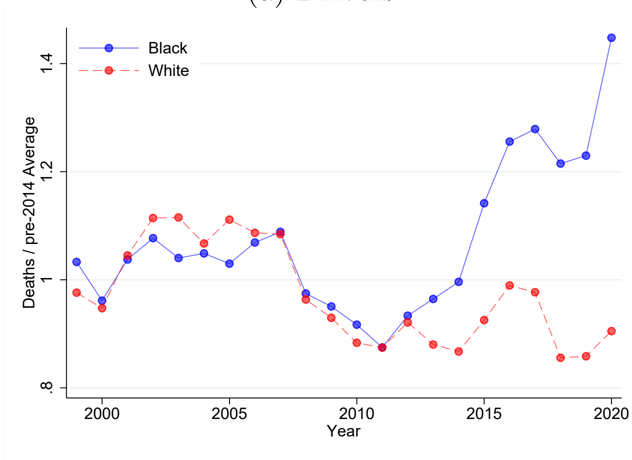
Figure A.5: Race-Specific Trends in Motor Vehicle Fatalities by Type of Accident, FARS Data



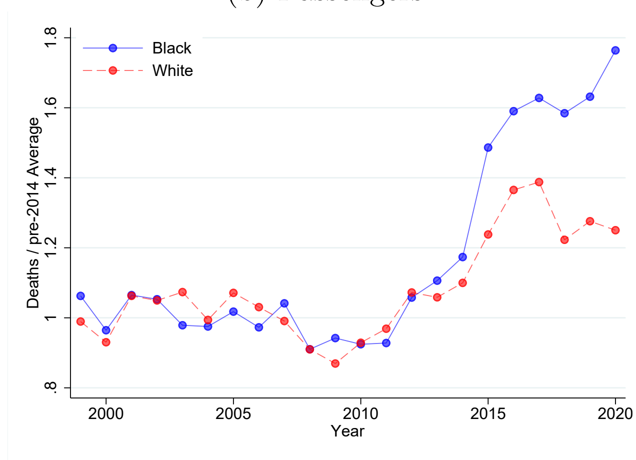
(a) Drivers



(b) Passengers



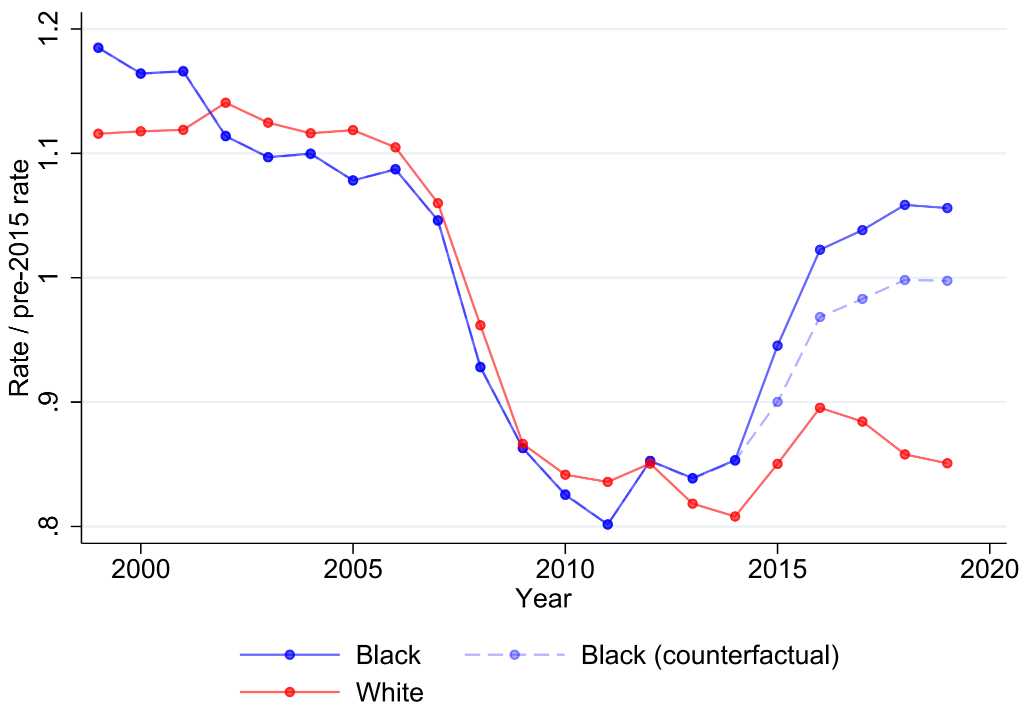
(c) Single car



(d) Pedestrians and cyclists

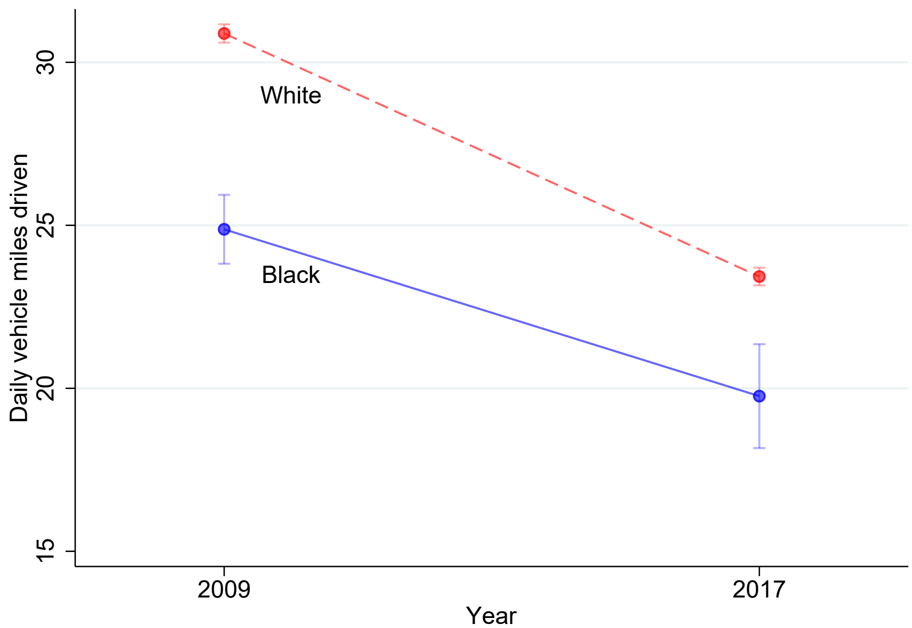
Notes: This figure shows race-specific motor vehicle fatalities split by the person type as recorded in the FARS data.

Figure A.6: Age Counterfactual, CDC Data



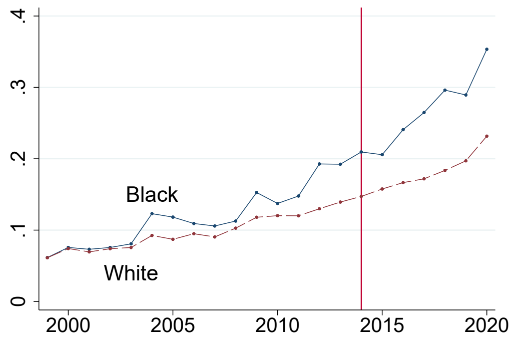
Notes: This plot shows the counterfactual growth in the fatality rate of Black Americans assuming deaths for individuals aged 15-24 had grown at the same rate as whites beginning in 2015. Source is CDC WONDER.

