Crash Course: How Michigan's Auto Insurance Policy Shapes Risky Driver Behavior

BY

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HONOR PLEDGE:

This paper represents my own work in accordance with University regulations.

/s/ William Huang

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I disclose that I used Generative AI in the development of this paper under the guidance of, and with the full knowledge of my faculty advisor. I assert that my use of Generative AI has been documented and that all prompts have been saved and can be produced on demand, if required.

/s/ William Huang

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Abstract

In July of 2020, Michigan implemented a new auto insurance policy reform that decreased insurance premiums by effectively setting a price ceiling. This paper studies how that new policy reform and a decrease in insurance prices affects the frequency of risky driver behaviors and fatal accidents. By utilizing the synthetic controls method and placebo/permutation tests to control for endogeneity in the difference-in-differences model, this paper finds that the new Michigan auto insurance policy has no statistically significant effect on either risky driver behavior or fatal accident rates. This result suggests that drivers choose their level of care on the road with more consideration for their own health and self-preservation rather than evaluating the monetary cost of an accident. This is contradictory to some of the current literature and provides policymakers with confidence that a reduction in insurance premiums does not lead to a more dangerous driving environment.

1. Introduction

In the United States, it is almost impossible to commute anywhere without using a car. It is by far the most preferred form of travel, as 77% of American workers state that they use a car to get to work each day. (Richter, 2023) Further, the average American spending more than 26 minutes on driving each day, emphasizing the heavy reliance on the use of automobiles. (Vigderman and Afilalo, 2025) Unfortunately, alternatives like the bus, subway, or other public transportation systems have terrible infrastructure and often only exist and work reliably in large cities such as New York City or Chicago. This makes policies around auto insurance incredibly important and influential on the daily lives of Americans.

For the last couple of decades, the people of Michigan have suffered from extremely high auto insurance rates, making the state one of the least affordable places to own a car in America. (Born and Klein, 2023; Insure.com, 2025) Michigan insurance prices are more than 20% higher than the national average (Robinson and Hill, 2025) and metropolitan areas such as Detroit see auto insurance costs that are around two times higher than other similar cities. (Balasco, 2025) As there are little to no good alternatives to commuting other than driving in Michigan, these absurdly high auto insurance rates have been a major issue for Michigan residents.

With Michigan governor or senate candidate election debates going back as far as 1992 mentioning ways to solve this issue, the auto insurance landscape has been under heavy scrutiny from policy makers. It wasn't until 2019 that the problem was addressed head on through the use of a price ceiling. Gretchen Whitmer, the current governor of Michigan, capped the price of auto insurance, forcing the price of auto insurance to drop.

The decrease in price, however, could lead to some unwanted side effects by potentially promoting risky driver behavior due to the cheaper cost of getting into an accident. This thesis uses empirical data to test whether this is true. Specifically, my paper looks to answer the question "did Michigan's new auto insurance price ceiling policy enacted in July of 2020 increase risky driver behaviors and create more fatal accidents on the road?" By studying this question, it would not only allow policymakers to better understand the externalities of their laws, but also give insight into how auto insurance prices influence the operation of automobiles.

While previous literature has examined how changes between no-fault and tort auto insurance policies affect driver behavior by altering the expected cost of accidents, my thesis isolates this effect by analyzing a clear decrease in insurance prices without any change in insurance plans. Further, by using the synthetic controls model and placebo/permutation tests, this thesis was able to find that there is no statistically significant effect that the new Michigan auto insurance policy increased the frequency of any risky driver behaviors or fatal accidents rates on the road. This result contributes to the existing literature by reinforcing the idea that a decrease in expected cost of accident does not change drivers' level of care when operating their vehicles. While these results are in the same direction as some of the current literature (Loughran, 2001; Kochanowski and Young, 1985; Zador and Lund, 1986; O'Connell and Levmore, 1983), the more robust methodology provides policymakers with more confidence that the reduction in Michigan insurance prices did not promote poor driving choices or make the driving environment more dangerous.

2. Background

2.1 Purpose of Auto Insurance

Accidents are bound to happen. Whether it's missing a stop sign or missing someone in the side mirror when changing lanes, accidents are a common occurrence. In fact, according to the Bureau of Transportation Statistics, there are 13 car accidents that occur every 60 seconds in the United States. (Bureau of Transportation Statistics, 2025) While these accidents might vary largely in severity, it remains true that it costs a lot of money to repair the damages of an accident. Even some of the most minor ones such as fender benders can cost an average of $1,000. (Goldlaw Personal Injury Lawyers, 2025; National Safety Council, 2025) Considering that the average American only makes around $1,300 a month before taxes, rent, and other expenses, getting into any type of accident regardless of severity could result in extreme financial difficulty. (Social Security Administration, 2025)

It is this financial risk that becomes the main motivation why most people, if they can afford it, choose to purchase auto insurance as they will cover the financial burden that come from the repairment costs of any damages to one's vehicle. (Allstate, 2025) Most insurance plans will cover any non-wear and tear costs regardless if the damage was sustained from an accident, robbery, or other incident beyond one's control. However, in addition to covering for the financial costs of car accidents, many basic auto insurance plans include medical coverage that compensates for the cost of any injury sustained in an accident. From these benefits it is clear that the main purpose of auto insurance is to allow drivers to mitigate the amount of risk that is associated with operating a vehicle on the road.

2.2 Tort Liability Insurance

While there are many different plans of auto insurance the most popular one in the United States is the at-fault or tort liability plan. Used in 38 out of the 50 states in America, tort liability remains the fundamental auto insurance policy. The way that it works is relatively simple as shown in the example below.

If person A and person B get into an accident because person A ran a red light, person A, who was the cause of the accident, would be subject to a lawsuit from person B for them to pay any damages that person B sustained from the accident. If the lawsuit was ruled in favor of person B (stating that person A caused the accident), person A's insurance firm would pay for person B's damages while person B's insurance firm would pay for nothing. These damages could include anything from medical bills, property damage, and even pain and suffering of the accident.

From the example above, the tort or at-fault auto insurance policy leverages our justice system to find a perpetrator and victim of each car accident. This is a reasonable system as it distinguishes between innocent bystanders that happened to be unlucky and risky drivers that are reckless and endanger other people. By having the person responsible for an accident be subject to a lawsuit and have them pay for the damages of the victim, it forces drivers to behave better and promote safer driving.

However, this system does not come without its flaws. Not every accident has a clear person at fault. Whether it was both drivers making a mistake or a worn away lane line confusing drivers, there are many accidents where it is difficult to determine the cause. Without clear evidence for who was at fault, both of these situations would lead to large, complex legal battles that become incredibly costly for the insurance firms that are covering the people involved in the

accident. (Loughran, 2001) It is estimated that almost a third of the money won in court is paid to cover for lawyers and legal fees. (O'Connell, 1975; Insurance Bureau Michigan Department of Commerce, 1976)

In addition to creating these expensive legal fees, these accident lawsuits also create massive delays in victims receiving the payments that they deserve. (O'Connell, 1975) Due to the complex and difficult nature of proving driver negligence with often times little to no evidence, these lawsuits drag out, preventing the necessary payments to be made to the victim. This then creates a massive financial burden on the victim, especially if they sustained large injuries that required medical treatment that they cannot afford.

Further, since all parties involved in the accident, including the doctors treating the victims, can be subject of the lawsuit, many medical professionals err on the side of caution and provide more care than necessary. (O'Connell, 1975) This is because doctors that are treating the accident victims want to ensure that there is no way that they can be sued for not providing enough care, thus sometimes ordering unnecessary exams such as x-rays and MRIs to be on record for evaluating the patient completely. This further exacerbates the financial burden of the accident victim as they are now also paying more medical procedures than what was necessary.

All of these issues arise specifically with tort liability insurance because it allows for the possibility of a lawsuit. It is the potential legal liability that generates high degrees of fraud within the system, unnecessary financial burden on the victims, and crowds the local courts with long cases. These pain points of tort liability insurance caught the attention of some law makers that decided it would be best to move to an alternative policy: no-fault auto insurance.

2.3 No-Fault Auto Insurance

Around the late 1960s and early 70s, the no-fault auto insurance policy was introduced as a solution to these long and expensive legal battles that was required of the tort policy. Under the no-fault system, there would no longer be a need to find the person responsible as each party's insurance would cover for the damages from the accident. (Thomson Law, 2025) Regardless of the amount or severity of the damages of the accident, insurance firms would cover their own clients, eliminating the need for a lawsuit.

The no-fault system immediately provided relief to all of the pain points previously associated with tort liability insurance. First off, it prevented the need for a legal battle to find who was responsible for the accident, allowing the entire funds provided from the insurance firm to go directly to compensating the damages sustained. The disappearance of the lawsuit also ensured that victims were compensated immediately, freeing them from further financial burden that would occur if payments for medical bills were withheld due to the ongoing legal dispute. Finally, doctors and hospitals no longer provided unnecessary services to ensure "full and wholistic" care for the patient in fear of getting sued. In theory, the no-fault system not only benefits the victims of automobile accidents but also provided positive externalities to local hospitals and courts that would be otherwise swamped with unnecessary patients and cases.

These were the benefits that some states were seeking, and 12 states fully adopted the system by the mid 1970s. While these states were all operating under this new no-fault auto insurance system, the implementation varied heavily across states. Some states such as New Jersey, Pennsylvania, and Kentucky gave their drivers the option to choose between the original tort liability and the new no-fault auto insurance. Most other states fully bought into the new no-fault policy but varied the maximum amount of coverage that insurance firms would need to cover for

their clients without a lawsuit. For example, Connecticut insurance firms do not have to cover accident damages that exceed $400 whereas insurance firms in Minnesota need to cover for the cost of damages upwards to $2000. (Landes, 1982) Michigan, on the other hand, has no maximum threshold for no-fault insurance compensation which has resulted in a very interesting auto insurance landscape.

2.4 The History of Michigan Auto Insurance

Michigan first adopted the no-fault auto insurance system in 1973, joining many of the other states that have made the switch from tort liability insurance. Initially, Michigan saw success with the new system as the issues from the previous tort systems began to disappear. As stated in a report to the governor from the Insurance Bureau of the Michigan State of Commerce just three years after the no-fault policy was in effect, "payment to injured parties has been prompt, benefit levels have increased, the proportion of premium dollar paid out for legal costs has dropped and duplication of insurance coverages has been reduced. The preliminary judgement is that the consumer has been well served by no-fault." (Michigan Department of Commerce, 1976) While the no-fault approach appeared to be an effective alternative, it's success only lasted in the short term and later revealed its severe downsides.

In the 1980s, just under a decade since the no-fault insurance policy was instated, Michigan saw its auto insurance premium begin to creep higher and higher. (Insurance Research, 2019) This increase in price was directly tied to the fundamental values of the Michigan's uncapped no-fault system. Since there was no maximum threshold for medical bills, all patients' medical procedures were covered by the auto insurance for any accident-related injuries. This resulted in doctors to be incentivized over treat and provide more services than necessary to their car accident patients in order to gain more profits and thus recreating an issue that the no-fault policy was meant to solve.

(Born et al., 2023) This skyrocketed the insurance premiums as auto plans essentially became both car insurance and health insurance. Further, with the lack of support from the legal system to investigate the accident, the no-fault policy fueled fraud which exacerbated the already climbing premiums. As insurance rates continued to shoot up, many people began to drive uninsured as they could no longer afford insurance. (Borba, 2019) These uninsured drivers, who were involved in accidents, could not afford the medical bills from hospitals, creating a net loss for hospitals that were forced to treat these patients. This caused hospitals to raise prices for procedures in an attempt to recover these losses. This action put more burden on insurance firms, causing premiums to rise even higher. Add all of this together and, by the mid 2010s, the state average had rates that were more than a third higher than the national average with some metropolitan areas such as Detroit being almost double the national average. (Born and Klein, 2023; Insurance Research, 2019; Corum, 2019)

In an attempt to solve this issue, Governor Gretchen Whitmer signed a historic no-fault auto insurance reform in May of 2019 that was designed to make rates more affordable again. (LeBlanc, 2019) The reform stripped away the mandatory unlimited medical coverage, which was the main driver of the high prices, and allowed insurers to sell reduced coverage policies that capped rates at which medical providers could charge for motorist care. Enacted in July of 2020, car owners are now able to select different personal injury protection (PIP) plans that range from no medical PIP, $50,000/accident, $250,000/accident, $500,000/accident, and the original unlimited PIP. (Michigan Department of Insurance, 2019) This has dramatically lowered the cost of auto insurance and made driving more affordable in Michigan. (Born and Klein., 2023)

While the reform has so far done a good job at lowering the price of insurance and making driving more accessible, it could potentially promote risky driving behavior. By lowering the

barrier to entry of driving in Michigan, previous risky drivers that did not drive due to the expensive insurance would now be on the road, making the streets more dangerous. This is the main question that this paper intends to answer through the use of empirical and data analysis.

3. Literature Review

While the effects of no-fault auto insurance policies are a heavily studied subject, there is quite a lot of disagreement among scholars. The current literature landscape is heavily conflicted with there seemingly being an equal number of academics arguing for either side. (Loughran, 2001; Kochanowski and Young, 1985; Zador and Lund, 1986; O'Connell et al., 1983; Landes, 1982; Cummins et al., 2001; Cohen et al., 2004) Scholars such as Landes, Cummins et al., and Cohen et al. argue that no-fault auto insurance has severe negative effect on road safety and that the policy should cease to exist. (Landes, 1982; Cummins et al., 2001; Cohen et al., 2004) However, other researchers such as Loughran, O'Connell et al., Kochanowski et al., and Zador et al. argue that they find no evidence that no-fault policies increase accidents on the road. This polarizing view of the subject has led to a lot of conflicts among policy makers that are running for office.

3.1 Debate of No-Fault's Effect on Fatal Accident Rates

In order to unpack this debate, it is important to understand the thought process of the scholars that argue against no-fault. Landes' 1982 paper titled *Insurance, Liability, and Accidents: A Theoretical and Empirical Investigation of the Effect of No-Fault Accidents* is the study that set the foundation for this logic. In her theoretical model, she argues that all drivers on the road choose the minimum level of care to minimize their costs without increasing their probability of getting into an accident. Under the normal tort liability insurance system, drivers not only had to factor in their own monetary and health costs of getting into an accident but also had to account for the potential cost of legal fees if they were being sued for causing the crash. This increased cost of accident would lead to drivers increasing their level of care as they would want to avoid getting into an accident more than they did before. However, once the no-fault auto insurance policy was

introduced, the ability to sue disappeared, thus suddenly lowering the cost and consequences of getting into an accident. It is this decrease in accident costs that Landes claims is the reason why drivers would decrease their level of care on the road and in turn cause more accidents.

In addition to creating the theory, Landes also backs this up with empirical analysis. She uses the Fatal Accident Reporting System (FARS) data instead of regular accident data because FARS provides a better image of driver incompetence. Fatal accidents must be reported and thus mitigates the potential of a small accident going unreported as the parties involved can settle the matter themselves without involving either the police or insurance companies. With the FARS data, Landes finds that no-fault has a statistically significant increase on fatalities by 4-10% depending on state specific insurance thresholds. (Landes, 1982) While these results shocked policymakers and sent them looking for a response, other academics questioned the validity of the results.

One of the Landes' largest skeptics was Jeffrey O'Connell, a professor of law at the University of Illinois. In his response titled *A Reply to Landes: A Fault Study of No-fault's effect on Fault?,* he criticizes the robustness of Landes' theoretical model. First, he disagrees with the way that Landes presented the regulation and how she failed to include the whole picture of the law. One of the many inaccuracies that he states Landes' paper contains is how she falsely claims that drivers are unable to sue for pain and suffering. This is not the case after the accident costs exceed a certain threshold. In addition to how Landes presents the law, O'Connell also disagrees with number of assumptions that Landes needed to prove her model. He bashes Landes' claim that every driver on the road is a "superrational" driver that can carefully account for probabilities with precision while foolishly decreasing their level of care to increase accident rates as a response to small changes in the medical bill threshold. (O'Connell et al., 1983) This is one of many

assumptions that he believes to undermine the paper's ability to be applied to the real world and provide substance to the debate.

O'Connell et al. was not Landes only critic either. Kochanowski and Young performed their own review of the study and found many holes in the theoretical model that they thought undermined the results. Similar to O'Connell, they thought that Landes model made a substantive number of assumptions that made no practical sense. Further, Kochanowski and Young found the sensitivity of drivers' level of care to financial compensation from insurance firms to be highly unlikely. They claim that no one, when operating a vehicle, is constantly thinking about the cost of an accident and adjusting their driving behavior accordingly. (Kochanowski and Young, 1985) They believe that the results Landes finds from her empirical study to be merely noise from state and driving environment specific characteristics, which they prove through the use of their own empirical analysis. From Kochanowski and Young's results, they find that state to state variation explained approximately 60% of fatality rates and that the state's auto insurance policy played no statistically significant role in explaining fatality rates. (Kochanowski and Young, 1985)

However, even with exaggerated assumptions and debatable results, Landes model remained the best as many other scholars adopted it in an attempt to tweak it for more robustness. Cummins et al. were some of these scholars that wanted to reinforce Landes' paper. In their study, they tweaked Landes' original model by considering the "possibility that the type of automobile compensation regime (tort vs. no-fault) that exists in a state may be endogenous; that is, the compensation regimes adopted by the states may be systematically related to accident rates or other state characteristics." They fix for this endogeneity through the introduction of an instrument variable and reverse Mill's ratios techniques. Through this more robust analysis, they find very similar results as Landes, suggesting "that no-fault is associated with fatality rates from 2.7 to 17.3

percent higher than tort, with a median predicted increase of 13.8 percent." (Cummins et al., 2001) These results are significant at the 95% confidence level, further emphasizing the validity of Landes' study.

Another study that sought for a better understanding of the situation was Cohen et al.'s paper titled *The Effect of Automobile Insurance and Accident Liability Laws on Traffic Fatalities.* Similar to Cummins et al., Cohen et al. structured their paper after Landes' original model but made a few adjustments to provide robustness. They factored in the effects of compulsory insurance requirements in addition to the effects of no-fault auto insurance policy, thus effectively distinguishing the separate effects. This was something that neither Landes nor Cummins et al. had considered and could be key in finding the true effects of no-fault auto insurance policy on fatal accidents. Even with by separating the two compounding effects, they find that no-fault insurance increases both fatalities per every 10,000 people and fatalities per every vehicle mile traveled by around 10%. (Cohen et al., 2004) Both of these results are significant at the 95% confidence level and continue to show the strength of both Landes' original theoretical model and the negative relationship between no-fault auto insurance and fatal car accidents.

3.2 Michigan's New Auto Insurance Policy on Insurance Prices

One of the main disagreements from scholars that are skeptical that no-fault insurance policies increase fatal accident rates is that they are unsure if no-fault insurance lowers the expected cost of an accident in the first place. (Loughran, 2001; O'Connell, 1983) These scholars claim that even if it is true that drivers' select their level of care to reflect their expected cost of an accident as Landes states in her theoretical model (Landes, 1982), the evidence that no-fault policies decrease the cost of accident is circumstantial at best. They claim that all of the theoretical models used make too many assumptions about how the auto insurance system works and that

there are many ways in which it is still possible to pursue legal action for an accident under no-fault insurance. (O'Connell, 183; Kochanowski and Young, 1985) This lack of clarity that no-fault insurance decreases accident costs give rise to many holes in Landes theoretical model.

This thesis circumvents these issues by comparing the frequency of risky driver behavior and fatal accident rates before and after the introduction of the new Michigan auto insurance policy, which is meant to reduce the cost of insurance through the use of a price ceiling. (Born and Klein, 2023) As seen by Born and Klein's 2023 study titled *No-Fault Auto Insurance Reform in Michigan: An Initial Assessment Revised,* this price ceiling implemented in July of 2020 by the Michigan government did indeed lower auto insurance prices. Depending on what personal injury protection (PIP) drivers decide to choose, Michigan drivers experienced a reduction of insurance premiums between 10% to upwards of more than 50%. (Born and Klein, 2023) This is clear evidence for a reduction in expected accident costs for the driver and provides a great opportunity for a sound empirical study.

Further, in addition to proving a significant reduction in insurance premiums that directly reduce the expected cost of an accident, this policy allows my thesis to study this specific price reduction with not only just the same insurance system, but also the same demographic of drivers. This allows me to isolate the effects of a decrease in expected accident costs, giving true insight about what influences drivers' level of care when operating their vehicles on the road.

3.3 Addition to the Current Literature

In addition to better determine the factors and influences being how drivers choose their level of care on the road through isolating the effects of a decrease in expected accident costs, my thesis includes a few aspects that were overlooked by previous scholars. While these scholars all

attempt to add robustness to Landes original methodology, it might worth it to approach the situation from a difference-in-differences analysis. Since one of the main issues with Landes methodology is the potential endogeneity between the states that switched to the no-fault insurance system and their fatal accident rates, it would be best compare the no-fault states alongside the tort states to examine the difference in fatality rates. My paper intends to leverage this empirical analysis model to hopefully bring more clarity to the current literature and provide a more robust methodology.

Another aspect that was overlooked by these scholars is the fact that not all fatal car crashes are the same. It is important that I separate the result of a fatal car crash from the cause of the crash, especially when understanding whether the crash was an accident as a result of human error or due to risky driver behavior and negligent driving. This distinction becomes highly evident when examining the difference between single vehicle and multi vehicle crashes.

Even at a surface level, multi vehicle crashes have many more plausible accident causes than single vehicle crashes because there are more drivers involved, thus increasing the chances of human error. Single vehicle crashes on the other hand, involve only one driver and thus limit the number of possibilities of an accidental crash and bring in a higher likelihood that the crash involved a risky driver behavior. In fact, Ostrom and Eriksson, who examined the details of single vehicle versus multi vehicle crashes in Sweden, and Martensen and Dupont, who examined broader European data, both found that single vehicle crashes are significantly more likely to contain risky driver behaviors than multi vehicle accidents. (Ostrom and Eriksson, 1993; Martensen and Dupont, 2012)

In fact, both of these studies found that depending on the behavior, drivers in single vehicle accidents are anywhere from 2 to 13 times more likely to exhibit poor driver choices such as drunk

driving, lack of seat belt use, distracted driving, and speeding. (Ostrom and Eriksson, 1993; Martensen and Dupont, 2012) Due to these large differences, it is clear that when examining the effects of no-fault auto insurance on risky driver behaviors, single vehicle and multi vehicle crashes must be treated differently. In this thesis, I intend to adjust the weighting of single vehicle crashes to be twice as much as multi vehicle crashes to accurately represent them within the data so they can reflect the average drivers' behaviors.