Figure A.7: Daily Vehicle Miles Driven, NHTS

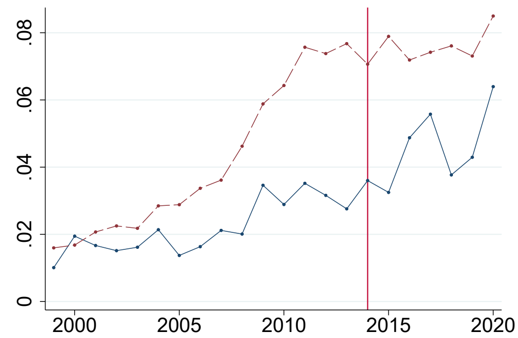


Notes: This figure gives average daily vehicle miles driven split by race. We plot the average miles for trips where a vehicle was driven (VMT_MILE), split by race and restricting to respondents 15 or older. The survey asks about all trips taken in the previous day. The amount increases for Black relative to whites by 2.3 miles. Source is survey data from the NHTS covering 2009 and 2017.

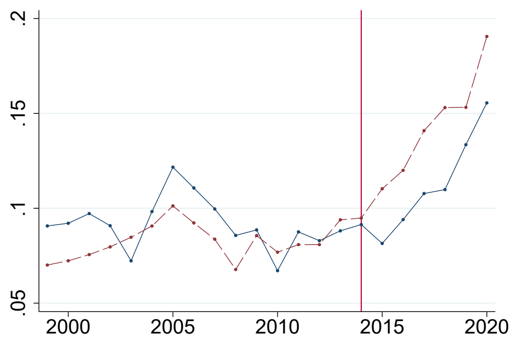
Figure A.8: Drug test results



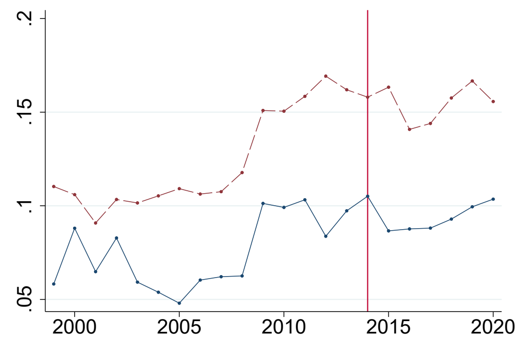
(a) Cannabis



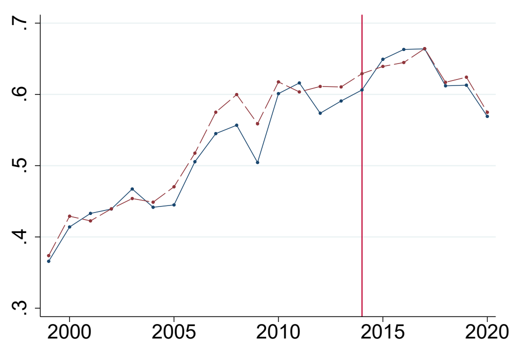
(b) Opioids



(c) Stimulants



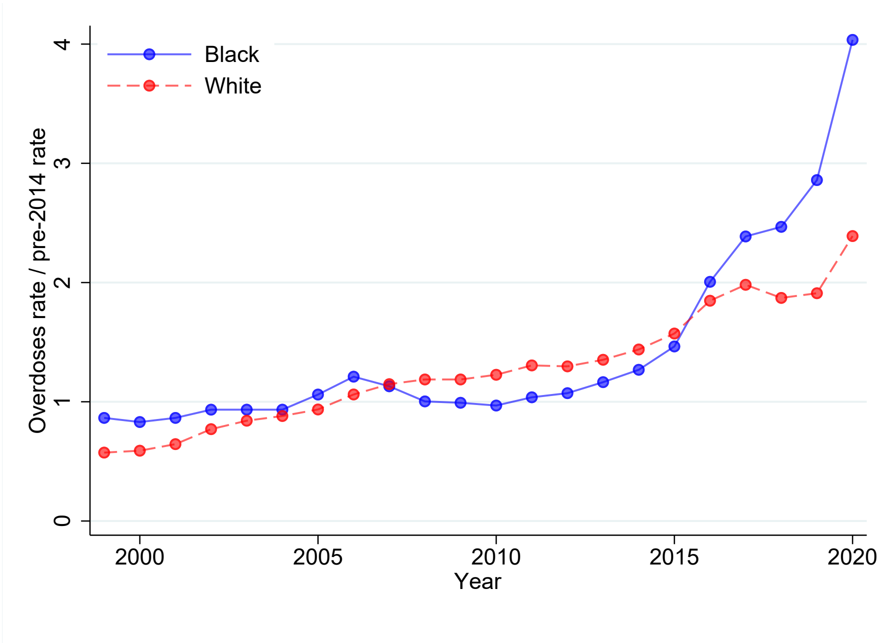
(d) Other drugs



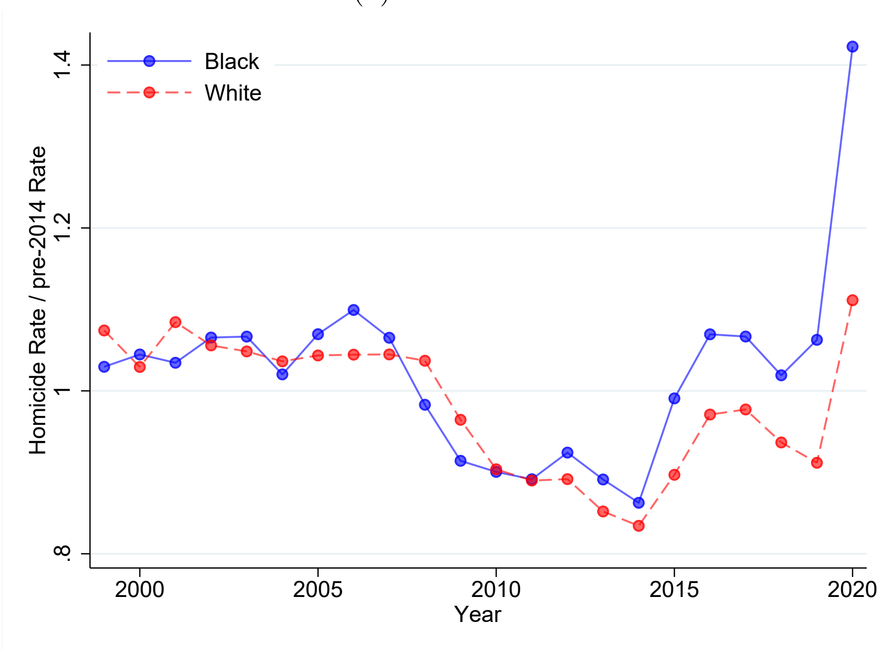
(e) Any drug test

Notes: This figure shows drug test results of car accident decedents, split by race. We restrict to drivers who were given a drug test. In panels (a)-(d), the y-axis gives the share of tested drivers testing positive for at least one drug in the drug category. Panel (e) gives the share of drivers given any drug test, split by race. Opioids includes fentanyl, morphine, oxycodone, opium, oxmorphone and hydrocodone. Stimulants includes cocaine, benzoylecgonine (the main metabolite of cocaine), and methamphetamine. Source is FARS data.