4. Data

4.1 Fatal Accident Reporting System (FARS) Data Overview

While this paper utilizes several data sources, the main dataset that is analyzed is the Fatal Accident Reporting System (FARS) data from the National Highway Traffic Safety Administration (NHTSA), which is a part of the US Department of Transportation. Going back to as far as 1975, the FARS data provides a public yearly census on all information regarding fatal injuries that were sustained in motor vehicle traffic crashes. (NHTSA, 2025) Like many other scholars that have written about similar topics (Landes, 1982; Cummins et al, 2001), the main reason why I selected the FARS data was due to the accuracy and detail that this dataset provides. Unlike other accident reporting systems such as the Crash Reporting Sampling System (CRSS) or the Crash Investigation Sampling System (CISS), FARS is a census that records every fatal car accident in the United States across all states and territories. This ensures accuracy and full representation of the characteristics that could have led to the cause of the accident.

Further, the reason why I choose to fatal accident data instead of total accident data is because it better represents risky driver behavior. Other datasets such as the CRSS or CISS that report all types of accidents could include small fender benders and bumps that are not representative of poor driver choices. Additionally, even if some of these smaller accidents were the result of a distracted driver or other poor driver choices, they often go unreported as the two parties can settle the matter directly themselves. Since fatal accidents must be reported and are recorded in the FARS data, it eliminates this bias and allows for better understanding of how the new Michigan auto insurance policy will affect risky driver behavior.

4.2 Dependent Variables

4.2.1 Dependent Variable Frequency

In this thesis, the dependent variables are categorized to be any variable that would give insight into risky driver behavior. These variables included the number of accidents, number of fatalities, drunk driving, drug use while driving, distracted driving, driving while impaired, seat belt misuse, and speeding. Since many of the data files within FARS are structured where each observation is one fatal accident, it was important to clean and aggregate the data properly to obtain my desired dataset that specified observations by state and time periods.

This process relatively easy for the number of accident and fatalities variables as those are just the sum of each observation and the number of fatalities per accident, respectively. However, variables that occur multiple times per accident, such as drunk driving, which is recorded at a per person level, requires a little more effort to clean. To change drunk driving from a per accident variable instead of a per person variable, I shifted variable to become a binary variable that holds a value of 1 when one or more people involved in the accident was inebriated. By doing so, I was able to successfully capture the number of accidents where alcohol played a role. This same process was repeated for the remaining per person variables of drug use while driving, distracted driving, driving while impaired, and driving without a seat belt.

Within these per person level dependent variables, there were a lot of redundancies as many drivers who are driving drunk are also counted as driving while impaired. While this was the case, it was still important to include these repeats since there are some cases, such as falling asleep at the wheel, where someone can be driving while impaired but be neither drunk nor using drugs.

4.2.2 Dependent Variable Rate Divisors

Finally, once these dependent variables have been cleaned properly, they were divided by a couple different rate divisors to translate these variables from frequencies to rates. The first divsior these dependent variables would be divided by would be population, which was obtained from the US Census Bureau for the most updated population estimate for each year. The reason why population was used is because more people mean more drivers on the road, which would reflect a higher number of accidents. By shifting my dependent variables to reflect per capita characteristics, it would allow me to control for this aspect and let me compare states with varying levels of population such as California to Michigan.

The other divisor that was used was vehicle miles traveled (VMT), which is defined to be the total number of miles traveled by vehicles in each state. This data was collected by the Federal Highway Administration under the US Department of Transportation and directly reflects the amount that people are driving on the road. States with more frequent drivers would naturally experience more accidents by turning my dependent variables to reflect per mile traveled characteristics, I can fix for the amount that each person travels in each state and compare across states with different travel frequencies.

4.2.3 Adjusted Accident Rate

One aspect that many studies before this thesis failed to account for is the fundamental difference between single vehicle and multi vehicle crashes. In a situation when there is more than one vehicle involved in an crash, the odds of it being accidental are much higher. (Ostrom and Eriksson, 1993; Martensen and Dupont, 2012) It could be the case that one of the drivers accidentally runs a red or one of the drivers failed to see the other when changing lanes. The possibilities of the accidental cause of the crash are endless.

However, when observing single vehicle crashes where there were no other vehicles on the road, there are only very limited causes for an accident. The lone driver has less factors to deal with and thus making the crash much more likely to be caused by risky driver behaviors. (Ostrom and Eriksson, 1993; Martensen and Dupont, 2012) From Ostrom and Eriksson's study, they find that single vehicle crashes had almost six times as many drunk drivers than multi vehicle crashes (58% vs 10%). Further, single vehicle crashes exhibit significantly lower seat belt use (33% vs 69%) and had three times as many invalid driver's license holdings (75% vs 25%). (Ostrom and Eriksson, 1993) Other scholars such as Martensen and Dupont obtain similar findings with single vehicle accidents showing more than a 300% increase in poor driver choices. (Martensen and Dupont, 2012)

Due to single vehicle accidents exhibiting a much higher frequency of risky driver behavior, I decided to create a variable called "adjusted accident" that would modify the weighting of single vehicle crash to be twice that of a multi vehicle crash. As shown from the literature above, this two times adjustment, while seeming large, is actually on the conservative end. Again, similar to all of the dependent variables described above, the "adjust accident" variable will be divided by both the population as well as the VMT of each state to preserve comparability across states.

4.3 Independent Variables

In this paper, since I am running a difference-in-difference regression, the independent variable is both time and treatment group specific. In this paper, I define the treatment to group be the state of Michigan. The time of treatment occurred on July 1, 2020, making any data point July 1, 2020 and onwards, post-treatment data. By combining these two characteristics together, I was able to create our independent variable which is just a binary variable that holds a value of 1 when the data point is both in Michigan and after July 1, 2020.

4.4 Control variables

Even though I am running a difference-in-difference regression model that controls for both time and state fixed effects, it is important that I be more explicit and specific in my control variables rather than just relying on the fixed effects model. Here, when considering the major factors that could influence a car accident, weather is the first variable that comes to mind. Adverse weather conditions can increase the likelihood of accidents by more than 24% and thus do not accurately represent risky driver behavior. (Becker et al., 2022) When cleaning this variable, I consolidated it from a 12-point categorical variable to a six point system that represented clear, fair, semi-fair, moderate, semi-moderate, and severe weather conditions.

Clear conditions are the best when there is no adverse weather, fair conditions were recorded to be when the weather was cloudy, semi-fair was when either fog, sand/dirt, or "other" weather conditions were experienced, moderate conditions were described as high to severe winds, semi-moderate was rain, and finally severe weather conditions included sleet/hail, snow, and freezing rain. These six separate levels were numbered from 0 to 5, allowing me to not only control for accidents with different weather conditions, but also control for the average climate of states to accurately let me compare warm weather states such as Florida to the cold climate experienced in Michigan.

Another common factor that heavily affects driving ability are the light conditions on the road. Lighting on the road significantly influences the vision of drivers and can attribute to accidents if drivers cannot see where they are going. The difference between driving during the day versus driving at night can influence accident rates by more than 3%. This difference, like weather, do not accurately show risky driver behavior, making it an important control variable.

(National Safety Council, 2025) Since the light condition variable in the FARS data, like the weather variable, is a large multi-point categorical variable, a similar cleaning process was used.

The final light condition variable that was used in this paper was a binary variable that was separated into good and poor light conditions. Good light conditions were defined to be any situation that was lit by daylight or nighttime situations that were well lit by artificial lighting. Poor light conditions were defined to any other types of lighting which mainly consisted of situations at dawn, dusk, or during the nighttime when the road had no lampposts. Here, the light condition control variable will hold a value of 1 during good conditions and a value of 0 during adverse ones.

Continuing with the theme of visual conditions, it is important that drivers have a clear line of vision when operating their vehicles. While uncommon, it is not surprising to see that there are accidents that are caused by an obstruction of vision whether it come in the form of a dirty windshield, trees, or other vehicles. Similar to the two other control variables discussed above, the vision variable is a highly detailed multi point categorical variable. I consolidate this by turning it into a binary variable that holds a value of 1 when the driver's vision is impaired and a 0 when the driver's vision is not.

Shifting gears away from the vision of the driver, the final control variable considers the ruralness of the area where the accident occurred. This binary variable holds a value of 1 when the area is defined as urban under the Roadway Function Class and 0 when the road is defined as rural. (NHTSA, 2025) This variable serves as a proxy for population density which is important in gauging whether or not the accident could be caused by an overly crowded road system. More urban road systems are often more complex than rural ones, making it harder for drivers to navigate and thus pull their attention away from the present driving situations. Further, more urban roads often have more traffic which means there are more cars for the drivers to maneuver through. This

increase in cars not only creates more distractions for the driver, but also puts them under more pressure, especially when trying to navigate through multiple exits and roadways. By controlling for this aspect, it will allow me to understand how drivers behave regardless of traffic and road complexity.

4.5 Summary Statistics Tables and Graphs

Shown below in Table 1 are the summary statistics for all independent, dependent, and control variables. Figure 1 is the linear trends model for Michigan versus the control group of All States. All other linear trends model look very similar to Figure 1 and are attached for the reader's reference in the Appendix section.

Table 1. Mean of State Month Variables

VARIABLES	(1) N	(2) Mean	(3) Std. Dev	(4) Min	(5) Max
Vision Obstructed	4,841	0.0420	0.0871	0	1
Light Condition	4,841	0.677	0.177	0	1
Weather Condition	4,841	0.601	0.649	0	5
Ruralness of Accident Location	4,841	0.491	0.258	0	1
Fatal Accidents Per 100,000 People	4,841	0.628	0.396	0.0115	3.252
Fatalities Per 100,000 People	4,841	0.687	0.444	0.0115	4.108
Fatal Accidents Per 100 million VMT	4,841	0.720	0.385	0.0127	2.672
Fatalities Per 100 million VMT	4,841	0.785	0.428	0.0127	2.948
Distracted Drivers Per 100,000 People	4,841	0.0661	0.0898	0	1.165
Distracted Drivers Per 100 million VMT	4,841	0.0751	0.0926	0	0.803
Impaired Drivers Per 100,000 People	4,841	0.198	0.175	0	1.883
Impaired Drivers Per 100 million VMT	4,841	0.227	0.175	0	1.527
Drunk Drivers Per 100,000 People	4,841	0.0737	0.0901	0	1.089
Drunk Drivers Per 100 million VMT	4,841	0.0864	0.101	0	1.439
Drug Use Per 100,000 People	4,841	0.120	0.148	0	1.692
Drug Use Per 100 million VMT	4,841	0.142	0.172	0	2.036
Seat Belt Misuse Per 100,000 People	4,841	0.320	0.384	0	3.308
Seat Belt Misuse Per 100 million VMT	4,841	0.361	0.393	0	3.849
Risky Behaviors Per 100,000 People	4,841	0.409	0.292	0	2.568
Risky Behaviors Per 100 million VMT	4,841	0.469	0.290	0	2.211
Adjusted Accident Per 100,000 People	4,841	0.931	0.612	0.0117	4.793
Adjusted Accident Per 100 million VMT	4,841	1.066	0.598	0.0127	4.198

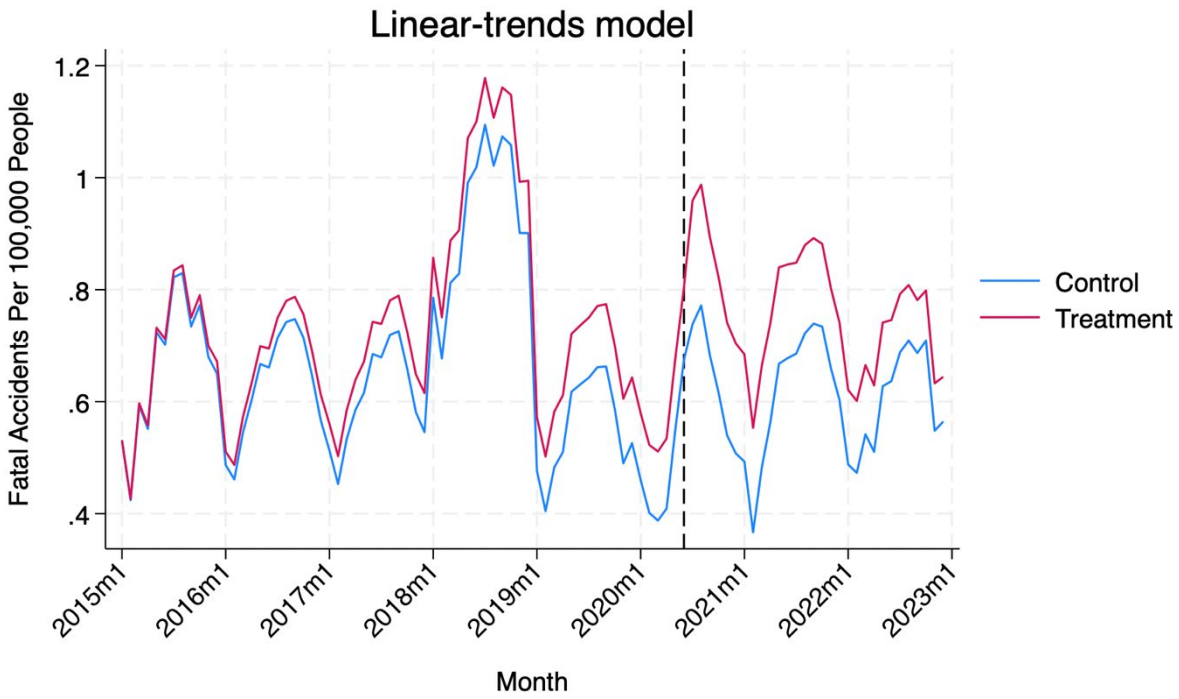


Figure 1. Michigan vs All States Linear Trends Model for Fatal Accidents Per 100,000 People

5. Methodology

5.1 Difference-in-Differences Set Up

After reviewing the current literature, I hypothesize that the decrease in insurance price from this new policy will lead to an increase in both risky driver behaviors and fatal accident rates. As mentioned previously, my paper will be implementing a difference-in-differences regression model to test for this hypothesis and examine the effects of Michigan's new auto insurance policy enacted in mid 2020. This methodology is surprising lacking from the current literature and will hopefully provide better clarity on how the decrease of auto insurance prices affect fatal car accident rates. Further, given the difficulty to find credible sources of exogenous variation in the adoption of no-fault laws, the difference-in-differences approach, is the most reliable estimation strategy in this situation. (Loughran, 2001)

In this thesis, I will be using a monthly timeframe for my difference-in-differences regression models as the shorter time frame will allow me to control better for weather/climate-based effects as well as holiday and other yearly cyclical travel patterns. Within each set of regressions, each model is identical except for the dependent variables so I can observe how the policy will affect specific risky driver behaviors. Listed below are the specific equations for one set of regression models.

$$Accident_Rate_{i,t} = \beta_0 + \beta_1 Time_i + \beta_2 Policy_i + \beta_3 (Time_i * Policy_i) + \beta_4 W_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$Fatality_Rate_{i,t} = \beta_0 + \beta_1 Time_i + \beta_2 Policy_i + \beta_3 (Time_i * Policy_i) + \beta_4 W_{i,t} + \varepsilon_{i,t} \quad (2)$$

$$Adjusted_Accident_Rate_{i,t} = \beta_0 + \beta_1 Time_i + \beta_2 Policy_i + \beta_3 (Time_i * Policy_i) + \beta_4 W_{i,t} + \varepsilon_{i,t}$$

(3)

$$Risky_Driver_Behaviors_{i,t} = \beta_0 + \beta_1 Time_i + \beta_2 Policy_i + \beta_3 (Time_i * Policy_i) + \beta_4 W_{i,t} + \varepsilon_{i,t}$$

(4)

$$Speeding_{i,t} = \beta_0 + \beta_1 Time_i + \beta_2 Policy_i + \beta_3 (Time_i * Policy_i) + \beta_4 W_{i,t} + \varepsilon_{i,t}$$

(5)

Here, beginning with the independent variables, $Time_t$ is the binary time variable that describes when the policy was enacted. In this case, this variable will hold a value of 1 if the date is at or after July 2020 and will hold a value of 0 for any observations before that date. The $Policy_i$ variable is another binary variable that holds a value of 1 when the observation occurred in the state of Michigan and holds a value of 0 when the observation was outside of Michigan. The interaction term of $(Time_i * Policy_i)$ represents the difference-in-differences estimator variable and shows the change in outcome variable rates on average in Michigan with respect to its baseline levels. $W_{i,t}$ represents the vector of control variables such as weather conditions, light conditions, visual impairment, and ruralness of accident location at the time of the crash.

Moving to the dependent/outcome variables, beginning with equation (1) $Accident_Rate_{i,t}$ describes the number of fatal accidents that occurred in the given month. Equation (2)'s $Fatality_Rate_{i,t}$, indicates the number of fatalities that occurred per 100,000 people or millions of VMT. In equation (3), $Adjusted_Accident_Rate_{i,t}$ shows the number of adjusted accidents per every 100,000 people or millions of VMT. As mentioned in the Data Section, adjusted accidents weigh single vehicle crashes twice as much as multi vehicle crashes due to the higher likelihood of single vehicle crashes to display risky driver behaviors. Equation

(4) uses $Risky_Driver_Behaviors_{i,t}$, which is a stand in for the six different types of risky driver behaviors I will be using as dependent/outcome variables.

The first risky driver behavior outcome variable that I will be using is $Distracted_Driving_Rate_{i,t}$, which shows the number of distracted drivers and is defined to be drivers that were distracted by behaviors such as engaging with other occupants in the vehicle, operating their mobile phone, or engaging in manipulation of audio or climate controls. The next variable is $Impaired_Drivers_Rate_{i,t}$, which shows the number of impaired drivers, which I categorize as drivers that are operating their vehicle under the influence of either substances such as drugs and alcohol, or drowsiness. $Drunk_Driving_Rate_{i,t}$ is the next risky driver behavior variable and describes the number of fatal accidents where drunk drivers were involved. I define drunk drivers as anyone that is driving above the legal limit of 0.08% blood alcohol content or if there were any open containers discovered in the car at the time of crash. Similarly, another variable, $Drug_Use_Rate_{i,t}$, shows the number of fatal accidents where drivers were using drugs while operating their vehicle. $Seat_Belt_Misuse_Rate_{i,t}$ is another outcome variable and shows the number fatal accidents where drivers misuse their seat belt while operating their vehicle. This misuse includes not using a seat belt or incorrect use of a seat belt. Finally, the last risky driver behavior variable is $Overall_Risky_Driver_Rate_{i,t}$. I define this as the number of accidents where either $Distracted_Driving_Rate_{i,t}$, $Impaired_Drivers_Rate_{i,t}$, $Drunk_Driving_Rate_{i,t}$, or $Drug_Use_Rate_{i,t}$ are exhibited in the accident. Finally, I separate $Speeding_{i,t}$ from these risky driver behaviors because it is the most common traffic violation and has the most direct effect on a driver's insurance premium. $Speeding_{i,t}$ is defined to exhibit any speed related traffic violation such as driving above the speed limit, driving too fast for the present road conditions, and even racing.

All outcome variables are presented with two different rate divisors: one in terms of population and the other in terms of vehicle miles traveled (VMT). The distinction of the frequency of an outcome variable per 100,000 people controls for outcomes per number of drivers on the road. This allows for accurate comparison across states with differing population sizes. The other outcome rate of outcomes per 100 million VMT is used as a robustness check and can be interpreted as the number of outcomes based on how much people drive. This would allow my results to be compared across states with different levels of automobile use. All results tables in the Results section, however, will reflect outcome variables in terms of frequency of outcomes per 100,000 people and the corresponding results tables with outcome per 100 million VMT will be available in the Appendix for the reader's reference.

5.2 Parallel Trends

In order for any type of difference-in-differences regression analysis to be valid, parallel trends must be established. Parallel trends simply shows that both the treatment and control groups have the same trajectory before the treatment. This is essential to for the difference-in-differences model as it shows that any movement in the treatment group after the treatment is applied cannot be a result of conditions or noise prior to the treatment. Thus, any discrepancies between the treatment and control groups after the treatment must be a result of the effectiveness of the treatment.

Unfortunately, when examining my dataset, parallel trends cannot be established. By examining the linear trends model in Figure 1 in the Data section visually, it is clear that there is a positive drift in the treatment group (dashed red line) since the beginning of the dataset. Even though the two lines move in the same direction and timing, the magnitude differs slightly showing that parallel trends cannot be established. Thus, it is impossible to distinguish any movement after

the treatment directly to the treatment itself as the difference could be attributed to the drift prior to the treatment.

This lack of parallel trends is further reinforced by using an F-statistic hypothesis test. As shown below in Table 3, I was able to reject the null hypothesis of a parallel trend at the 95% confidence level. While Table 3 below only shows the rejection of parallel trends for fatal accidents per 100,000 people, this quality is sadly consistent across all outcome variables regardless of rate divisors. This failure to prove parallel trends renders the difference-in-difference regression model completely useless as it is impossible to tell whether or not the movements of the treatment group after the application of the treatment is due to the effectiveness of the treatment or from prior unrelated drift from the control group.

Table 2. Rejection of Parallel Trends for Fatal Accidents Per 100,000 People using F-Statistic Hypothesis Test

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Prob > F-Statistic	0.0005	0.0062	0.0083	0.0078
Observations	4,841	288	1,151	3,882
Number of States	51	3	12	41

Even though parallel trends cannot be established, there is still away to run something similar to a difference-in-differences regression model. This technique that is used in thesis to study the effects of the new Michigan auto insurance policy on risky driver behaviors is known as the synthetic controls method.