Figure A.9: Homicides and Overdoses, CDC



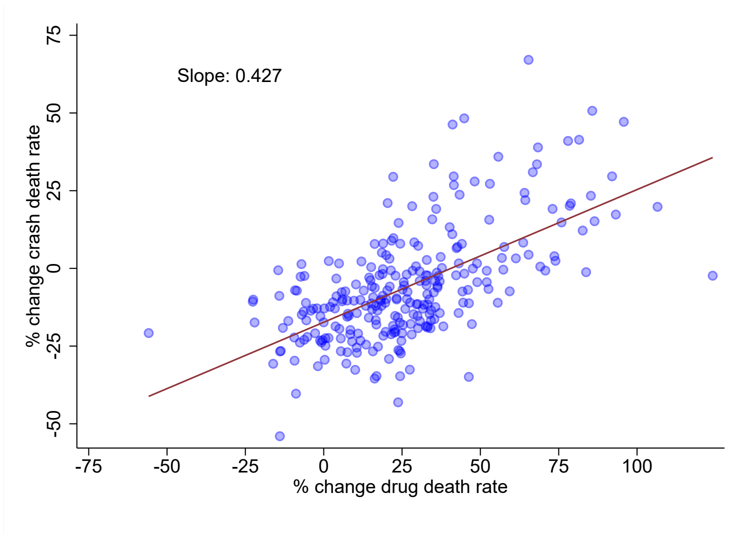
(a) Overdoses



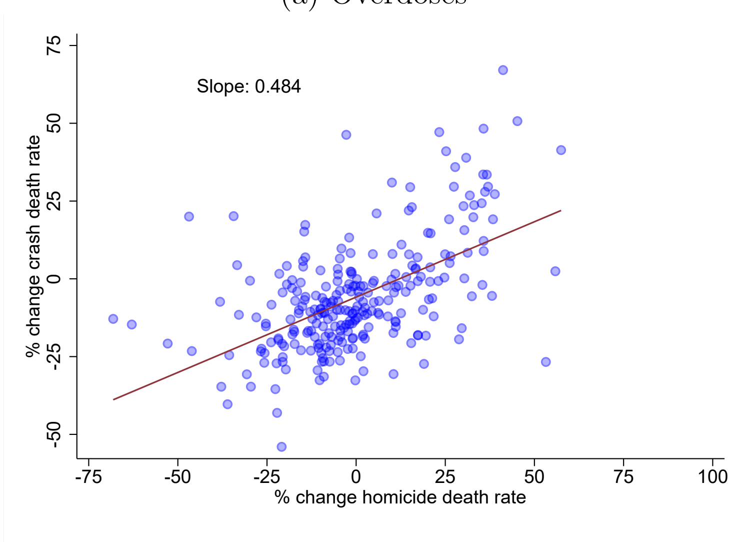
(b) Homicides

Notes: This figure shows the same normalized plots as in Figure 1, but for overdoses (panel a) and homicides (panel b). Each series is divided by its average in 1999-2013. Source is CDC WONDER.

Figure A.10: Motor Vehicle Death Rate vs.Overdose Death Rate and Homicides, CDC



(a) Overdoses



(b) Homicides

Notes: This figure shows the relationship between vehicle fatalities and two other external causes of death: homicides and overdoses. Panel (a) is a scatterplot showing the percent change in the crash death rate vs. the percent change in the overdose rate. Panel (b) shows the same with homicides in the x-axis. Deaths are aggregated by state, race, and 5-year periods from 2000 to 2020, with the exception of the last bin (2015-2020). A log change is calculated for every period by state-race cell. For instance, one of the dots in panel (a) captures that, in 2015-2020, the white crash fatality rate in California was 21.0 log points higher and the white drug overdose rate 20.5 log points higher than in 2010-2014. The red line shows a linear fit, weighted by cell population. slope estimates correspond to the coefficients in column (1) and (2) in Table A2. Source is CDC WONDER, 2000-2020.

B Appendix Tables

Table A1: Transport death rates by race per 100,000, CDC and ATUS

	Deaths per 100,000		Deaths per 10m hours	
Year	Black	White	Black	White
1999	16.1	16.8		
2000	15.8	16.8		
2001	15.6	16.8		
2002	15.1	17.2		
2003	14.9	16.9	6.1	5.6
2004	14.9	16.8	6.2	5.8
2005	14.6	16.8	6.3	5.8
2006	14.8	16.6	6.3	5.9
2007	14.2	15.9	6.1	5.6
2008	12.4	14.5	5.4	5.3
2009	11.7	13.0	5.2	4.7
2010	11.1	12.6	4.5	4.6
2011	10.9	12.6	4.7	4.6
2012	11.4	12.8	4.6	4.7
2013	11.2	12.3	4.8	4.5
2014	11.4	12.1	5.1	4.7
2015	12.7	12.8	5.2	4.9
2016	13.9	13.5	5.4	4.9
2017	14.1	13.3	5.8	5.0
2018	14.2	12.9	5.7	4.9
2019	14.3	12.8	5.5	4.7
2020	17.9	13.4	11.7	7.4
Mean 1999-2013	13.6	15.2		
Mean 2014-2019	13.4	12.9		