5.3 Synthetic Controls Method

Since parallel trends could not be established within the data of this thesis, synthetic controls are introduced to artificially create parallel trends. The synthetic controls method is a technique that assigns each member of the control group a specific weight in order to mimic the movements of the treatment group before the treatment is applied. By changing the weights so that some states in the control group weigh more than others, the synthetic controls method maps the trajectory of the control group onto the treatment group, eliminating the possibility that any discrepancy in the differences post treatment to be attributed to pretreatment movements.

One issue with the synthetic controls method is that other than through visual examination, there is no test that displays whether or not the difference between the treatment and control groups are statistically significant. In order to find this information, I leverage a test called the placebo/permutation test.

The placebo/permutation test is a technique that shows whether or not the difference between the treatment and control group is statistically significant for every time unit after the treatment. Further, it tests for statistical significance by testing that difference between the treatment and control group against every single member and permutation of the control group, hence why it is called the permutation test. Using the model where the treatment group as Michigan and the control group as all states, the placebo/permutation test would measure the difference in groups in August 2020 (2020m8) against the difference between Michigan and all states except for Alabama, Michigan and all states except for Arkansas, so and so forth until it has compared the difference between Michigan and all states compared to the difference between Michigan and every possible control group. The permutation test will then provide a p-value which would be less than 0.05 if the difference between Michigan and all states is statistically significant.

Because of this methodology, I have excluded the comparison of Michigan to its neighboring states of Ohio and Wisconsin. This is because there are only two other possible control groups (just Ohio or just Wisconsin) in this situation. Thus, when the placebo/permutation test is run, the p-value will become a binary variable because there are only two control groups to compare the difference to. This provides no insight into the significance of the movement of the treatment group in comparison to the control group after the treatment, and thus this model is dropped from my methodology.

During this process of creating and running synthetic controls, there were a few adjustments that were made to my data. Throughout the cleaning process that is described in the Data Section, there were many observations that were missing control variable data points and thus had to be dropped from the dataset completely. Unfortunately, due to this method of cleaning, some of the lower population states such as Alaska failed to have any observations remaining in the monthly dataset. Using this unbalanced dataset makes it impossible to create any synthetic controls. To solve this issue, I decided to drop all states that had any missing values in the monthly dataset. Thus, instead of having 51 states (50 states including Washington DC), there were only 44 states as Alaska, Washington DC, Kansas, New Hampshire, Rhode Island, South Dakota, and Vermont were dropped from the dataset. While this may affect the results, it will most likely have a very small impact as these states have little in common with Michigan in terms of population and driving characteristics.

While the synthetic control models and placebo/permutation tests that I use in this thesis no longer directly show the equations seen earlier in this Methodology section, all outcome variables and control groups remain the same. The equations are still good theoretical models for

how I go about producing my results as there are many similarities between the synthetic controls model and the difference-in-differences model.

6. Results

6.1 Difference-in-Differences Results

This section presents the results from the difference-in-differences regression models. Each model was run against four different control groups and will be shown in each of the columns of the regression output table. The first column contains the regression model with all 50 territories[1] as the control group, the second column with just the neighboring states[2] as a control group, the third column with just the other no-fault states[3] as the control group, and then finally with just the tort liability insurance states[4] as the control group. Shown below in Table 3 are the results from the difference-in-differences regression model where the outcome variable is the number of fatal accidents per 100,000 people.

[1] 49 other states and Washington DC
[2] Ohio and Wisconsin
[3] FL, HI, KS, KY, MA, MN, NJ, NY, ND, PA, UT
[4] AL, AK, AZ, AR, CA, CO, CT, DE, GA, ID, IL, IN, IA, LA, ME, MD, MS, MO, MT, NE, NV, NH, NM, NC, OH, OK, OR, RI, SC, SD, TN, TX, VT, VA, WA, WV, WI, WY

Table 3. Fatal Accidents Per 100,000 People for State Month Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0760***	0.0919**	0.0909**	0.0720***
	(0.0181)	(0.0170)	(0.0302)	(0.0213)
Light Conditions	0.0596*	-0.135*	0.0359	0.0660*
	(0.0327)	(0.0329)	(0.0471)	(0.0386)
Weather Conditions	-0.0380**	-0.0326	-0.0520	-0.0325*
	(0.0161)	(0.0231)	(0.0317)	(0.0189)
Vision Obstruction	-0.0709	-0.0498	-0.0309	-0.0770
	(0.0427)	(0.163)	(0.0548)	(0.0516)
Ruralness of Accident	-0.0533*	-0.167	-0.0437	-0.0536
	(0.0307)	(0.102)	(0.0507)	(0.0364)
Constant	0.563***	0.661**	0.553***	0.551***
	(0.0476)	(0.103)	(0.0700)	(0.0551)
Observations	4,841	288	1,151	3,882
R-squared	0.195	0.792	0.266	0.199
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As seen from the coefficients for the difference-in-differences estimator in the first row, Table 3 shows that the new no-fault policy enacted in Michigan in July of 2020 did indeed have a statistically significant impact on fatal accident rates across all four different control groups at the 95% confidence level. More specifically, it is observed that Michigan experiences a 0.0760, 0.0919, 0.0909, and 0.0720 increase in number of fatal accidents per every 100,000 people compared to all other US states (column 1), neighboring states of Ohio and Wisconsin (column 2), all other no-fault auto insurance policy states (column 3), and finally against all tort liability insurance states (column 4), respectively.

In addition to these significant results for fatal accident rate per 100,000 people, there were some interesting results yielded from the control variables. Surprisingly, little to none of the control variables had a statistically significant impact on the number of fatal accidents per 100,000 people. The only consistent significant result from the control variables was the weather condition for Michigan vs All Other States which was significant at the 95% confidence level. This relationship is completely unexpected as the coefficient is negative, suggesting that as the weather conditions increases in adversity, there are less fatal accidents that occur on the roads. This contradictory relationship was also observed in the vision obstruction variable as it also carried a negative coefficient. However, this result is not significant at the 95% confidence level. It is also surprising to note that the ruralness of accident location has little to no effect on the number of fatal accidents per every 100,000 people, since I expected that rural areas would experience more fatal accidents since there is less traffic.

Since parallel trends could not be established, the focus of the Results section will shift to unpack the synthetic controls model and the placebo/permutation tests. The remaining regression models reflected by the five equations in the Methodology section are attached in the Appendix section for the reader's reference.

6.2 Synthetic Controls Model Results

As mentioned in the Methodology section, the data this thesis utilizes does not have parallel trends, thus undermining all difference-in-differences regression results as they could be confounding with pretreatment trends. To solve this, the synthetic controls model was used instead to artificially create parallel trends, which ensures a more robust methodology. It is clear from this subsection that the difference-in-difference regression models were indeed endogenous and that

the results from the synthetic controls model and placebo/permutation tests should be the main focus when interpreting results in the Discussion section.

For each synthetic controls model run, there will be a graph that shows the trajectory of both the treatment and control groups across the entire timeline of this thesis. This is meant for visual analysis of both pretreatment parallel trends and post treatment movement between the two groups. After the graph, a table with the results of the placebo/permutation tests are displayed with the first column containing model with all 44 territories as the control group (the model shown in the graph), the second column with just the other no-fault states as the control group, and then finally the third column with just the tort liability insurance states as the control group.

For clarification, the graphs that contain the label "Synthetic Control Group (All States)" in this subsection refer directly to the 44 territories described in the Methodology section. All results tables and graphs will only display the model where the outcome rate is the frequency of outcomes per 100,000 people. Tables and graphs of the robustness check of frequency of outcomes per 100 million VMT is available in the Appendix section for the reader's reference.

6.2.1 Fatal Accidents Per 100,000 People

Figure 2 and Table 4 below show the results of the synthetic controls model and the placebo/permutation test, respectively, where the outcome is fatal accidents per 100,000 people.

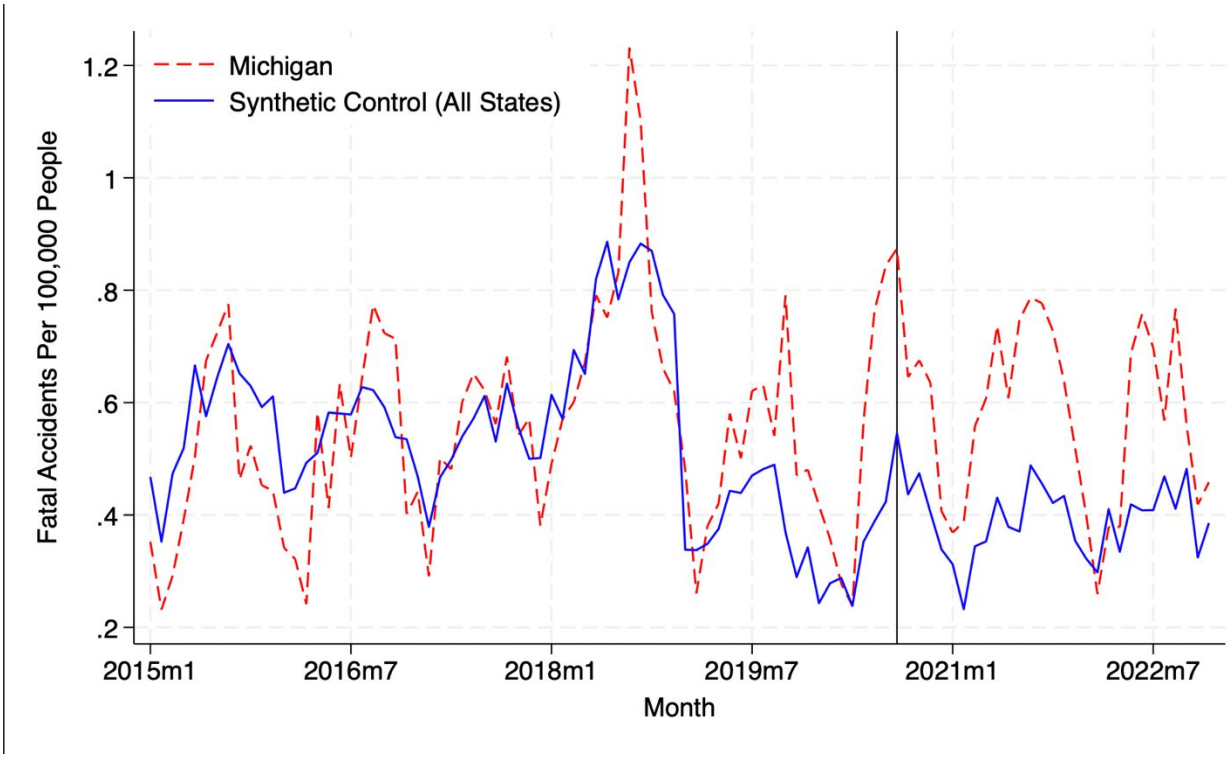


Figure 2. Michigan vs Synthetic Control Group of All States (Fatal Accidents Per 100,000 People)

Just at a glance, it is easy to tell that there is a large change between Figure 2 and Figure 1 in the Data section. Here, both the treated group (dashed red line) and the control group (solid blue line) are less divergent before the treatment showing a successful artificial creation of parallel trends. This close pattern seems to drift a little bit after the treatment and create a gap in the post treatment time period, suggesting that there could be a statistically significant difference between the treatment and control group. This result is clarified with more quantified and specific results from the placebo/permutation test with different control groups presented in Table 4 below.

Table 4. Fatal Accidents Per 100,000 People for Placebo/Permutation Model

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
Jul 2020	0.420	0.256	0.000	-0.030	1.000	1.000	-0.278	0.382	0.412
Aug 2020	0.328	0.372	0.140	-0.125	0.700	0.600	0.313	0.412	0.471
Sep 2020	0.209	0.628	0.209	-0.030	1.000	1.000	-0.178	0.588	0.676
Oct 2020	0.201	0.628	0.372	-0.162	0.900	0.800	-0.067	0.853	0.882
Nov 2020	0.230	0.465	0.116	-0.113	0.900	0.900	0.339	0.353	0.235
Dec 2020	0.068	0.791	0.744	-0.373	0.600	0.200	-0.047	0.853	0.912
Jan 2021	0.056	0.860	0.791	-0.248	0.600	0.200	-0.222	0.529	0.618
Feb 2021	0.156	0.395	0.093	-0.188	0.700	0.700	-0.134	0.382	0.471
Mar 2021	0.214	0.558	0.116	-0.171	0.700	0.700	-0.266	0.294	0.324
Apr 2021	0.255	0.395	0.093	-0.204	0.700	0.900	-0.364	0.235	0.176
May 2021	0.306	0.488	0.093	-0.119	0.900	0.900	0.255	0.559	0.588
Jun 2021	0.229	0.558	0.233	-0.189	0.800	0.500	0.106	0.824	0.794
Jul 2021	0.376	0.349	0.023	-0.056	0.900	0.900	0.104	0.765	0.882
Aug 2021	0.299	0.442	0.186	-0.102	0.900	1.000	0.464	0.235	0.206
Sep 2021	0.321	0.372	0.070	-0.106	1.000	1.000	-0.068	0.912	0.912
Oct 2021	0.306	0.558	0.326	-0.191	0.900	0.700	0.286	0.618	0.676
Nov 2021	0.204	0.721	0.419	-0.172	0.900	0.800	-0.091	0.824	0.824
Dec 2021	0.164	0.767	0.558	-0.208	0.700	0.600	0.228	0.529	0.588
Jan 2022	0.077	0.744	0.581	-0.228	0.500	0.600	0.439	0.118	0.088
Feb 2022	-0.039	0.953	0.953	-0.350	0.600	0.100	0.488	0.147	0.059
Mar 2022	-0.032	1.000	0.930	-0.388	0.600	0.000	-0.323	0.235	0.265
Apr 2022	0.044	0.907	0.884	-0.305	0.600	0.100	0.101	0.735	0.794
May 2022	0.269	0.535	0.186	0.034	0.900	0.900	0.681*	0.059	0.029
Jun 2022	0.349	0.349	0.000	0.037	1.000	1.000	0.701*	0.088	0.000
Jul 2022	0.289	0.395	0.070	-0.062	0.900	0.900	-0.241	0.412	0.382
Aug 2022	0.099	0.860	0.767	-0.170	0.500	0.300	0.193	0.676	0.735
Sep 2022	0.356	0.326	0.023	-0.093	0.900	0.900	-0.263	0.412	0.324
Oct 2022	0.076	0.791	0.814	-0.286	0.700	0.300	0.433	0.294	0.206
Nov 2022	0.094	0.860	0.767	-0.394	0.600	0.200	0.488*	0.088	0.000
Dec 2022	0.073	0.930	0.884	-0.149	0.600	0.800	0.493	0.176	0.118

*** p<0.01, ** p<0.05, * p<0.1

Examining all of the p-values in Table 4, there are only very few values smaller than 0.1, let alone 0.05. This indicates that at the 95% confidence level, there is no statistically significant difference between the treated group and the control group, suggesting that the new policy in Michigan had no effect on fatal accidents per 100,000 people.

Further examination of the results yielded by the outcome variable of fatal accidents per 100 million VMT in Table 25 in the Appendix show very similar findings. Further, Figure 30 in the Appendix, while displaying some drift between the solid blue line and the dashed red line after the treatment was applied, they still follow each other relatively closely. This suggests that both the treatment and control groups move together regardless of the treatment, most likely showing that the treatment had no statistically significant effect on the outcome variable.

6.2.2 Fatalities Per 100,000 People

Figure 3 and Table 5 below show the results from the synthetic controls model and the placebo/permutation test, respectively. Both models show results when the outcome variable is the frequency of fatalities per 100,000 people.

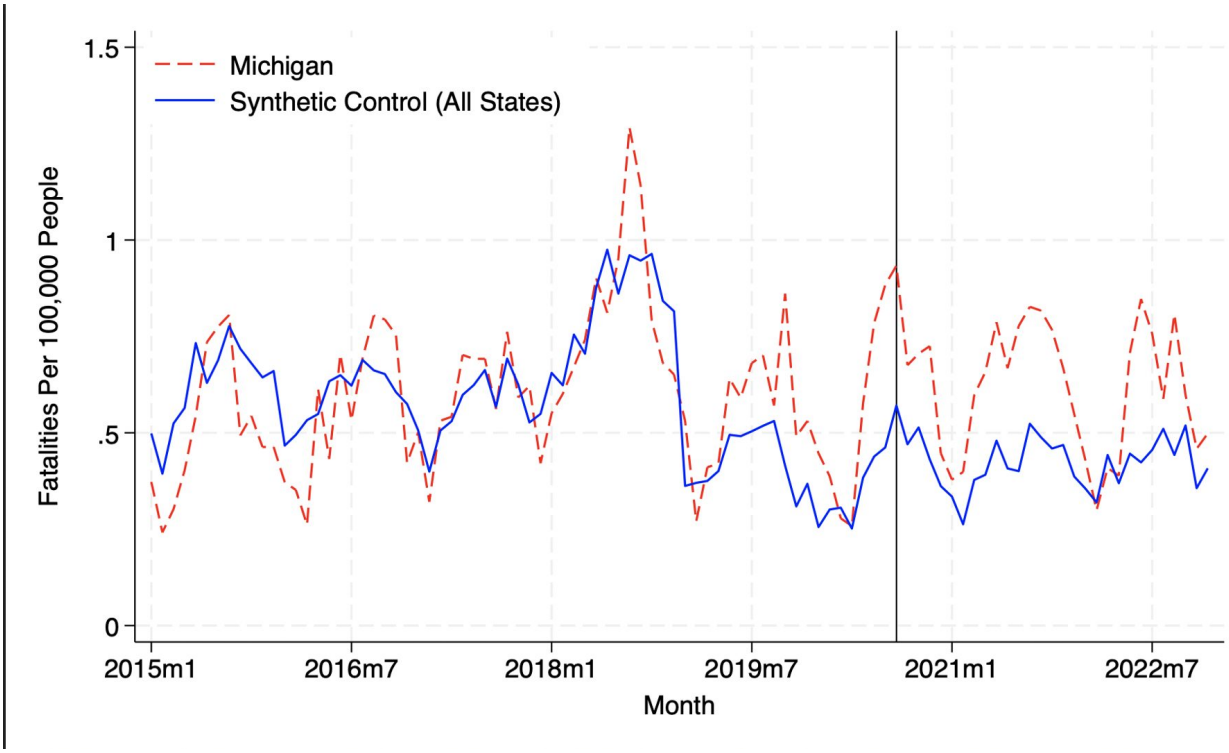


Figure 3. Michigan vs Synthetic Control Group of All States (Fatalities Per 100,000 People)

Similarly to Figure 2 from the subsection above, the treatment and control group stay similar before the treatment, showing strong evidence for parallel trends. However, this graph seems to show that the treatment group has a larger deviation from the control group as the gap between the dashed red line and the solid blue drift further apart after the treatment was applied in July of 2020. Figure 3 seems to suggest that the policy had a statistically significant increase of fatalities per every 100,000 people, but more confirmation, in the form of the placebo/permutation test, is needed to come to that conclusion.

Table 5. Fatalities Per 100,000 People

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
2020m7	0.422	0.256	0.023	-0.047	1.000	1.000	-0.292	0.500	0.471
2020m8	0.363	0.372	0.070	-0.139	0.700	0.600	0.357	0.382	0.471
2020m9	0.205	0.674	0.279	-0.068	1.000	1.000	-0.134	0.735	0.735
2020m10	0.191	0.605	0.326	-0.197	0.800	0.800	-0.079	0.824	0.882
2020m11	0.294	0.349	0.070	-0.067	0.900	0.900	0.364	0.294	0.265
2020m12	0.085	0.791	0.698	-0.370	0.600	0.400	-0.204	0.559	0.618
2021m1	0.044	0.884	0.884	-0.288	0.500	0.200	-0.180	0.618	0.676
2021m2	0.136	0.488	0.302	-0.239	0.600	0.600	-0.141	0.500	0.500
2021m3	0.220	0.558	0.163	-0.187	0.700	0.600	-0.378	0.265	0.206
2021m4	0.266	0.442	0.140	-0.250	0.600	0.800	-0.393	0.265	0.206
2021m5	0.307	0.512	0.140	-0.141	0.900	0.900	0.618	0.176	0.206
2021m6	0.260	0.512	0.233	-0.277	0.600	0.600	0.026	0.912	1.000
2021m7	0.376	0.395	0.047	-0.070	0.800	0.800	0.039	0.971	0.971
2021m8	0.303	0.442	0.140	-0.161	0.800	1.000	0.427	0.265	0.324
2021m9	0.328	0.372	0.070	-0.110	0.800	0.700	-0.049	0.941	0.941
2021m10	0.308	0.581	0.372	-0.232	0.700	0.700	0.398	0.588	0.500
2021m11	0.199	0.767	0.465	-0.191	0.900	0.700	-0.050	0.853	0.912
2021m12	0.161	0.814	0.558	-0.230	0.600	0.600	0.156	0.765	0.765
2022m1	0.073	0.814	0.628	-0.260	0.600	0.600	0.426*	0.088	0.088
2022m2	-0.021	0.930	0.930	-0.352	0.600	0.100	0.450	0.265	0.176
2022m3	-0.034	0.977	0.907	-0.431	0.600	0.000	-0.377	0.265	0.265
2022m4	0.019	0.953	0.953	-0.345	0.600	0.100	0.044	0.912	1.000
2022m5	0.262	0.558	0.186	0.025	1.000	1.000	0.698*	0.088	0.059
2022m6	0.424	0.302	0.000	0.078	1.000	1.000	0.605*	0.088	0.029
2022m7	0.302	0.349	0.070	-0.091	0.900	1.000	-0.538	0.265	0.147
2022m8	0.078	0.907	0.814	-0.176	0.500	0.400	0.296	0.529	0.618
2022m9	0.365	0.349	0.047	-0.094	1.000	1.000	-0.431	0.265	0.265
2022m10	0.079	0.860	0.860	-0.291	0.700	0.300	0.384	0.353	0.353
2022m11	0.102	0.814	0.791	-0.416	0.600	0.200	0.537	0.118	0.029
2022m12	0.090	0.884	0.814	-0.144	0.700	0.800	0.707	0.118	0.059

*** p<0.01, ** p<0.05, * p<0.1

As seen in Table 5 above, while a large majority of the coefficients for the Michigan vs All States model is positive, they all have p-values larger than 0.05. This indicates that the policy had no statistically significant effect on fatalities per 100,000 people at the 95% confidence level. Further, the p-values are so large showing that the positive relationship between Michigan post treatment and fatalities per 100,000 people is just noise rather than the effect of the treatment at any confidence level.

These results are also reflected by Figure 33 and Table 27 in the Appendix section which display the robustness check on Figure 3 and Table 5 above. Figure 33 and Table 27 show the exact same model as Figure 3 and Table 5 except that the outcome variable is fatalities per 100 million VMT. This outcome variable intends to control for the frequency of travel rather than the number of travelers. Since these models in the Appendix also display the same statistically insignificant result, it further reinforces the idea that the new Michigan auto insurance policy had no effect on increasing fatalities on the road.

6.2.3 Adjusted Accidents Per 100,000 People

Figure 4 and Table 6 below show the results of the synthetic controls model and placebo/permutation tests, respectively. The results of both models are in terms of the outcome variable the number adjusted accidents per 100,000 people. As mentioned in the Data section, adjusted accidents just reweigh single vehicle crashes twice as heavily as multi vehicle crashes as they are found to be more than two times as likely to display risky driver behaviors.

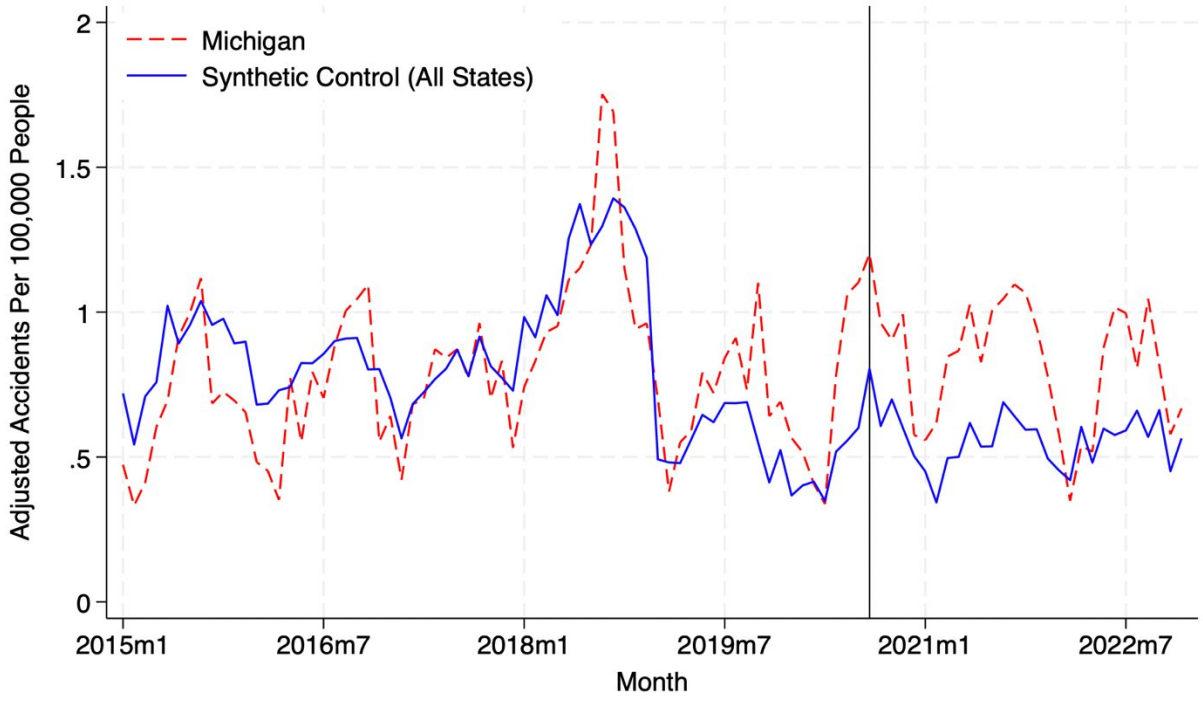


Figure 4. Michigan vs Synthetic Control Group of All States (Adjusted Accidents Per 100,000 People)

Figure 4 shown above has very similar characteristics as Figure 3 in the previous subsection. Again, both lines follow each other very closely before the treatment, showing good evidence for parallel trends. However, right around the time of the treatment, the dashed red line of the treatment group seems to experience a significant increase and remains above the solid blue line of the control group for the remaining time periods. This increase needs to further

examined through the more quantitative measurements of the placebo/permutation test displayed in Table 6 below.

Table 6. Adjusted Accidents Per 100,000 People

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
Jul 2020	0.502	0.279	0.047	-0.250	0.800	0.900	-0.515	0.324	0.324
Aug 2020	0.397	0.442	0.209	-0.321	0.500	0.500	0.777	0.176	0.176
Sep 2020	0.356	0.488	0.140	-0.041	1.000	1.000	-0.249	0.647	0.676
Oct 2020	0.205	0.698	0.419	-0.317	0.600	0.700	0.085	0.853	0.853
Nov 2020	0.393	0.372	0.047	-0.220	0.700	0.900	0.492	0.324	0.324
Dec 2020	0.073	0.884	0.814	-0.683	0.600	0.300	0.027	0.941	0.941
Jan 2021	0.107	0.767	0.674	-0.346	0.600	0.200	-0.343	0.500	0.676
Feb 2021	0.274	0.326	0.023	-0.267	0.700	0.500	-0.248	0.324	0.382
Mar 2021	0.351	0.442	0.116	-0.288	0.700	0.900	-0.221	0.647	0.647
Apr 2021	0.366	0.395	0.093	-0.349	0.600	0.900	-0.483	0.294	0.235
May 2021	0.409	0.465	0.140	-0.183	0.900	0.900	0.584	0.294	0.441
Jun 2021	0.291	0.605	0.395	-0.341	0.700	0.300	0.092	0.765	0.853
Jul 2021	0.469	0.395	0.070	-0.203	0.900	0.900	0.342	0.529	0.618
Aug 2021	0.357	0.465	0.233	-0.272	0.700	1.000	0.733	0.176	0.265
Sep 2021	0.455	0.419	0.070	-0.219	0.900	1.000	-0.150	0.794	0.882
Oct 2021	0.472	0.488	0.209	-0.314	0.800	0.800	0.584	0.529	0.529
Nov 2021	0.351	0.605	0.326	-0.221	0.900	0.900	-0.101	0.794	0.824
Dec 2021	0.283	0.791	0.488	-0.325	0.700	0.700	0.283	0.706	0.794
Jan 2022	0.124	0.698	0.535	-0.323	0.600	0.800	0.824***	0.000	0.059
Feb 2022	-0.071	0.930	0.907	-0.600	0.600	0.100	0.798*	0.088	0.059
Mar 2022	-0.066	0.814	0.767	-0.623	0.500	0.100	-0.368	0.412	0.471
Apr 2022	0.038	0.907	0.884	-0.534	0.500	0.200	0.188	0.588	0.706
May 2022	0.279	0.744	0.279	-0.090	0.900	0.900	1.249**	0.029	0.029
Jun 2022	0.441	0.349	0.047	-0.133	0.900	0.800	1.159*	0.059	0.000
Jul 2022	0.405	0.279	0.047	-0.175	0.700	0.700	-0.249	0.500	0.647
Aug 2022	0.147	0.860	0.674	-0.304	0.500	0.300	0.094	0.882	0.912
Sep 2022	0.477	0.326	0.023	-0.282	0.700	0.700	-0.412	0.382	0.324
Oct 2022	0.156	0.767	0.767	-0.475	0.600	0.500	0.915	0.118	0.088
Nov 2022	0.127	0.860	0.767	-0.664	0.600	0.200	1.068***	0.000	0.000
Dec 2022	0.103	0.860	0.837	-0.278	0.700	0.700	1.003	0.118	0.059

*** p<0.01, ** p<0.05, * p<0.1

Similar to the results from all the previous subsections, the placebo/permutation test finds that the increase observed in Figure 4 is not statistically significant at any confidence level. This is shown by the lack of p-values smaller than 0.05 in any of the models despite the variance of control groups. This means that the positive drift in the graph of Figure 5 has no connection to the effect of the policy but is rather the result of noise.

Again, these results are consistent with the robustness check found in the Appendix section in the form of Figure 36 and Table 29. Figure 36 and Table 29 show the exact same models as Figure 4 and Table 6 but have the rate divisor of 100 million VMT rather than 100,000 people. The results from Figure 36 and Table 29 observed in the Appendix section shows that the new Michigan auto insurance policy has no effect on adjusted accidents regardless of fixing for the number of drivers (per 100,000 people) or the frequency of driving (per 100 million VMT).

6.2.4 Risky Driver Behaviors Per 100,000 People

Figure 5 and Table 7 shown below describe the results from the synthetic controls model and the placebo/permutation test, respectively. Both Figure 5 and Table 7 display results in terms of the number of risky driver behaviors per 100,000 people where risky driver behaviors are described to be either drunk driving, impaired driving, distracted driving, drug use while driving, or seat belt misuse. More specific models for each of these variables are shown in the Appendix section from pages 62 to 128 for the reader's reference.

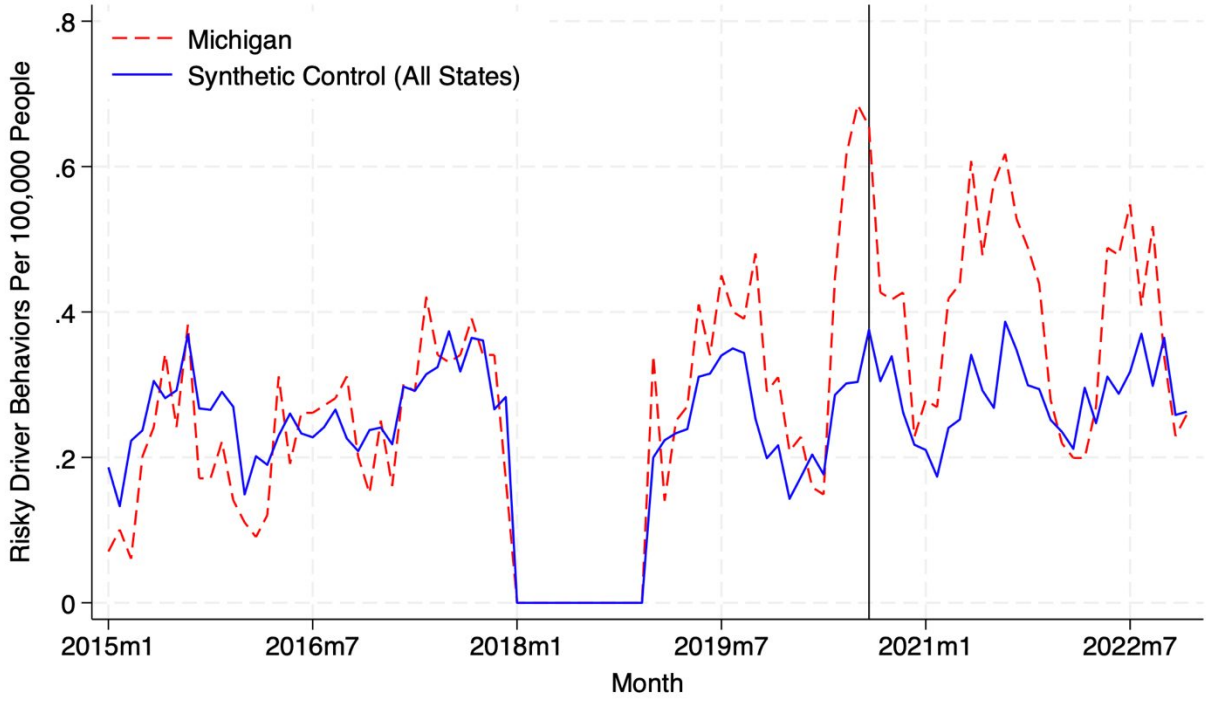


Figure 5. Michigan vs Synthetic Control Group of All States (Risky Driver Behaviors Per 100,000 People)

As seen in this graph, the treatment and control groups follow each other closely during the pretreatment period suggesting parallel trends. However, there is major dip where both groups seem to display no risky driver behaviors in the year of 2018. This is not because drivers across the United States decided to become responsible drivers as a collective, but rather a gap in

the FARS data. This dip is consistent across all specific risky driver behaviors as seen from the models in the Appendix section from pages 62 to 128.

Similarly to previous subsections, while the two control groups track each other quite closely during the pretreatment period, there is a steep increase in risky driver behaviors from the dashed red line (treatment group) around the time that the treatment is applied. This appears to suggest that there was a significant effect of the treatment on risky driver behaviors. While this is observed visually, it needs to be confirmed by the placebo/permutation test in Table 7 below.

Table 7. Risky Driver Behavior Per 100,000 People

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
Jul 2020	0.381	0.140	0.000	-0.011	0.900	0.900	-0.376	0.147	0.206
Aug 2020	0.280	0.372	0.163	-0.074	0.700	0.700	0.540*	0.059	0.118
Sep 2020	0.122	0.558	0.395	-0.071	0.900	0.900	-0.358	0.176	0.176
Oct 2020	0.078	0.791	0.651	-0.180	0.800	0.700	0.166	0.382	0.618
Nov 2020	0.165	0.419	0.116	-0.067	0.900	0.800	0.255	0.235	0.294
Dec 2020	0.011	0.953	0.930	-0.317	0.500	0.200	0.039	0.735	0.824
Jan 2021	0.069	0.628	0.558	-0.185	0.600	0.300	-0.304	0.147	0.147
Feb 2021	0.095	0.535	0.233	-0.137	0.700	0.700	-0.150	0.294	0.324
Mar 2021	0.178	0.419	0.140	-0.151	0.600	0.700	-0.327*	0.059	0.088
Apr 2021	0.186	0.326	0.233	-0.170	0.700	0.700	-0.289	0.235	0.235
May 2021	0.267	0.442	0.140	-0.059	1.000	1.000	0.369	0.206	0.441
Jun 2021	0.186	0.442	0.233	-0.172	0.600	0.300	-0.004	0.971	0.971
Jul 2021	0.310	0.209	0.023	-0.061	0.800	0.900	0.056	0.794	0.824
Aug 2021	0.231	0.465	0.209	-0.041	0.900	0.900	0.505	0.118	0.176
Sep 2021	0.180	0.535	0.279	-0.141	0.900	0.600	-0.194	0.559	0.588
Oct 2021	0.189	0.581	0.372	-0.232	0.500	0.200	0.327	0.441	0.500
Nov 2021	0.144	0.628	0.488	-0.128	0.700	0.700	-0.152	0.529	0.647
Dec 2021	0.027	0.953	0.930	-0.234	0.600	0.400	0.166	0.353	0.529
Jan 2022	-0.016	0.953	0.907	-0.213	0.400	0.400	0.313*	0.059	0.147
Feb 2022	-0.012	0.884	0.884	-0.268	0.600	0.200	0.464*	0.088	0.029
Mar 2022	-0.096	0.651	0.465	-0.366	0.500	0.000	-0.242	0.324	0.294
Apr 2022	0.022	0.953	0.930	-0.267	0.600	0.200	0.047	0.765	0.882
May 2022	0.177	0.512	0.279	-0.014	1.000	1.000	0.578*	0.059	0.059
Jun 2022	0.191	0.419	0.209	-0.085	0.700	0.800	0.579*	0.088	0.000
Jul 2022	0.231	0.349	0.093	-0.060	0.700	0.600	-0.500	0.118	0.059
Aug 2022	0.038	0.860	0.837	-0.186	0.500	0.100	0.212	0.471	0.647
Sep 2022	0.220	0.442	0.140	-0.126	0.600	0.500	-0.415	0.147	0.176
Oct 2022	-0.026	0.953	0.884	-0.265	0.300	0.200	0.200	0.500	0.676
Nov 2022	-0.029	0.907	0.860	-0.347	0.400	0.000	0.206	0.353	0.529
Dec 2022	-0.004	1.000	1.000	-0.162	0.500	0.400	0.260	0.294	0.382

*** p<0.01, ** p<0.05, * p<0.1

Again, the results in Table 7 are consistent with the results of the placebo/permutation tests seen in the previous subsections. As evidenced by the large number of p-values greater than 0.05, it is clear that the placebo/permutation test shows that there was no statistically significant effect of the new Michigan auto insurance policy on risky driver behaviors per 100,000 people. This statistical insignificance is shown regardless of control groups, further emphasizing the lack of connection between the policy and risky driver behavior.

These results are also observed in the robustness check of Figure 54 and Table 41 in the Appendix section. Figure 54 and Table 41 again show the same models as Figure 5 and Table 7 with the exception that the rate divisor is now 100 million VMT and not 100,00 people. The lack of statistically significant results in this robustness check reinforces the idea that the new Michigan auto insurance policy has no effect on the frequency of risky driver behaviors.

6.2.5 Speeding Per 100,000 People

Figure 6 and Table 9 show the results of the synthetic controls model and placebo/permutation test with the outcome variable being the frequency of speeding per 100,000 people.

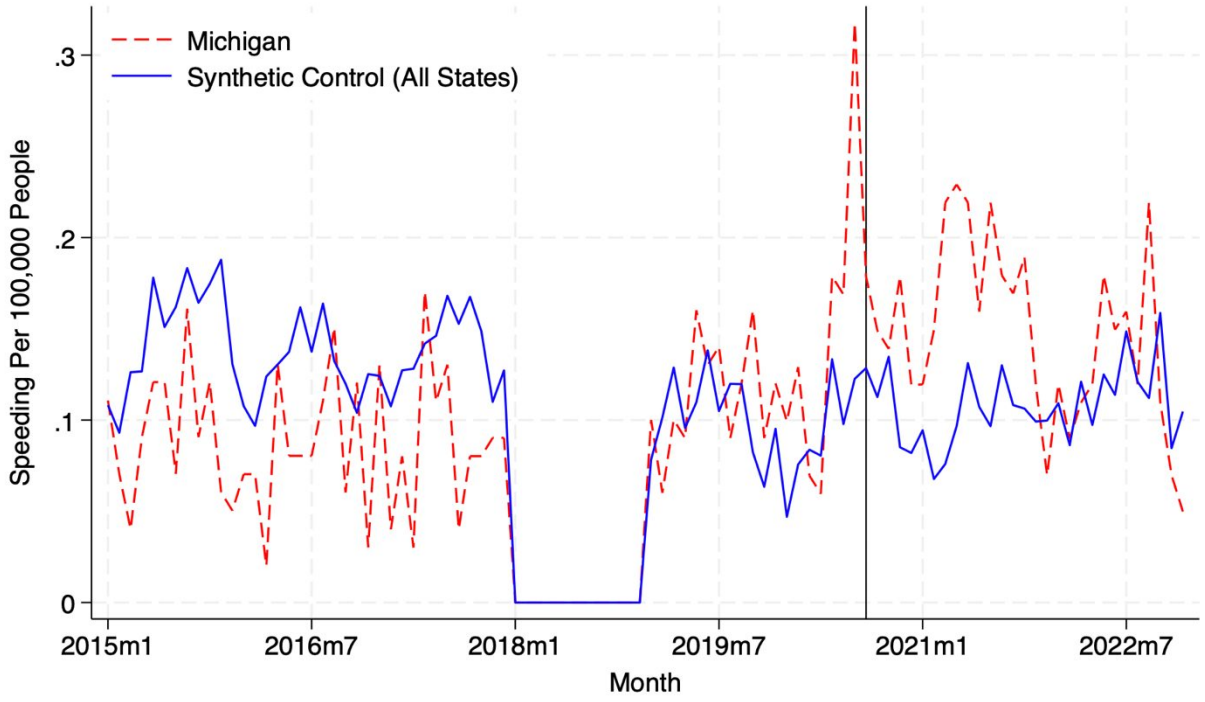


Figure 6. Michigan vs Synthetic Control Group of All States (Speeding Per 100,000 People)

Similar to the previous subsection, the first thing to note is the massive dip seen in 2018. This is again caused by a gap in the FARS data during 2018 where there were no risky driver behavior variables recorded for that year. Moving on, Figure 6 is a little different than some of the other graphs seen before. This is the first graph where we observe that the solid blue line (control group) to be slightly higher than the dashed red line (treatment group) during the pretreatment period. This relationship is flipped around the time of treatment and it is clear that the dashed red line is now above the solid blue line and seems to remain that way for the rest of

the observed time period. This change in difference could suggest that the new policy had a more significant effect on speeding than any other outcome variable. Table 9 below describes this relationship at a more measurable level.