Notes: Source is CDC WONDER data, Underlying Cause of Death 1999-2020, restricts to ICD-10 Codes V01-V99 (Transport accidents). Deaths per 10m hours is calculated using total hours spent in a vehicle from the ATUS.

Table A2: Crash fatalities vs. drug and homicide deaths

	% change crash rate			change in crash rate gap		
	(1)	(2)	(3)	(4)	(5)	(6)
% Change homicide rate	0.486***		0.379***			
	(0.102)		(0.086)			
% Change overdose rate		0.413***	0.281***			
		(0.053)	(0.060)			
Change in BW homicide rate gap				0.229***		0.150***
				(0.036)		(0.039)
Change in BW overdose rate gap					0.144***	0.121***
					(0.025)	(0.031)
Outcome mean, 2015-2020	7.427	7.395	7.427	2.820	2.789	2.820
R-squared	0.345	0.273	0.455	0.280	0.231	0.379
Observations	260	263	257	109	110	106

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Source is CDC WONDER, 2000-2020. Each column shows a linear regression estimated using OLS and weighted by population. The unit of observation is state, race (Black or white), and 5-year periods from 2000 to 2020, with the exception of the last bin (2015-2020). In columns (1)-(3), the outcome is the log change in the crash rate within the given state-by-race in the time period. The outcome mean shows that the average increase in the crash rate—combining racial groups and states—was 7.4%. In columns (4)-(6), the outcome is the change in the Black-White gap, where the gap in any period is the Black rate per 100,000 minus the white rate per 100,000. The outcome mean shows that, on average, this gap increased by 2.8 per 100,000 between 2010-2014 and 2015-2020. The number of observations changes across columns due small values in the smallest race-state-time cells.

C Oaxaca-Blinder decomposition

The simple averages reported in Figure 9 suggest that the race-specific divergence in fatalities after 2014 cannot be clearly tied to shifts in driving behavior. To more formally test this idea—as well as for the importance of other situational factors—we analyze the emerging racial gap in vehicle fatalities using a Oaxaca-Blinder decomposition (Kitagawa, 1955; Oaxaca, 1973; Blinder, 1973) and the FARS data. Ideally our Oaxaca-Blinder decomposition would use information on driving behaviors and accidents among a broad, nationally-representative sample of drivers. The FARS data only collects race on decedents from car accidents. Within the FARS, one way to understand the contribution of different factors in this data is to model the increase in the probability that a decedent is Black.

We begin by estimating two linear probability models of the following form:

$$P(Black_{it}) = \alpha + \mathbf{X}'_{it}\beta + e_{it} \tag{3}$$

In (3), the dependent variable is an indicator variable for whether a fatal accident involved a Black driver. We regress this variable on a vector of characteristics, $\mathbf{X}_{it}$, that potentially explain variation in the race of the driver. We estimate one model using crashes occurring prior to 2014 and a second model for crashes occurring in 2014 or later. The percentage of Black decedents in the analysis sample increased from 13 to 16 percent over this period, the purpose of the Oaxaca-Blinder analysis is to explain the 3 percentage point change in this quantity since 2014. We express the overall difference between the two periods as:

$$D = E(Black_{post2014}) - E(Black_{pre2014}) \tag{4}$$

D can then be de-composed into three parts, suppressing the subscripts, i and t for legibility. $\mathbf{X}_{period}$ and β_{period} denote the attributes and estimated coefficients for the pre (1999-2013) or post (2014-2020) periods. Then, using the framework from Jann (2008), the first component is:

$$\textbf{Endowments: } \{E(\mathbf{X}_{post}) - E(\mathbf{X}_{pre})\}'\beta_{pre} \tag{5}$$

This quantity represents changes that were predicted given the pre-period association between race and attributes, β_{pre}, and the post-period change in crash attributes, $E(\mathbf{X}_{post}) - E(\mathbf{X}_{pre})$. For example, if drunk driving accidents increased substantially after 2014 and if Black drivers were more likely to be involved in such accidents prior to 2014, this would indicate that changes in drunk driving explain a portion of increase explained due to a change in endowments.