Table 9. Speeding Per 100,000 People

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
Jul 2020	0.195*	0.070	0.000	0.172	0.300	0.000	-0.201*	0.088	0.294
Aug 2020	0.050	0.674	0.512	0.044	0.600	0.500	0.192	0.118	0.235
Sep 2020	0.036	0.721	0.512	0.034	0.600	0.400	-0.061	0.529	0.676
Oct 2020	0.004	1.000	0.977	0.042	0.500	0.500	-0.102	0.294	0.500
Nov 2020	0.094	0.233	0.000	0.075	0.200	0.000	-0.060	0.412	0.676
Dec 2020	0.037	0.651	0.372	-0.010	0.800	0.800	0.028	0.735	0.794
Jan 2021	0.025	0.860	0.744	0.033	0.700	0.400	-0.096	0.412	0.559
Feb 2021	0.082	0.302	0.093	0.058	0.600	0.400	-0.188***	0.000	0.059
Mar 2021	0.143	0.140	0.000	0.135***	0.000	0.000	0.031	0.647	0.706
Apr 2021	0.133	0.163	0.023	0.090	0.600	0.100	-0.153*	0.088	0.353
May 2021	0.088	0.581	0.349	0.053	0.900	0.900	-0.202	0.294	0.471
Jun 2021	0.052	0.628	0.512	0.072	0.700	0.600	-0.105	0.382	0.471
Jul 2021	0.123	0.302	0.047	0.098	0.200	0.000	0.018	0.735	0.735
Aug 2021	0.049	0.674	0.419	0.049	0.900	0.700	-0.061	0.618	0.735
Sep 2021	0.061	0.535	0.302	0.069	0.200	0.200	-0.067	0.529	0.676
Oct 2021	0.083	0.488	0.256	0.093	0.200	0.000	-0.012	1.000	1.000
Nov 2021	0.020	0.814	0.767	-0.018	0.900	0.800	0.027	0.735	0.882
Dec 2021	-0.030	0.767	0.605	-0.030	0.600	0.400	-0.108	0.265	0.471
Jan 2022	0.010	0.907	0.837	0.034	0.900	0.900	0.294*	0.059	0.029
Feb 2022	0.003	0.977	0.953	0.003	1.000	1.000	0.183*	0.059	0.118
Mar 2022	-0.011	0.953	0.907	-0.018	0.800	0.800	-0.014	0.882	0.941
Apr 2022	0.022	0.674	0.581	0.026	0.600	0.400	0.047	0.559	0.735
May 2022	0.054	0.767	0.628	0.084	0.400	0.200	0.187	0.235	0.412
Jun 2022	0.036	0.791	0.651	0.048	0.600	0.400	0.165	0.176	0.324
Jul 2022	0.011	0.953	0.953	0.010	0.900	0.900	-0.118	0.324	0.559
Aug 2022	-0.001	1.000	1.000	0.027	0.700	0.700	-0.161	0.294	0.559
Sep 2022	0.107	0.512	0.116	0.110	0.100	0.000	0.115	0.441	0.500
Oct 2022	-0.049	0.605	0.581	0.013	0.700	0.600	0.198	0.235	0.382
Nov 2022	-0.015	0.860	0.814	-0.020	0.700	0.700	0.120	0.353	0.471
Dec 2022	-0.055	0.628	0.465	-0.051	0.600	0.300	0.055	0.588	0.735

*** p<0.01, ** p<0.05, * p<0.1

Unfortunately, like all of the other models before, there is no statistically significant relationship observed between the new policy and speeding at the 95% confidence level or any other confidence level either. The p-values once again are all greater than 0.05 for all control groups, further reinforcing the lack of a relationship between the Michigan policy and speeding per 100,000 people.

This result is also reflected in the robustness check of Figure 57 and Table 43 in the Appendix section which shows the same models as Figure 6 and Table 9 but uses 100 million VMT instead of 100,000 people as the rate divisor. These results show that there is no statistically significant relationship between the new Michigan auto insurance policy and speeding regardless of controlling for the number of drivers on the road (per 100,000 people) or the frequency of driving (100 million VMT).

7. Discussion

7.1 Interpretation of Results

My findings from these synthetic controls models and placebo/permutation tests completely disprove my hypothesis that the new Michigan auto insurance policy would promote risky driver behavior and increase the number of fatal accidents on the road. The results suggest that not only does the policy have no negative effect on driver behavior, but there is also no correlation between the two at all. While this is a rather surprising result, it becomes well justified when the data is examined a little closer.

Beginning with the results where risky driver behaviors were the outcome variable, the placebo/permutation test displays a large majority of p-values to be larger than 0.05, suggesting no correlation between the implementation of the policy and change in risky driver behaviors involving drunk driving, distracted driving, driving while using drugs, impaired driving, or seat belt misuse. I originally expected to see an increase in these risky driver behaviors after the policy as the expected consequences of these actions were lower since there was a decrease in insurance premiums based off the logic from Landes' theoretical model.

However, if I consider and unpack Landes' theoretical model at a fundamental level, it becomes clear why this result was observed. One of the main assumptions that the theoretical model from Landes makes, is that all drivers are and reflect their behaviors to be rational. Further, she assumes that all drivers are trying to maximize their utilities and minimize their costs by doing whatever is most convenient for them. (Landes, 1982) When I apply this concept that drivers act with "convenience first," it becomes clear why there is no incentive to increase risky driver behaviors.

First, looking at behaviors like driving while drunk, on drugs, or impaired, the consequences drastically exceed that of an increase in insurance premiums. These behaviors would categorize as driving under the influence (DUI) which is a misdemeanor in all states and punishable with up to 6 months in jail. (LegalZoom, 2025) Further, in the case of this data, which only includes fatal accidents, DUI cases that result in the death of one or more persons are categorized as a felony and can result in more than a year in prison. (LegalZoom, 2025) This severe, but justifiable, punishment for driving while drunk, on drugs, or impaired, is most likely what deters people for exhibiting these poor driving choices regardless of the price of insurance. Jail time is a lot more consequential than a bump in insurance prices, showing that there is too little to gain and too much to lose from these behaviors, making it incredibly inconvenient to the driver.

Further utilizing this concept of convenient behaviors for the driver again, it becomes easy to see why this new policy had no effect on seat belt misuse rates either. The beginning of my dataset that I have compiled for this thesis began in 2015, a time recent enough where 88.5% of cars on the road had seat belts (NHTSA, 2015) and more than a decade after the seat belt chime was required to be outfitted in every automobile in 2002. (Citizen, 2004) These modern cars were designed to be annoying until both drivers and passengers were detected to be using a seat belt. It's this annoying seat belt chime that makes seat belt misuse inconvenient for drivers and more encouraging for them to wear one. Because of this, the behavior of misusing a seat belt has little to no connection to with someone's insurance premiums and would not change if insurance prices were to drop.

Since the drop in insurance price from the result of the new policy does not generate any more convenience to drivers to perform risky driver behaviors such as drunk driving, distracted

driving, driving while using drugs, impaired driving, and seat belt misuse, there should be no change in the amount of these behaviors. This is exactly predicted by the results of my placebo/permutation tests.

However, if I keep applying this concept that drivers acting with convenience first to other outcome variables, the logic begins to break down. Looking at the results of the placebo/permutation tests where speeding per 100,000 people is the outcome variable, it is still observed that there is no change. This result is quite the opposite as to what the theoretical model predicts.

Unlike the other risky driver behaviors described above, speeding is something that most if not all drivers are guilty for at some point during their time operating a vehicle. Speeding is one of the most frequently observed traffic violations and is directly associated with the cost of insurance. (Huffman Kendrick, 2025) Further, the consequence of speeding is to relatively low, with the most common penalty being a ticket rather than the jail time from the risky driver behaviors previously described. In addition to this light consequence, speeding is not a behavior that is strictly enforced by the police, with most drivers being able to get away with being a few miles an hour over the speed limit. Further, the ability to arrive at destinations quicker is highly beneficial for the driver and gives more reasons for people to speed. It is this cheap, balanced risk-reward of speeding that makes it such a convenient and attractive risky driver behavior.

However, if speeding is directly tied to insurance prices and convenient for drivers, why do the results show no statistically significant change in speeding behavior after a decrease in insurance price from the new Michigan policy? This suggests that convenience is not the only thing that drivers factor in when choosing their level of care on the roads.

One possible explanation is that drivers choose their actions on the road with more consideration about self-preservation rather than convenience or other monetary motives. Even though speeding is highly convenient and something that all of us are guilty of at some point, speeding significantly increases the driver's risk of an accident. Since the data used for this thesis only accounts for fatal accidents, drivers that were recorded speeding were most likely going a little faster than just a few miles an hour over the limit. At those speeds, the consequences of speeding are no longer just a ticket, it could be the driver's life. According to many scholars, speed related traffic violations are found to have a statistically significant increase on accident rates, putting an increased risk on both the speeding driver and surrounding motorists. (Quddus, 2013; Aarts and Schagen, 2006; Elvik et al., 2004) This is something that drivers are likely considering when operating their vehicles. Thus, the lack of increase in speeding behavior after a decrease in insurance premiums shows that they are more concerned about their safety and avoiding an accident rather than a small decrease in the cost of an accident.

This follows the logic described by scholars that were skeptical of Landes' theoretical model. Loughran was incredibly vocal about his disagreement with Landes' theoretical model, particularly when Landes shows that the drivers' actions is directly tied to the cost of an accident. (Loughran, 2001) He argues that no logical driver is getting into a car and changing their actions and driving more recklessly because the cost of an accident is a few thousand dollars cheaper. Loughran states that people are way more concerned about the potential injuries and trauma that comes with an accident rather than the monetary cost of accident, showing that drivers prioritize their own safety and self-preservation over anything else. (Loughran, 2001) The results from my thesis directly supports this claim as I observe no changes in any form of outcome variable from risky driver behaviors to fatal accident or fatality rates.

7.2 Limitations

One of the main limitations of this thesis comes in the form of the data that is chosen. Since fatal accident data in the form of FARS data was the most reliable and complete dataset I could find, the results only show the effects of the policy on fatal accidents and may be skewed towards larger and more severe risky driver behavior variables. This may not be representative of all risky driver behaviors as not every display of these choices results in a fatal accident. If there was a dataset or a way to accurately estimate normal accidents, it would provide better insight into how drivers behave under policy changes. Normal accident data would most likely better incapsulate distracted drivers with mobile phone use as most drivers exhibit these behaviors at lower speeds where the risk of a fatal accident is very low. (Delgado et al., 2016)

Another limitation of this thesis comes from the missing data for the risky driver behaviors. Unfortunately, in the year of 2018, the FARS dataset is missing the data file that includes all of the risky driver behaviors and thus I was unable to generate any observations for that time period. This is why there is a large dip that goes to 0 in all of the figures that show the results of the synthetic controls model for risky driver behaviors including drunk driving, impaired driving, distracted driving, drug use while driving, seat belt misuse, and speeding. While it wasn't crucial that this data was missing, having the data would provide better insight into pretreatment trends and a better-established parallel trends.

7.3 Directions for Future Research

While this thesis does not find any statistically significant results between Michigan's 2020 auto insurance reform and risky driver behaviors, this thesis opens the avenue to continued areas of research. The policy change is still relatively young, having only been passed five years ago, and its long-term effects may still not be fully visible yet. This is especially true as the

FARS dataset I used for this thesis ended in 2022, providing with only 30 months of post treatment data. Further examination in the future is necessary to fully understand the true effects of this decrease in insurance price on driver behaviors.

Another major avenue of future research remains in the examination of normal accident data. As mentioned in the subsection above, the use of strictly fatal accident data may skew my results to reflect severe risky driver behaviors instead of more mild choices that still adversely impact the driving conditions. Obviously, this would come to better fruition with better data, but methods for better estimation such as the attempt made by Loughran (2001) would provide policymakers with a great view into how a decrease in cost of accident would affect driver behavior. This information would go to create better policies that would not only save lives, but Americans money as well.

The final aspect that would approve upon this thesis in a future project would be the addition of a socioeconomic status control variable. I made an attempt to create this variable by creating a categorical variable that sorted vehicle level data into low, lower-middle, middle, upper-middle, and upper class based off the car that they were driving and the price of the car at the time of crash. Unfortunately, this process was incredibly painful with merging vehicle price data and sorting the FARS vehicle level data into the separate classes and was thus excluded from my thesis as I focused on building a more robust methodology with the use of synthetic controls. However, the inclusion of a socioeconomic status control variable would show how people with different incomes react to a decrease in insurance prices. Since a speeding ticket to wealthier individuals are less costly than they are to poorer ones, there could be a large change in driver behavior between socioeconomic classes.

7.4 Policy Recommendations

The results of this thesis, along with the conclusions from Loughran (2001), Kochanowski et al. (1985), Zador et al. (1986), and O'Connell et al. (1983), show that a decrease in cost of accident or insurance price has no connection to fatal accident rates or an increase in risky driver behaviors. While there are many reasons for policymakers to try and reform the auto insurance landscape in Michigan, a concern for increased fatalities and a more dangerous driving condition should not be a factor in the consideration for policy changes.

8. Conclusion

In this thesis, I hypothesize that the new Michigan auto insurance policy enacted in July of 2020 would have a negative effect on road safety and increase risky driver behaviors. I expected statistically significant results across all outcome variables and control groups. However, after empirical analysis through the synthetic controls method and placebo/permutation tests, my hypothesis is found to be incorrect. There were no statistically significant effects among any outcome variable or control group, showing strong evidence that the new Michigan auto insurance policy had no effect on driver behavior or in changing the safety levels of the road.

While surprising, these results made complete sense after further investigation of the data and a better understand of the theoretical model that led to my hypothesis. My hypothesis was rooted in the concept that drivers behave rationally to the cost of accidents, which included both monetary and health costs. However, the model that I was using underestimated drivers value of their own health and well-being and overestimated their care towards monetary compensation. Since my results from both the synthetic controls method and the placebo/permutation tests show no change in risky driver behaviors even when there was a definitive decrease in insurance price, thus lowering the cost of accidents, drivers must be choosing their level of care on the road relative to their health and self-preservation rather than monetary compensations. Drivers prioritize their ability to preserve the same health and well-being throughout the drive rather than the small benefit they might gain from decreasing their level of care due to a cheaper cost of accident. Ultimately, this suggests that policies that only aim to alter driver behavior through small to medium financial incentives are ineffective when compared to policies that change drivers' intrinsic concern for personal safety.

9. Appendix

Fatal Accidents Per 100,000 People

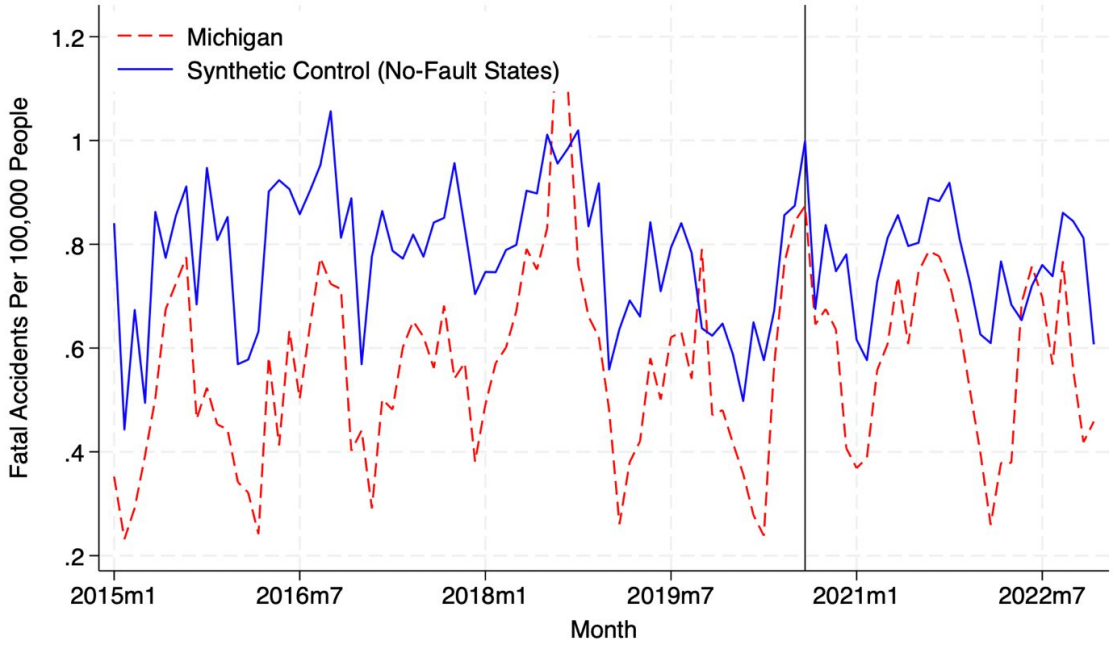


Figure 7.. Michigan vs Synthetic Control Group of No-Fault States (Fatal Accidents Per 100,000 People)

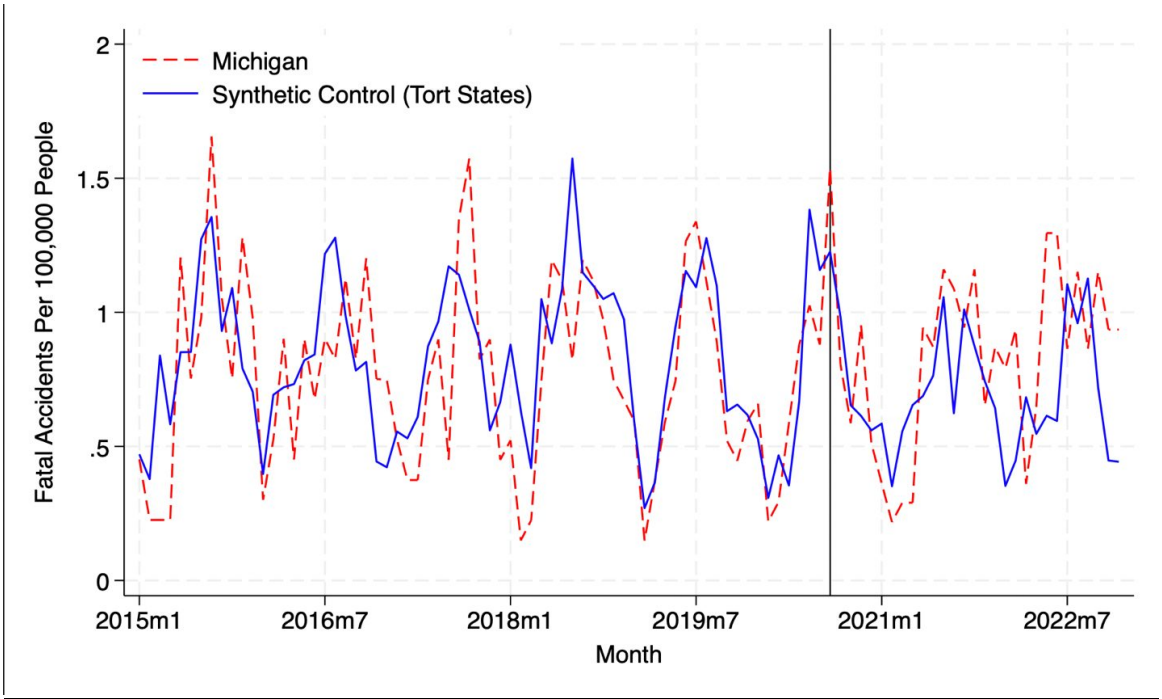


Figure 8. Michigan vs Synthetic Control Group of Tort States (Fatal Accidents Per 100,000 People)

Fatalities

Table 10. Fatalities Per 100,000 People for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0750***	0.0922**	0.0998**	0.0684***
	(0.0197)	(0.0177)	(0.0334)	(0.0230)
Light Conditions	0.0758**	-0.116	0.0285	0.0873*
	(0.0369)	(0.0441)	(0.0496)	(0.0437)
Weather Conditions	-0.0428**	-0.0452	-0.0561	-0.0373*
	(0.0176)	(0.0282)	(0.0336)	(0.0208)
Vision Obstruction	-0.0673	-0.0279	-0.0611	-0.0640
	(0.0443)	(0.198)	(0.0557)	(0.0551)
Ruralness of Accident	-0.0420	-0.188	-0.0420	-0.0403
	(0.0342)	(0.101)	(0.0562)	(0.0407)
Constant	0.599***	0.702**	0.611***	0.580***
	(0.0534)	(0.121)	(0.0789)	(0.0610)
Observations	4,841	288	1,151	3,882
R-squared	0.181	0.782	0.264	0.184
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

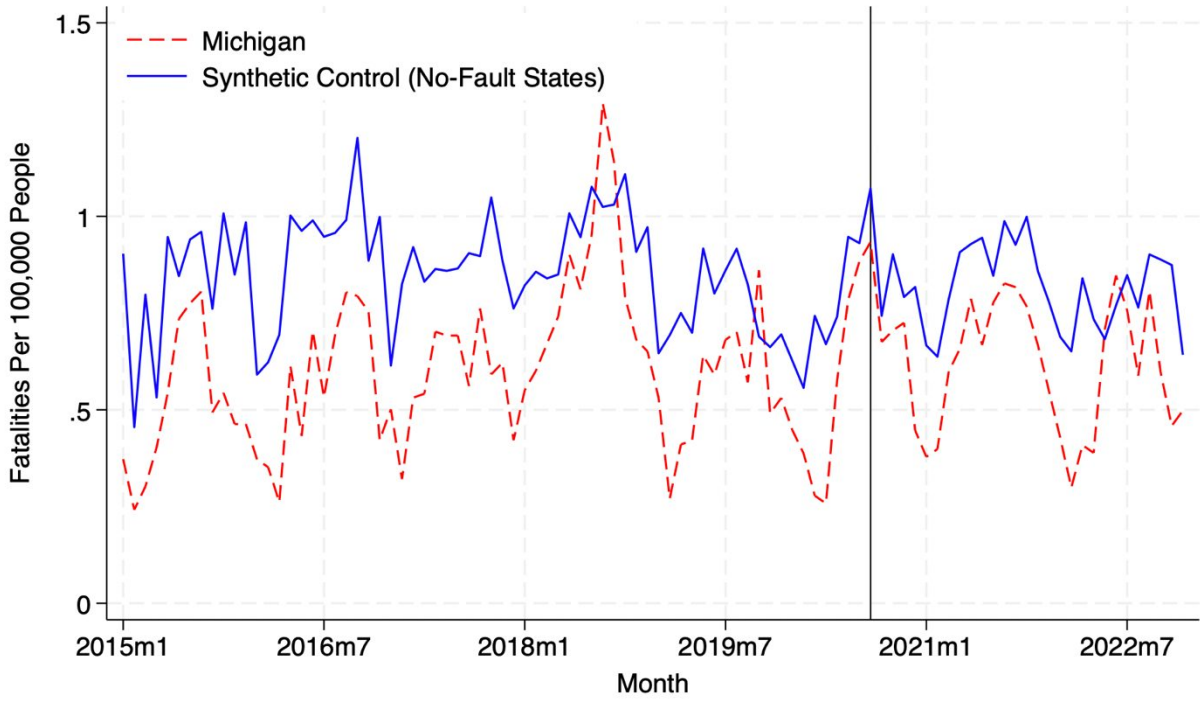


Figure 9. Michigan vs Synthetic Control Group of No-Fault (Fatalities Per 100,000 People)