The next component is given by:

$$\textbf{Coefficients: } E(\mathbf{X}_{pre})'(\beta_{post} - \beta_{pre}) \tag{6}$$

This equation captures the share of the increase that is attributable to a changing correlation between each of the attributes and race. For example, if $\beta_{post} > \beta_{pre}$ in a model with a single control variable — for example, speeding — it would indicate that the probability that a decedent was Black conditional on the accident being speeding-related had increased across time periods.

Finally, we capture simultaneous shifts in the attributes and their association with race across the two periods:

$$\textbf{Interaction: } \{E(\mathbf{X}_{post}) - E(\mathbf{X}_{pre})\}'(\beta_{post} - \beta_{pre}). \tag{7}$$

A core challenge with the Oaxaca-Blinder decomposition is that the choice of reference or omitted category in the categorical predictor variables can affect the resulting estimates (Fortin et al., 2011). To address this issue, we use the normalization suggested by Yun (2005) and implemented in Jann (2008).

The results of this analysis are presented in Table A3. Each row shows the estimated percentage of the variation that is explained across the three channels by the variable listed in the left-most column. In column (1), we estimate the decomposition with only situational factors such as the type of car that was involved and whether the accident occurred on the weekend or a weekday. In general, shifts in these variables predict a fall in the Black share of decedents, not an increase. For example, the indicator for whether the vehicle was a sedan explains -21% of the change. This reflects the fact that sedans were previously strongly predictive of Black drivers, but the share of sedans in accidents dropped after 2014 (see Table 1). The small or negative contributions of these factors reinforce the idea from Figure 8 that the new gap cannot be easily connected to the type of road, time of day, day of week, or driver license status.

In column (2), we estimate the decomposition using risky driving behaviors: drunk driving, drug involvement, no seat belt, a single car accident, and speeding. With the exception of drug involvement, all factors explain a small or negative share of the increase. In column (3), we estimate the same model including both variable sets. This tests whether any of the percent explained by risky behaviors is due to shifts in the situations factors we consider in column (1). In general, the estimates are similar, particularly the percent explained by drug involvement.

Table A3: Decomposition

	(1)	(2)	(3)
Interstate Hwy	1.52		2.31
	(0.83)		(0.97)
Late Night	-23.38		-20.19
	(2.14)		(2.43)
No License	-16.14		-12.61
	(3.41)		(3.64)
Sedan	-22.18		-21.60
	(1.20)		(1.38)
Truck	-8.28		-4.26
	(4.50)		(4.92)
Weekend	-0.31		0.56
	(1.29)		(1.41)
Drunk Driving		-16.86	-15.72
		(1.73)	(1.90)
Drug involvement		20.60	26.48
		(6.63)	(7.26)
No Seatbelt		-16.73	-14.02
		(0.99)	(0.94)
Single Car		1.47	1.00
		(0.35)	(0.30)
Speeding		-8.62	-6.50
		(2.20)	(2.29)
Observations	569,936	529,747	529,747

Notes: This table shows a Oaxaca-Blinder decomposition explaining the difference in the fraction of Black vehicle fatalities between 2003-2013 and 2014-2020, restricting to Black and white fatalities in the FARS data. Each column gives the percent of the difference explained by the variable, combining the endowment, coefficient, and interaction effect. The standard error of the estimate is in parentheses. In all cases, we normalize categorical variables as in Yun (2005, also see Jann (2008)). See Appendix Section C.