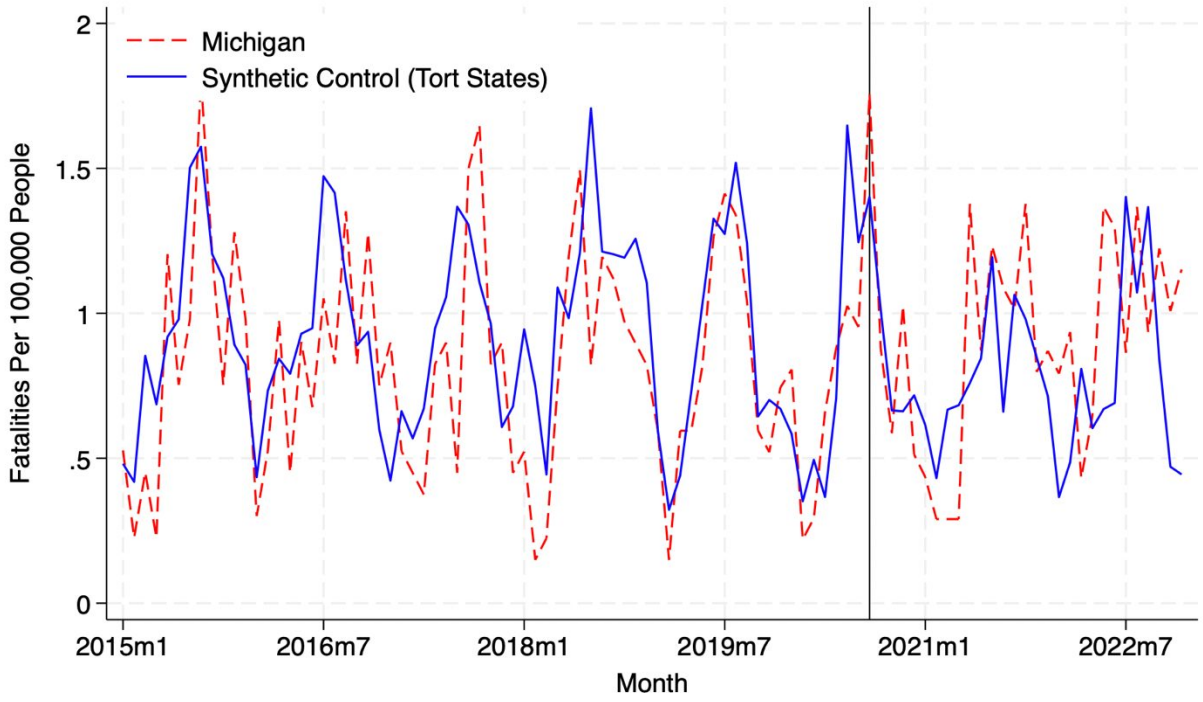


Figure 10. Michigan vs Synthetic Control Group of Tort States (Fatalities Per 100,000 People)

Adjusted Accidents

Table 11. Adjusted Accidents Per 100,000 People State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.134***	0.176*	0.150***	0.131***
	(0.0274)	(0.0465)	(0.0471)	(0.0320)
Light Condition	0.0309	-0.263*	0.0197	0.0336
	(0.0531)	(0.0635)	(0.0828)	(0.0618)
Weather Condition	-0.0594**	-0.0360	-0.0781	-0.0510*
	(0.0246)	(0.0309)	(0.0443)	(0.0298)
Vision Obstruction	-0.140**	-0.0788	-0.0603	-0.152*
	(0.0690)	(0.220)	(0.0911)	(0.0827)
Ruralness of Accident	-0.0812*	-0.224	-0.0652	-0.0817
	(0.0483)	(0.154)	(0.0772)	(0.0575)
Constant	0.893***	0.976**	0.847***	0.881***
	(0.0735)	(0.128)	(0.113)	(0.0860)
Observations	4,841	288	1,151	3,882
R-squared	0.180	0.773	0.255	0.182
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

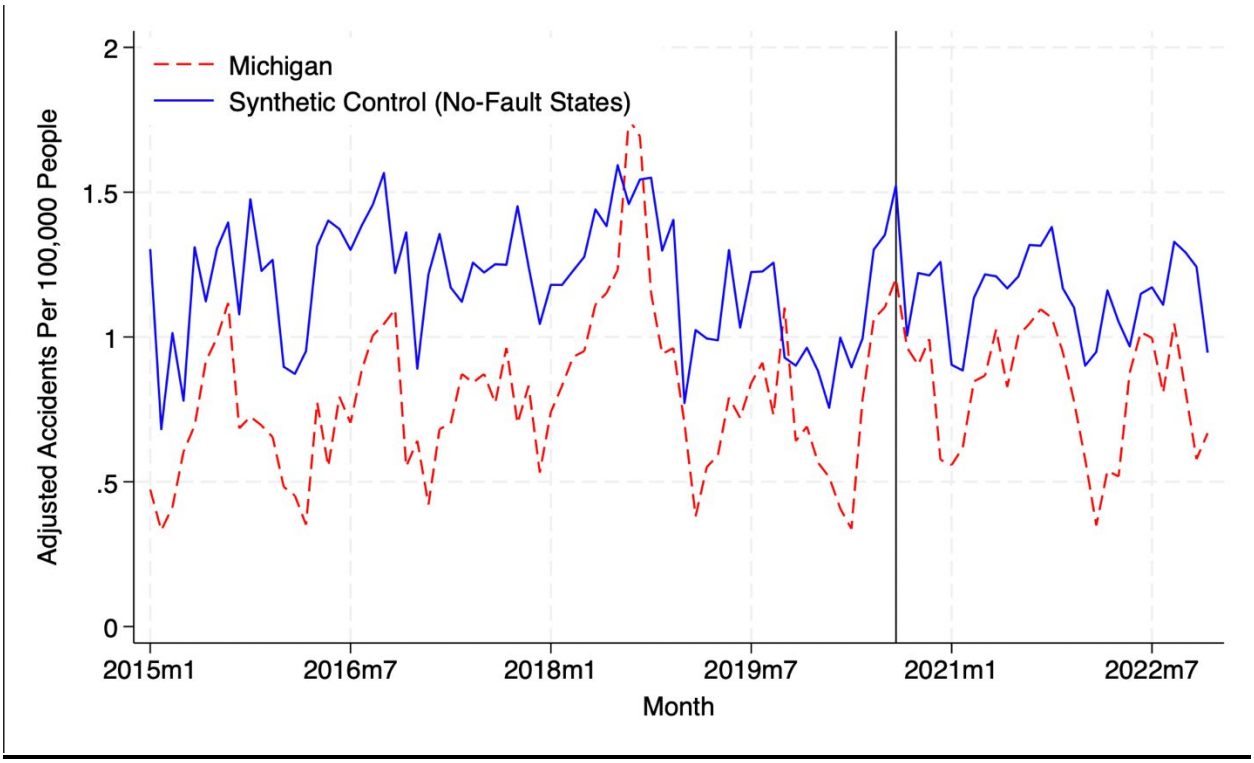


Figure 11. Michigan vs Synthetic Control Group No-Fault (Adjusted Accidents Per 100,000 People)

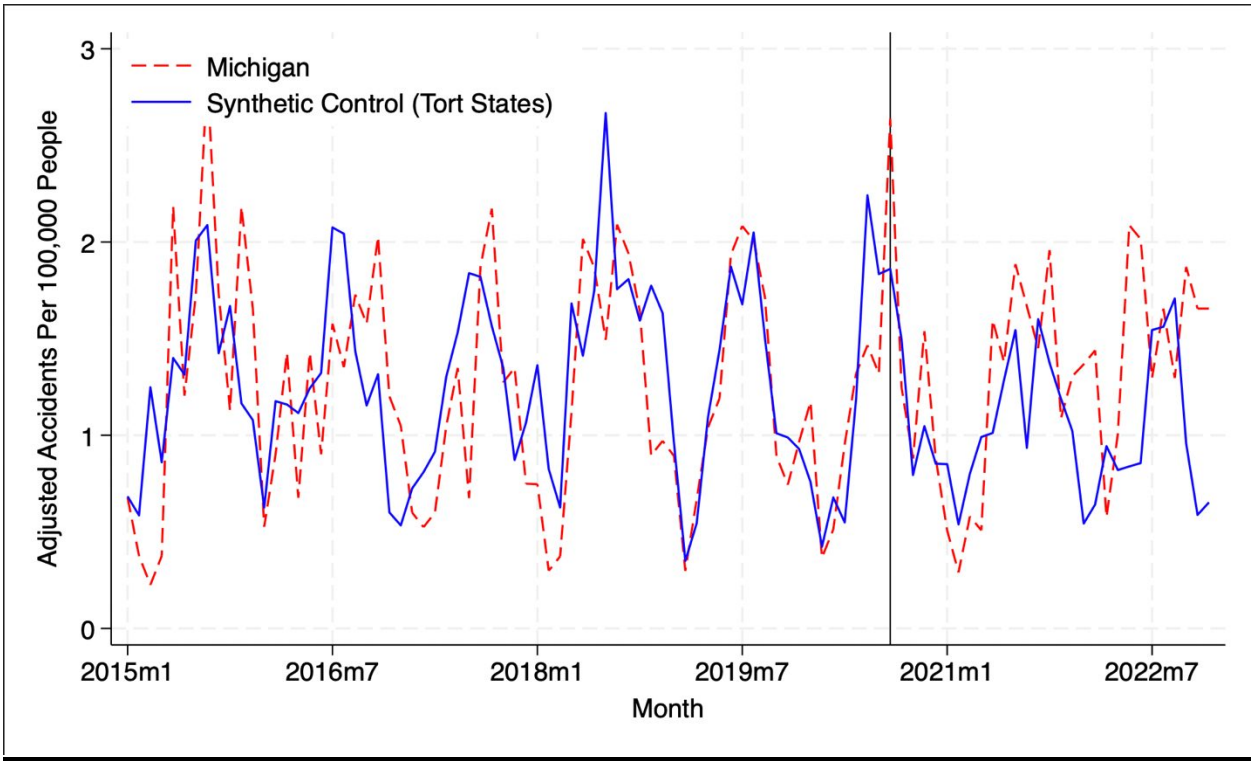


Figure 12. Michigan vs Synthetic Control Group of Tort States (Adjusted Accidents Per 100,000 People)

Risky Driver Behavior Per 100,000 People

Table 12. Risky Driver Behaviors Per 100,000 People for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0350**	0.0400	0.0591*	0.0297*
	(0.0152)	(0.0153)	(0.0305)	(0.0173)
Light Condition	0.0123	-0.0365	0.0269	0.00811
	(0.0242)	(0.0645)	(0.0296)	(0.0293)
Weather Condition	-0.0329***	-0.0263	-0.0380*	-0.0306**
	(0.0116)	(0.0119)	(0.0200)	(0.0144)
Vision Obstruction	-0.0821**	-0.199*	-0.00151	-0.0995**
	(0.0362)	(0.0468)	(0.0260)	(0.0482)
Ruralness of Accident	-0.0180	-0.0583	-0.0399	-0.0123
	(0.0263)	(0.127)	(0.0387)	(0.0311)
Constant	0.277***	0.221*	0.227***	0.283***
	(0.0343)	(0.0719)	(0.0557)	(0.0400)
Observations	4,841	288	1,151	3,882
R-squared	0.233	0.801	0.272	0.243
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

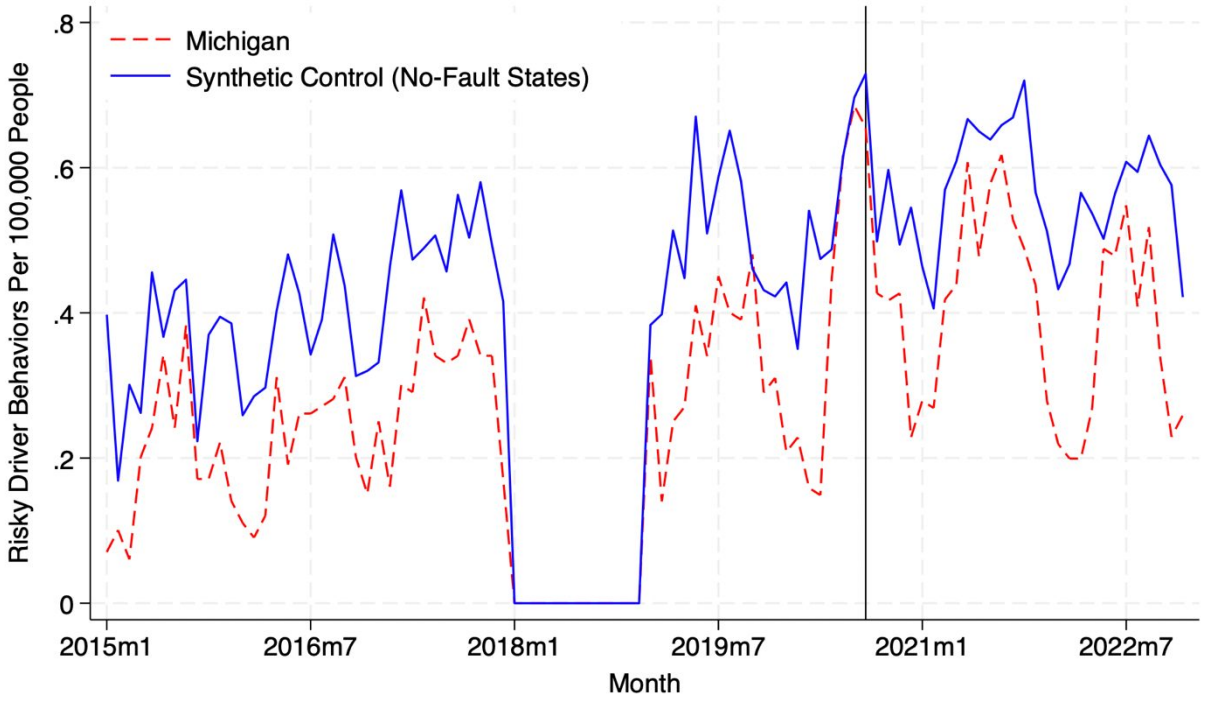


Figure 13. Michigan vs Synthetic Control Group of No-Fault (Risky Driver Behavior Per 100,000 People)

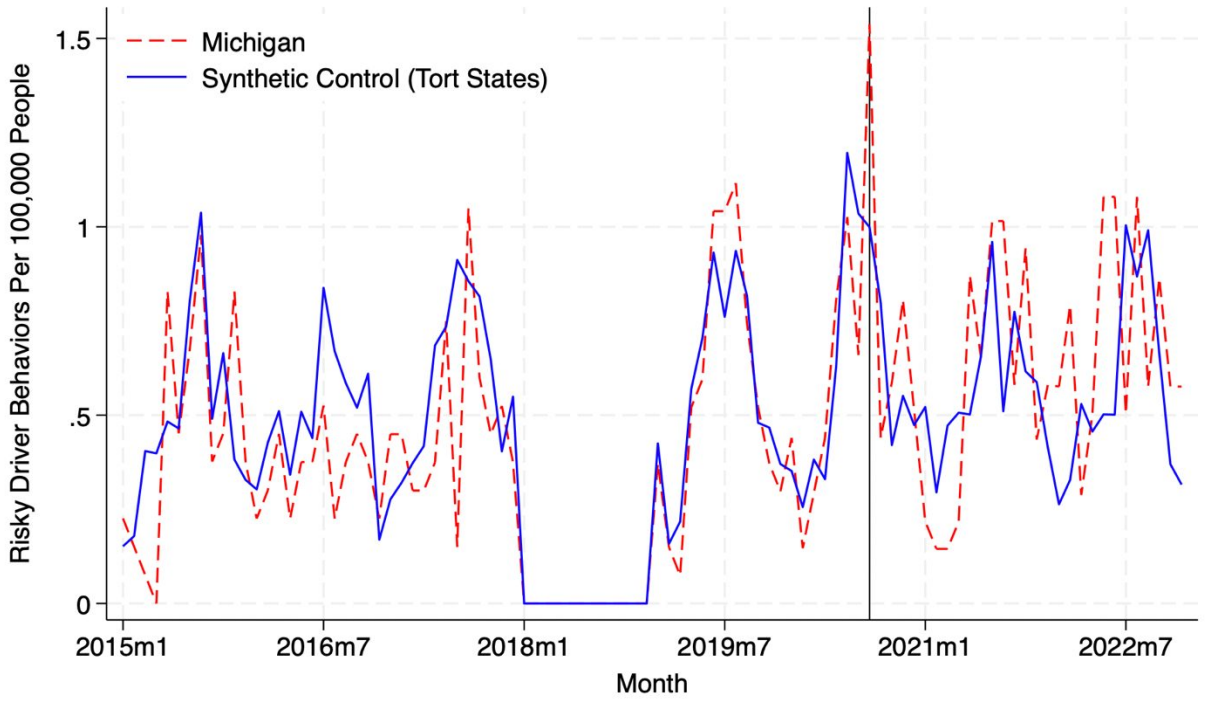


Figure 14. Michigan vs Synthetic Control Group of Tort (Risky Driver Behavior Per 100,000 People)

Drunk Drivers

Table 13. Drunk Drivers Per 100,000 People for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimators	0.00651	-0.0362	0.0151**	0.00436
	(0.00397)	(0.0159)	(0.00538)	(0.00471)
Light Condition	-0.00934	-0.00341	-0.0200	-0.00608
	(0.00958)	(0.0317)	(0.0172)	(0.0108)
Weather Condition	-0.00777*	0.00758	-0.0106***	-0.00662
	(0.00389)	(0.0122)	(0.00306)	(0.00528)
Vision Obstruction	-0.0410**	-0.105***	-0.0169	-0.0451**
	(0.0170)	(0.00787)	(0.0222)	(0.0189)
Ruralness of Accident	-0.0128	-0.0814*	-0.0236	-0.0134
	(0.00794)	(0.0260)	(0.0155)	(0.00944)
Constant	0.0697***	0.0548*	0.0750***	0.0667***
	(0.0104)	(0.0154)	(0.0162)	(0.0120)
Observations	4,841	288	1,151	3,882
R-squared	0.065	0.603	0.151	0.067
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14. Drunk Drivers Per 100,000 People (Placebo/Permutation Test)

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
2020m7	0.039	0.442	0.326	0.030	0.300	0.200	0.298**	0.029	0.059
2020m8	-0.013	0.907	0.884	-0.054	0.500	0.400	-0.122	0.353	0.676
2020m9	0.003	0.977	0.953	0.004	1.000	1.000	-0.270*	0.088	0.088
2020m10	0.013	0.814	0.698	-0.008	0.700	0.700	-0.184*	0.088	0.088
2020m11	0.019	0.767	0.605	-0.038	0.600	0.500	-0.020	0.794	0.853
2020m12	0.019	0.698	0.558	0.003	1.000	1.000	0.005	0.882	0.971
2021m1	0.008	0.814	0.791	0.015	0.600	0.500	-0.039	0.500	0.676
2021m2	0.021	0.605	0.442	0.002	1.000	1.000	0.000	1.000	1.000
2021m3	-0.012	0.767	0.744	-0.012	0.500	0.500	-0.028	0.618	0.794
2021m4	0.002	0.953	0.930	-0.052	0.300	0.200	-0.012	0.735	0.853
2021m5	-0.038	0.558	0.465	0.000	1.000	1.000	0.098	0.206	0.588
2021m6	0.015	0.814	0.698	-0.014	0.400	0.300	0.218***	0.000	0.118
2021m7	0.019	0.814	0.721	-0.016	0.800	0.700	0.047	0.588	0.735
2021m8	-0.019	0.791	0.651	-0.029	0.900	0.600	0.363	0.059	0.000
2021m9	-0.016	0.814	0.721	-0.016	0.800	0.700	0.074	0.324	0.529
2021m10	0.060	0.349	0.186	0.051	0.200	0.000	0.044	0.706	0.882
2021m11	-0.028	0.744	0.605	-0.015	0.600	0.600	-0.014	0.941	1.000
2021m12	-0.021	0.767	0.651	-0.009	0.800	0.700	0.059	0.382	0.618
2022m1	-0.080	0.372	0.140	-0.071	0.200	0.000	0.255**	0.029	0.118
2022m2	-0.018	0.721	0.698	-0.024	0.400	0.100	0.288***	0.000	0.029
2022m3	-0.051	0.535	0.395	-0.069	0.300	0.100	0.006	0.971	1.000
2022m4	-0.009	0.791	0.767	-0.032	0.500	0.400	-0.012	0.824	0.882
2022m5	0.011	0.907	0.814	0.000	1.000	1.000	0.203**	0.029	0.265
2022m6	0.003	1.000	0.977	-0.027	0.600	0.400	0.131	0.176	0.471
2022m7	-0.015	0.907	0.814	-0.031	0.300	0.200	-0.019	0.765	0.882
2022m8	-0.035	0.605	0.465	-0.005	1.000	1.000	0.196*	0.059	0.176
2022m9	0.008	0.930	0.907	0.028	0.600	0.300	0.013	0.882	1.000
2022m10	-0.031	0.651	0.395	-0.004	1.000	1.000	0.059	0.382	0.618
2022m11	-0.013	0.884	0.744	-0.016	0.500	0.300	-0.007	0.882	0.941
2022m12	-0.002	1.000	1.000	-0.019	0.700	0.600	0.327***	0.000	0.029

*** p<0.01, ** p<0.05, * p<0.1

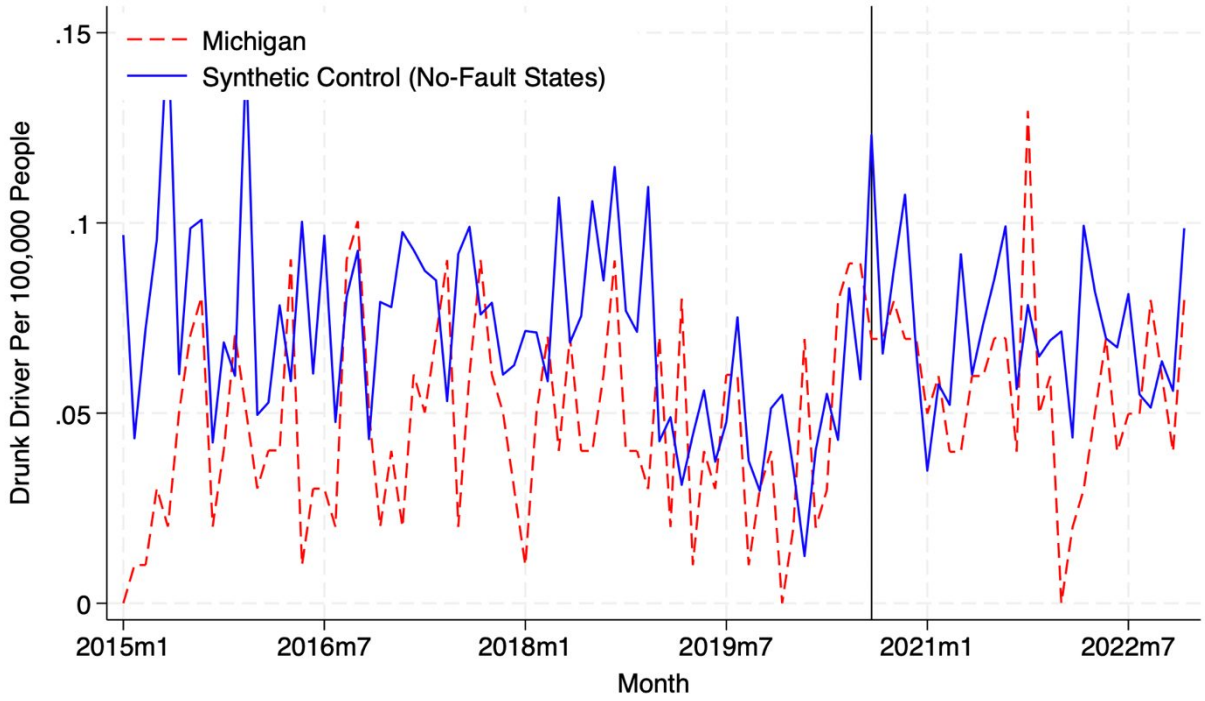


Figure 15. Michigan vs Synthetic Control Group of No-Fault States (Drunk Drivers Per 100,000 People)

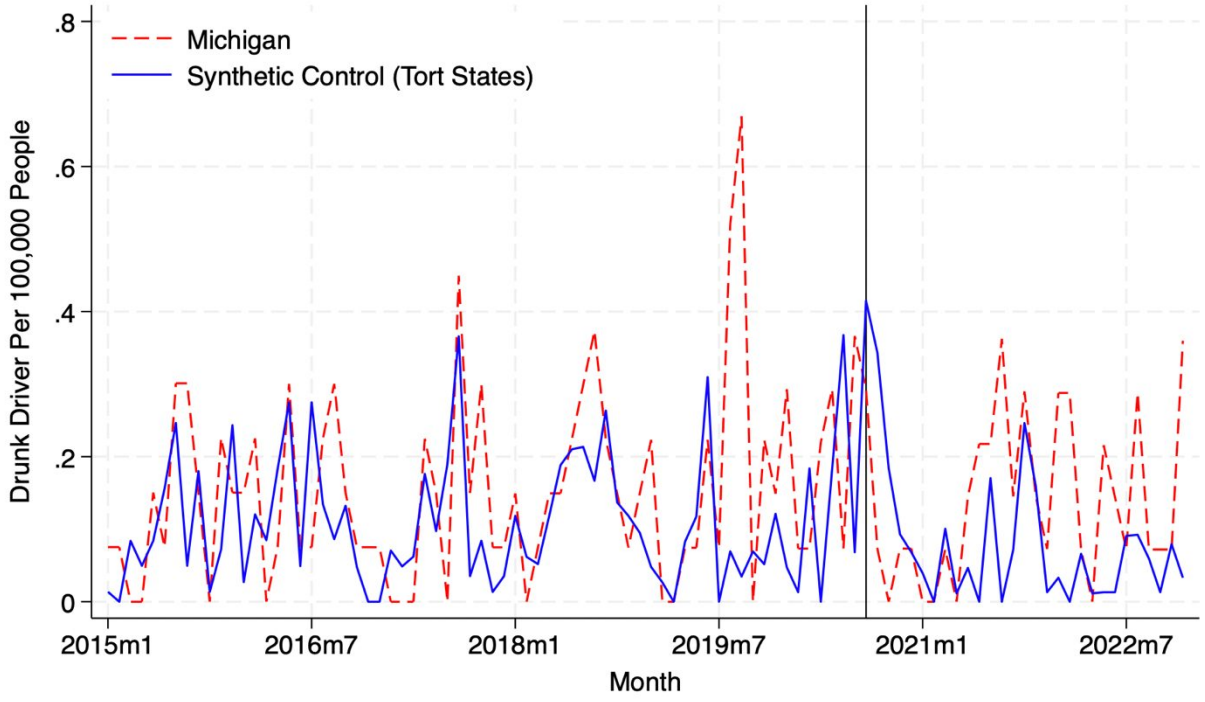


Figure 16. Michigan vs Synthetic Control Group of Tort States (Drunk Drivers Per 100,000 People)

Impaired Drivers

Table 15. Impaired Drivers Per 100,000 People for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0148*	0.0439***	0.0271*	0.0121
	(0.00754)	(0.00223)	(0.0138)	(0.00873)
Light Condition	-0.0402**	-0.127**	-0.0321	-0.0432**
	(0.0151)	(0.0206)	(0.0187)	(0.0179)
Weather Condition	-0.0224***	-0.00512	-0.0142*	-0.0260***
	(0.00726)	(0.0169)	(0.00754)	(0.00934)
Vision Obstruction	-0.0984***	-0.0102	-0.0462	-0.110**
	(0.0304)	(0.0526)	(0.0259)	(0.0412)
Ruralness of Accident	0.00845	-0.108	-0.0208	0.0145
	(0.0167)	(0.0707)	(0.0180)	(0.0204)
Constant	0.192***	0.222***	0.144***	0.204***
	(0.0193)	(0.0145)	(0.0298)	(0.0232)
Observations	4,841	288	1,151	3,882
R-squared	0.127	0.646	0.176	0.133
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16. Impaired Drivers Per 100,000 People (Placebo/Permutation Test)

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
2020m7	0.296*	0.093	0.000	0.248***	0.000	0.000	-0.383**	0.029	0.118
2020m8	0.148	0.302	0.326	0.115	0.300	0.200	0.199	0.265	0.500
2020m9	0.085	0.419	0.442	0.035	0.600	0.700	-0.334**	0.029	0.000
2020m10	0.055	0.535	0.535	-0.017	0.900	0.900	0.154	0.176	0.324
2020m11	0.183	0.163	0.000	0.166***	0.000	0.000	0.123	0.412	0.647
2020m12	0.041	0.698	0.628	-0.081	0.800	0.800	0.074	0.529	0.765
2021m1	0.062	0.628	0.581	-0.040	0.800	0.800	-0.430***	0.000	0.000
2021m2	0.123*	0.070	0.023	0.061	0.300	0.400	-0.034	0.676	0.824
2021m3	0.126	0.186	0.070	0.017	1.000	1.000	-0.185**	0.029	0.235
2021m4	0.130	0.163	0.140	0.031	0.800	0.800	-0.223***	0.000	0.118
2021m5	0.144	0.256	0.209	0.082	0.800	0.800	0.091	0.529	0.765
2021m6	0.132	0.302	0.349	0.028	0.900	0.800	-0.137	0.324	0.588
2021m7	0.236**	0.047	0.000	0.115	0.400	0.300	-0.091	0.676	0.882
2021m8	0.118	0.326	0.209	0.051	0.600	0.600	0.080	0.529	0.735
2021m9	0.157	0.302	0.256	0.103	0.300	0.100	-0.259	0.206	0.324
2021m10	0.185	0.256	0.163	0.039	1.000	0.900	-0.203	0.294	0.500
2021m11	0.078	0.558	0.535	0.031	0.800	0.800	-0.100	0.559	0.824
2021m12	0.085	0.419	0.442	-0.003	1.000	1.000	0.075	0.382	0.588
2022m1	-0.062	0.442	0.465	-0.118	0.400	0.100	0.098	0.294	0.353
2022m2	-0.001	0.977	1.000	-0.101	0.500	0.400	0.116	0.265	0.529
2022m3	-0.044	0.744	0.721	-0.145	0.500	0.400	-0.065	0.500	0.676
2022m4	-0.007	0.907	0.907	-0.114	0.400	0.300	0.049	0.706	0.794
2022m5	0.005	0.977	0.953	-0.017	1.000	1.000	0.295***	0.000	0.147
2022m6	0.018	0.930	0.930	-0.040	0.400	0.600	0.120	0.500	0.706
2022m7	0.048	0.814	0.767	-0.032	0.900	0.800	-0.266	0.118	0.235
2022m8	-0.055	0.791	0.744	-0.098	0.400	0.200	-0.223	0.265	0.353
2022m9	-0.003	1.000	1.000	-0.060	0.500	0.400	-0.525**	0.029	0.000
2022m10	0.002	0.953	0.977	0.016	0.800	0.900	0.147	0.382	0.588
2022m11	-0.018	0.814	0.791	-0.094	0.400	0.400	0.124	0.294	0.471
2022m12	-0.039	0.744	0.674	-0.037	0.500	0.600	0.016	0.912	0.941

*** p<0.01, ** p<0.05, * p<0.1

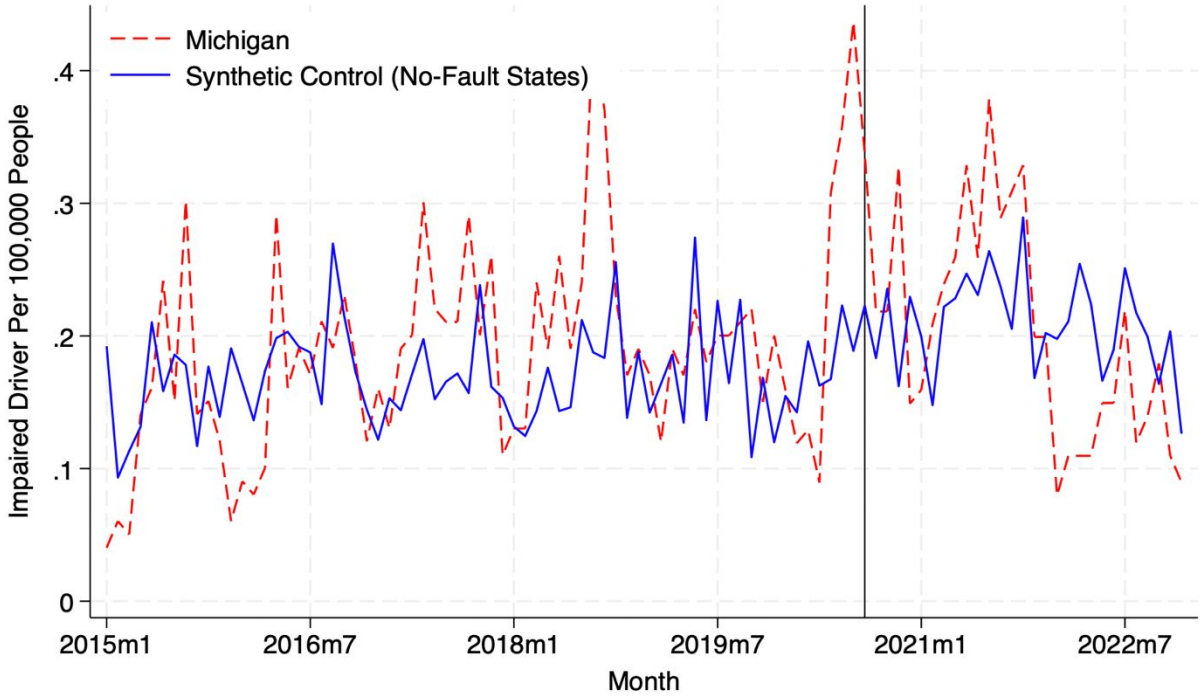


Figure 27. Michigan vs Synthetic Control Group of No-Fault (Impaired Driver Per 100,000 People)

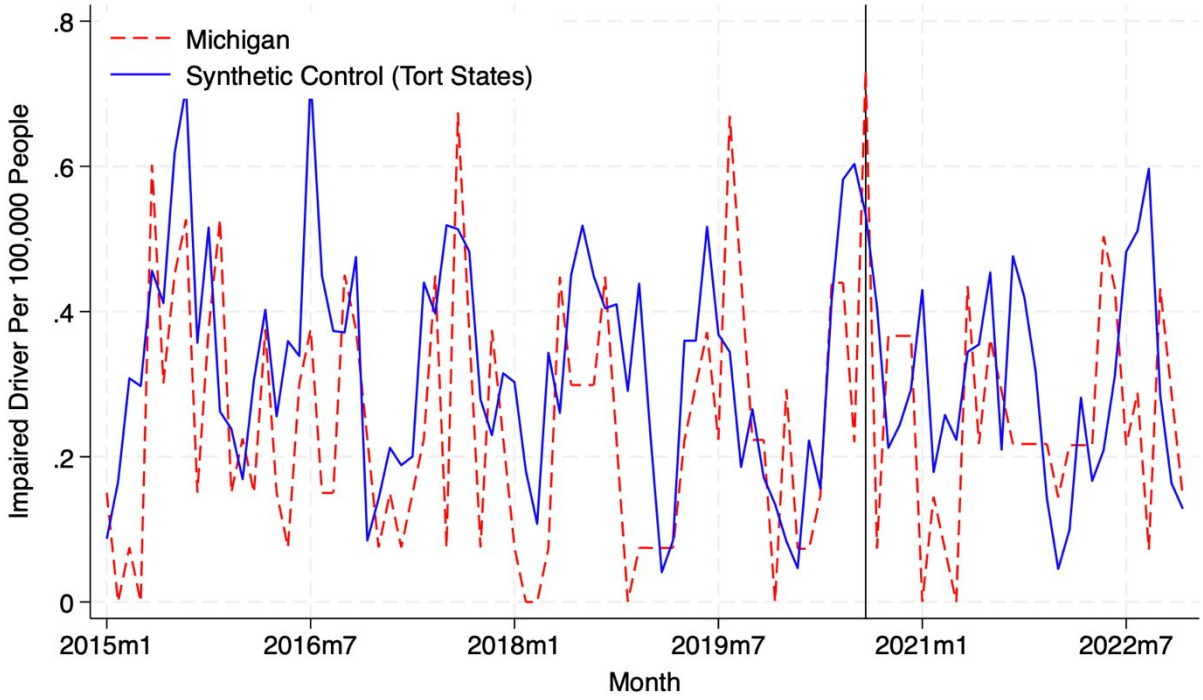


Figure 18. Michigan vs Synthetic Control Group of Tort States (Impaired Driver Per 100,000 People)

Speeding

Table 17. Speeding Per 100,000 People for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0358***	0.0430***	0.0463***	0.0330***
	(0.00715)	(0.00351)	(0.0117)	(0.00841)
Light Condition	0.0189	0.107***	0.0229	0.0157
	(0.0117)	(0.00370)	(0.0138)	(0.0144)
Weather Condition	-0.000881	-0.00525	-0.00709	0.00112
	(0.00438)	(0.00808)	(0.0100)	(0.00544)
Vision Obstruction	-0.0474**	-0.0479	0.000528	-0.0595**
	(0.0208)	(0.0934)	(0.0162)	(0.0248)
Ruralness of Accident	0.00567	-0.0585	0.00645	0.00659
	(0.0165)	(0.0324)	(0.0222)	(0.0199)
Constant	0.132***	0.0625*	0.122***	0.133***
	(0.0216)	(0.0185)	(0.0309)	(0.0256)
Observations	4,835	288	1,151	3,876
R-squared	0.280	0.707	0.300	0.293
Number of state	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

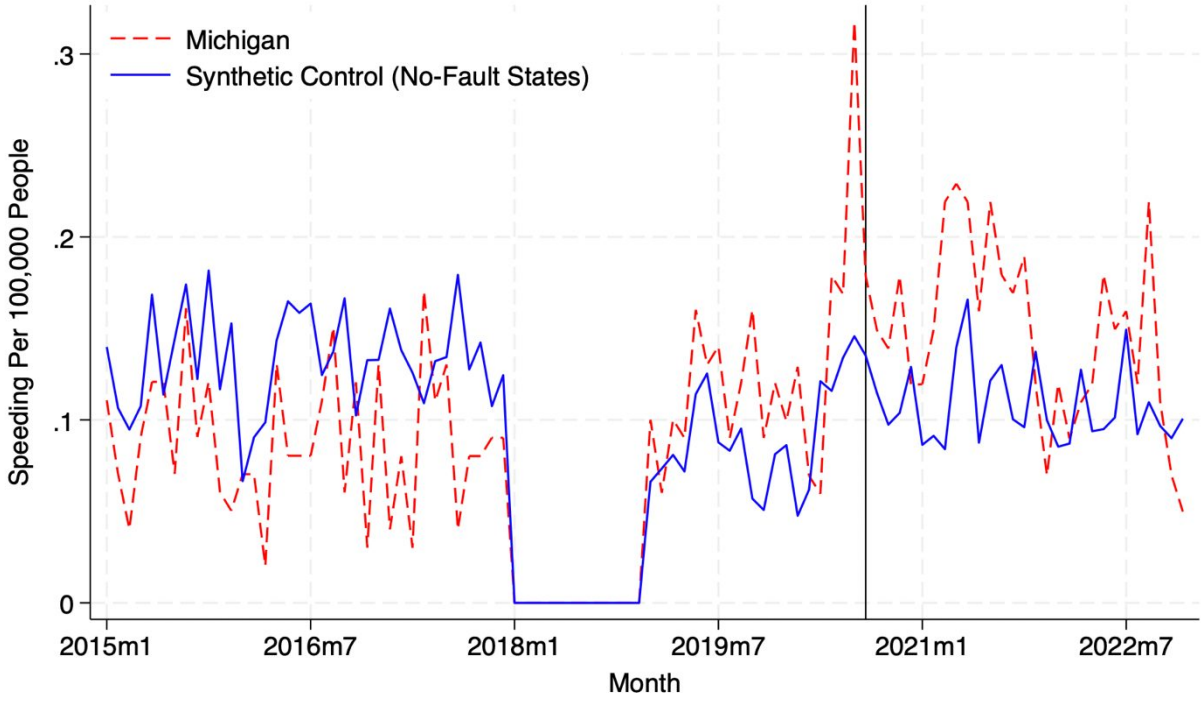


Figure 19. Michigan vs Synthetic Control Group of No-Fault (Speeding Per 100,000 People)

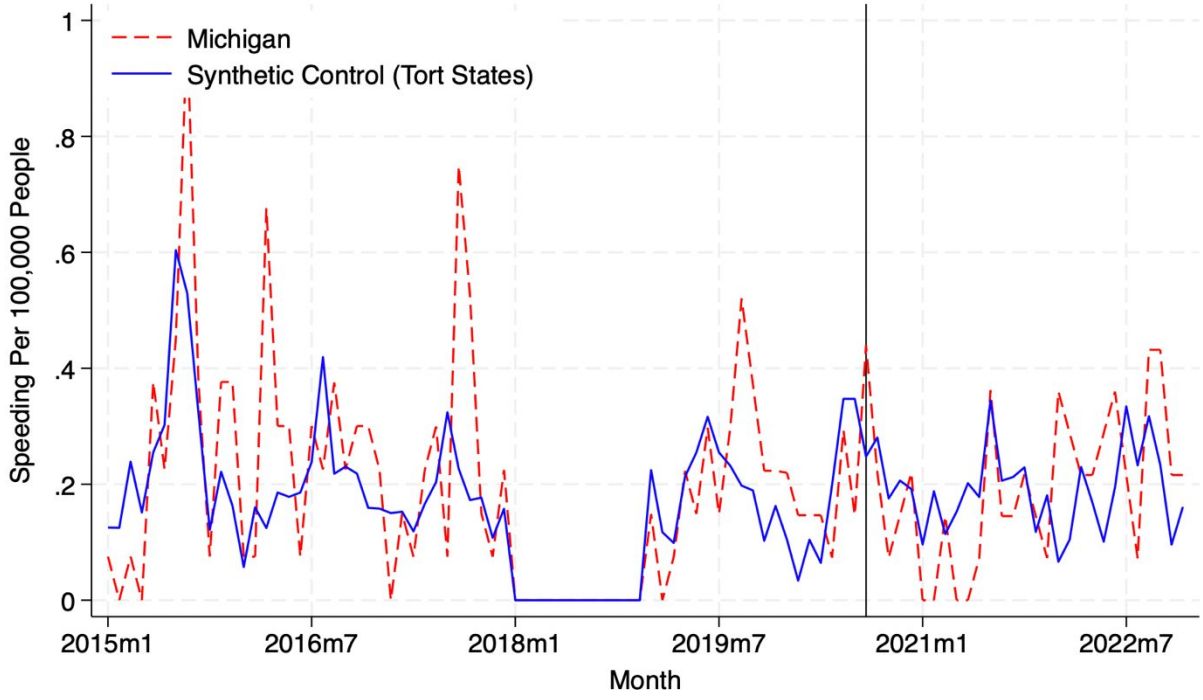


Figure 20. Michigan vs Synthetic Control Group of Tort States (Speeding Per 100,000 People)

Distracted Drivers

Table 18. Distracted Drivers Per 100,000 People for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.00826**	0.0160	0.0112	0.00703
	(0.00398)	(0.00846)	(0.00928)	(0.00441)
Light Condition	0.0127**	0.0377	0.0221*	0.00926
	(0.00502)	(0.0579)	(0.0103)	(0.00582)
Weather Condition	-0.00485*	0.0100*	-0.00896***	-0.00271
	(0.00269)	(0.00282)	(0.00236)	(0.00342)
Vision Obstruction	-0.0135	-0.0555	-0.0126	-0.0143
	(0.00995)	(0.0460)	(0.0220)	(0.0106)
Ruralness of Accident	0.00224	-0.0364	0.00645	0.000254
	(0.0102)	(0.0279)	(0.0218)	(0.0117)
Constant	0.0797***	0.0474	0.0950***	0.0746***
	(0.0137)	(0.0409)	(0.0271)	(0.0156)
Observations	4,841	288	1,151	3,882
R-squared	0.061	0.360	0.114	0.061
Number of state	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19. Distracted Drivers Per 100,000 People (Placebo/Permutation Test)

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
Jul 2020	-0.007	0.930	0.837	-0.048	0.500	0.400	-0.025	0.794	0.912
Aug 2020	0.009	0.791	0.628	-0.047	0.600	0.700	0.153	0.147	0.118
Sep 2020	0.033	0.535	0.163	-0.035	0.600	0.600	0.031	0.588	0.559
Oct 2020	0.013	0.744	0.651	-0.110	0.400	0.100	0.067	0.324	0.353
Nov 2020	-0.020	0.581	0.233	-0.038	0.800	0.700	-0.078*	0.088	0.088
Dec 2020	0.014	0.581	0.326	-0.070	0.400	0.300	-0.029	0.471	0.588
Jan 2021	-0.026	0.558	0.256	-0.122	0.400	0.000	0.121*	0.088	0.000
Feb 2021	0.009	0.907	0.721	-0.091	0.400	0.100	-0.023	0.588	0.676
Mar 2021	-0.002	0.907	0.907	-0.082	0.500	0.400	-0.062	0.324	0.353
Apr 2021	0.032	0.558	0.116	-0.051	0.700	0.700	-0.011	0.853	0.853
May 2021	-0.019	0.744	0.465	-0.091	0.600	0.300	0.000	1.000	1.000
Jun 2021	0.053	0.419	0.023	-0.011	0.900	0.900	0.033	0.647	0.706
Jul 2021	0.005	1.000	0.953	-0.059	0.500	0.600	-0.044	0.382	0.441
Aug 2021	0.060	0.372	0.070	-0.006	1.000	1.000	0.050	0.471	0.529
Sep 2021	0.024	0.581	0.395	-0.072	0.500	0.400	0.035	0.500	0.559
Oct 2021	0.040	0.558	0.209	-0.102	0.700	0.700	0.102	0.324	0.294
Nov 2021	0.006	0.907	0.837	-0.098	0.200	0.400	0.040	0.618	0.647
Dec 2021	0.028	0.605	0.256	-0.057	0.600	0.600	-0.082	0.265	0.294
Jan 2022	0.016	0.767	0.512	-0.080	0.400	0.400	-0.098	0.147	0.088
Feb 2022	0.003	0.953	0.930	-0.044	0.700	0.600	0.016	0.853	0.912
Mar 2022	-0.019	0.581	0.349	-0.103	0.200	0.100	-0.028	0.529	0.647
Apr 2022	0.038	0.465	0.070	-0.032	0.800	0.900	-0.080	0.235	0.176
May 2022	0.010	0.814	0.674	-0.073	0.700	0.800	0.117	0.206	0.176
Jun 2022	0.004	0.930	0.884	-0.076	0.600	0.400	0.025	0.676	0.765
Jul 2022	0.021	0.721	0.465	-0.074	0.700	0.800	0.046	0.471	0.618
Aug 2022	0.014	0.605	0.512	-0.068	0.400	0.500	-0.117	0.118	0.059
Sep 2022	-0.011	0.814	0.674	-0.083	0.700	0.400	0.015	0.706	0.794
Oct 2022	0.034	0.558	0.256	-0.035	0.800	0.900	0.144	0.176	0.059
Nov 2022	0.005	0.884	0.791	-0.068	0.700	0.600	-0.033	0.412	0.441
Dec 2022	-0.022	0.674	0.302	-0.103	0.500	0.400	-0.012	0.824	0.735

*** p<0.01, ** p<0.05, * p<0.1

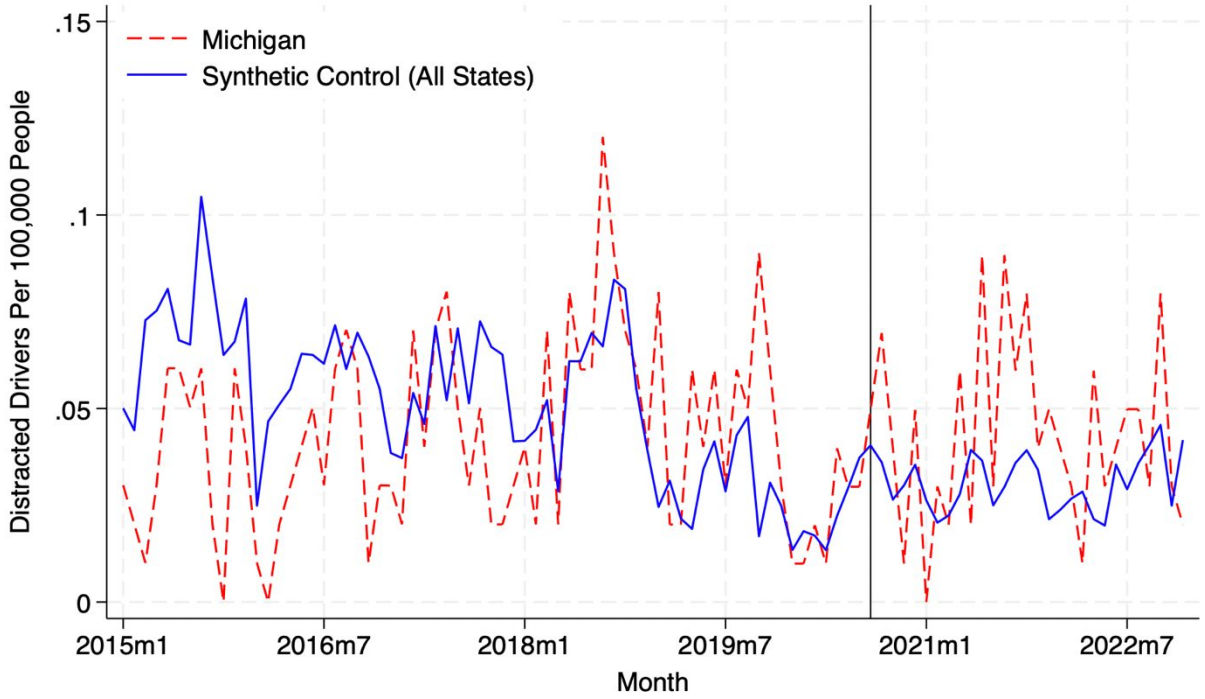


Figure 21. Michigan vs Synthetic Control Group of All States (Distracted Drivers Per 100,000 People)

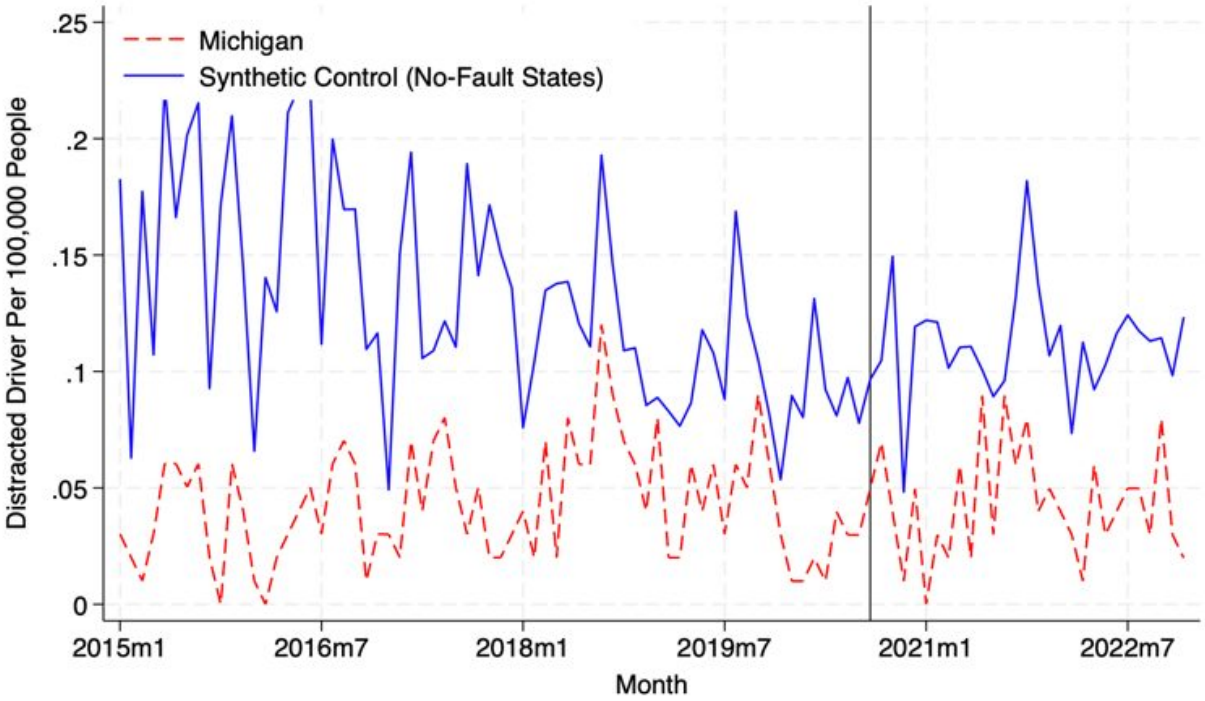


Figure 22. Michigan vs Synthetic Control Group of No-Fault (Distracted Drivers Per 100,000 People)

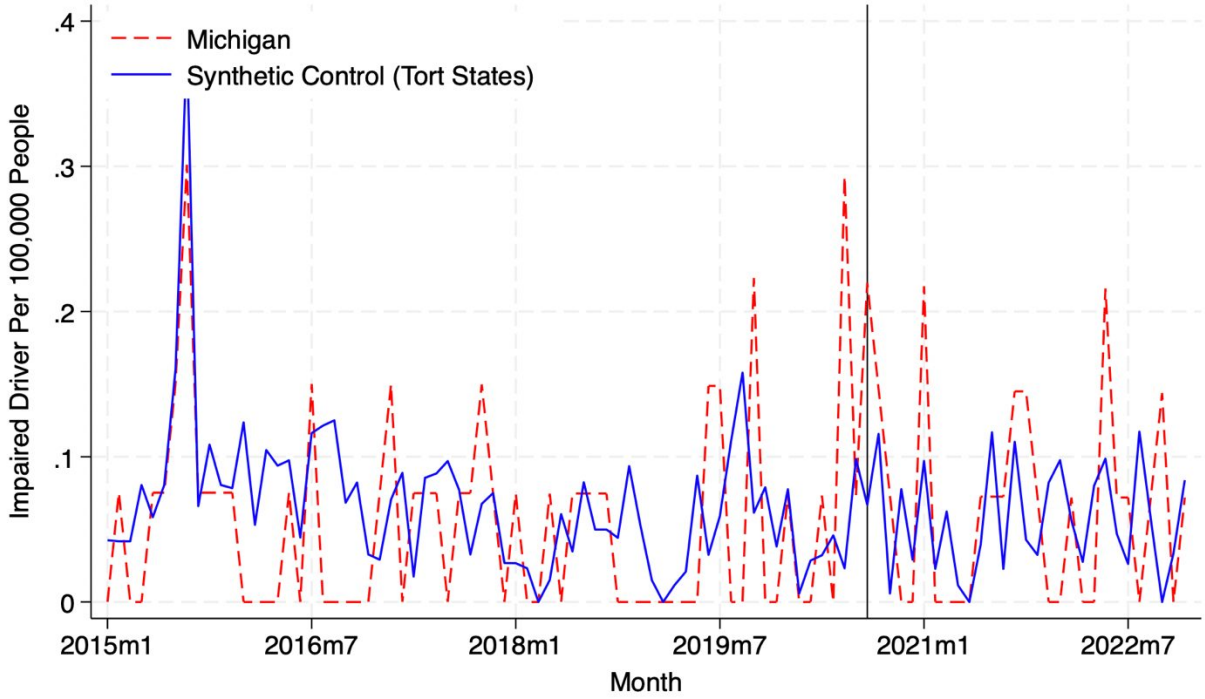


Figure 23. Michigan vs Synthetic Control Group of Tort States (Distracted Drivers Per 100,000 People)

Drug Use Drivers

Table 20. Drug Use Drivers Per 100,000 People for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0105	0.0491	0.0170	0.00801
	(0.00984)	(0.0200)	(0.0123)	(0.0120)
Light Condition	-0.0260*	-0.0454	-0.0389	-0.0260
	(0.0136)	(0.0206)	(0.0257)	(0.0161)
Weather Condition	-0.00745	-0.0183**	-0.00833	-0.00755
	(0.00486)	(0.00416)	(0.00710)	(0.00620)
Vision Obstruction	-0.0303	0.0294	0.0227	-0.0419
	(0.0280)	(0.0799)	(0.0283)	(0.0359)
Ruralness of Accident	-0.0177	-0.0464	-0.00468	-0.0197
	(0.0106)	(0.0322)	(0.0175)	(0.0121)
Constant	0.104***	0.108*	0.0836***	0.112***
	(0.0177)	(0.0292)	(0.0159)	(0.0216)
Observations	4,841	288	1,151	3,882
R-squared	0.071	0.568	0.159	0.081
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21. Drug Use Drivers Per 100,000 People

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
Jul 2020	0.176	0.209	0.023	0.148	0.300	0.000	-0.186	0.235	0.529
Aug 2020	0.101	0.488	0.279	0.070	0.500	0.100	-0.032	0.912	0.912
Sep 2020	0.050	0.651	0.558	0.012	0.900	0.800	-0.226	0.206	0.471
Oct 2020	0.086	0.372	0.116	0.016	1.000	1.000	0.039	0.765	0.882
Nov 2020	0.129	0.209	0.000	0.115	0.400	0.000	0.041	0.794	0.912
Dec 2020	-0.042	0.721	0.605	-0.105	0.300	0.000	-0.073	0.676	0.824
Jan 2021	0.012	0.837	0.814	-0.018	0.900	0.900	-0.252*	0.059	0.088
Feb 2021	0.045	0.628	0.395	0.015	0.900	0.900	-0.141	0.176	0.382
Mar 2021	0.053	0.581	0.419	-0.037	0.800	0.800	-0.176	0.176	0.471
Apr 2021	0.081	0.442	0.209	0.053	0.700	0.300	-0.198	0.235	0.382
May 2021	0.108	0.419	0.163	0.025	0.900	0.900	-0.203	0.206	0.500
Jun 2021	0.079	0.674	0.419	0.037	1.000	0.700	-0.211	0.176	0.441
Jul 2021	0.150	0.302	0.000	0.111	0.300	0.000	-0.131	0.382	0.618
Aug 2021	0.134	0.302	0.070	0.094	0.700	0.300	-0.219*	0.088	0.471
Sep 2021	0.024	0.884	0.814	-0.002	1.000	1.000	-0.283	0.118	0.382
Oct 2021	0.153	0.302	0.116	0.061	0.700	0.300	-0.154	0.324	0.647
Nov 2021	0.116	0.558	0.186	0.086	0.600	0.100	-0.134	0.412	0.559
Dec 2021	0.064	0.558	0.326	0.006	1.000	1.000	-0.096	0.353	0.588
Jan 2022	-0.013	0.837	0.814	-0.059	0.800	0.700	-0.033	0.735	0.794
Feb 2022	-0.004	0.977	0.977	-0.081	0.500	0.100	0.049	0.588	0.706
Mar 2022	0.017	0.791	0.767	-0.055	0.800	0.700	-0.215	0.118	0.382
Apr 2022	0.019	0.814	0.767	-0.022	1.000	0.900	0.008	0.941	1.000
May 2022	0.063	0.674	0.488	0.041	0.900	0.400	-0.027	0.824	0.882
Jun 2022	0.068	0.605	0.488	0.054	0.900	0.800	-0.071	0.618	0.853
Jul 2022	0.037	0.767	0.698	-0.011	1.000	0.900	-0.430*	0.088	0.176
Aug 2022	-0.035	0.767	0.767	-0.091	0.800	0.400	-0.222	0.147	0.471
Sep 2022	0.033	0.837	0.698	0.014	1.000	1.000	-0.396*	0.088	0.118
Oct 2022	0.034	0.953	0.837	0.001	1.000	1.000	0.087	0.706	0.882
Nov 2022	0.092	0.465	0.140	0.039	0.700	0.800	-0.269*	0.059	0.235
Dec 2022	0.009	0.907	0.884	-0.004	1.000	1.000	-0.007	1.000	1.000

*** p<0.01, ** p<0.05, * p<0.1

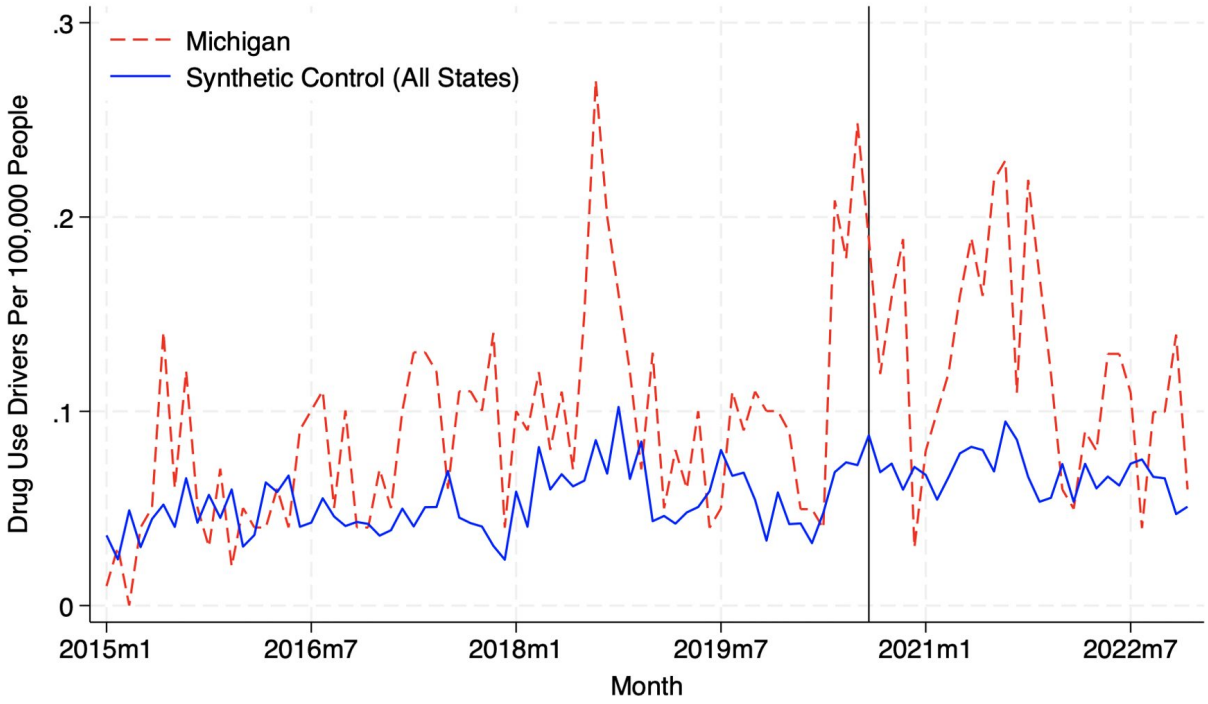


Figure 24. Michigan vs Synthetic Control Group of All States (Drug Use Drivers Per 100,000 People)

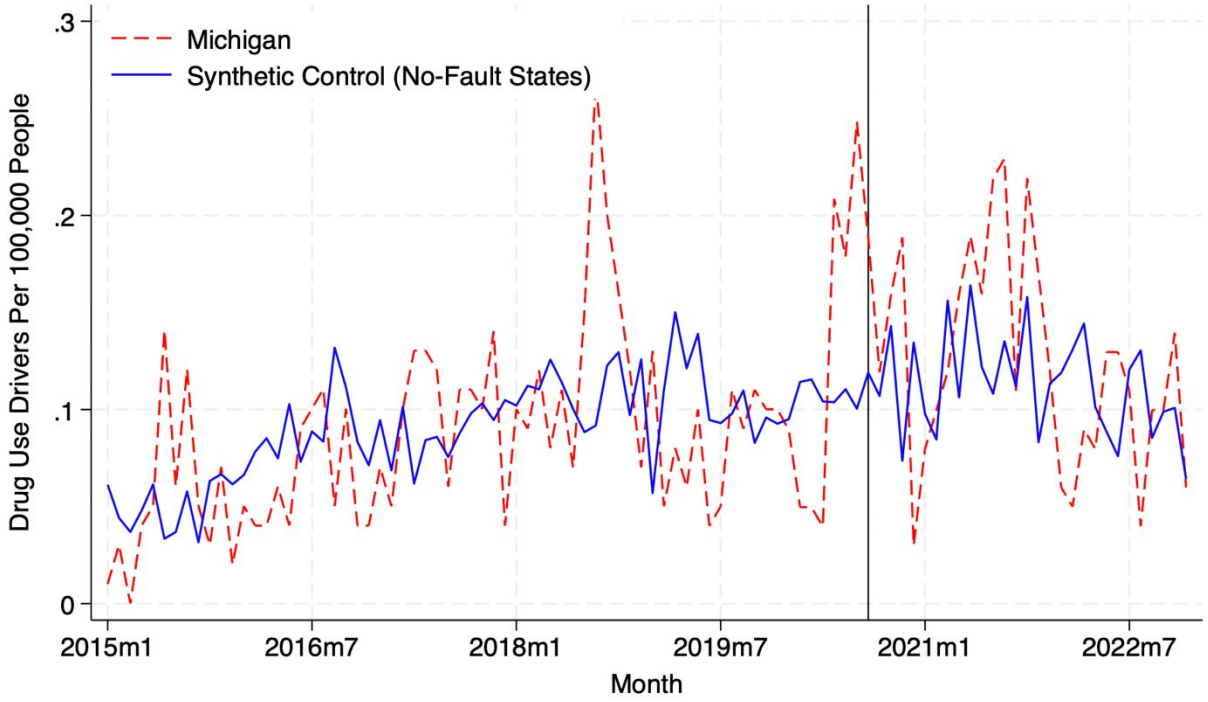


Figure 25. Michigan vs Synthetic Control Group of No-Fault (Drug Use Drivers Per 100,000 People)

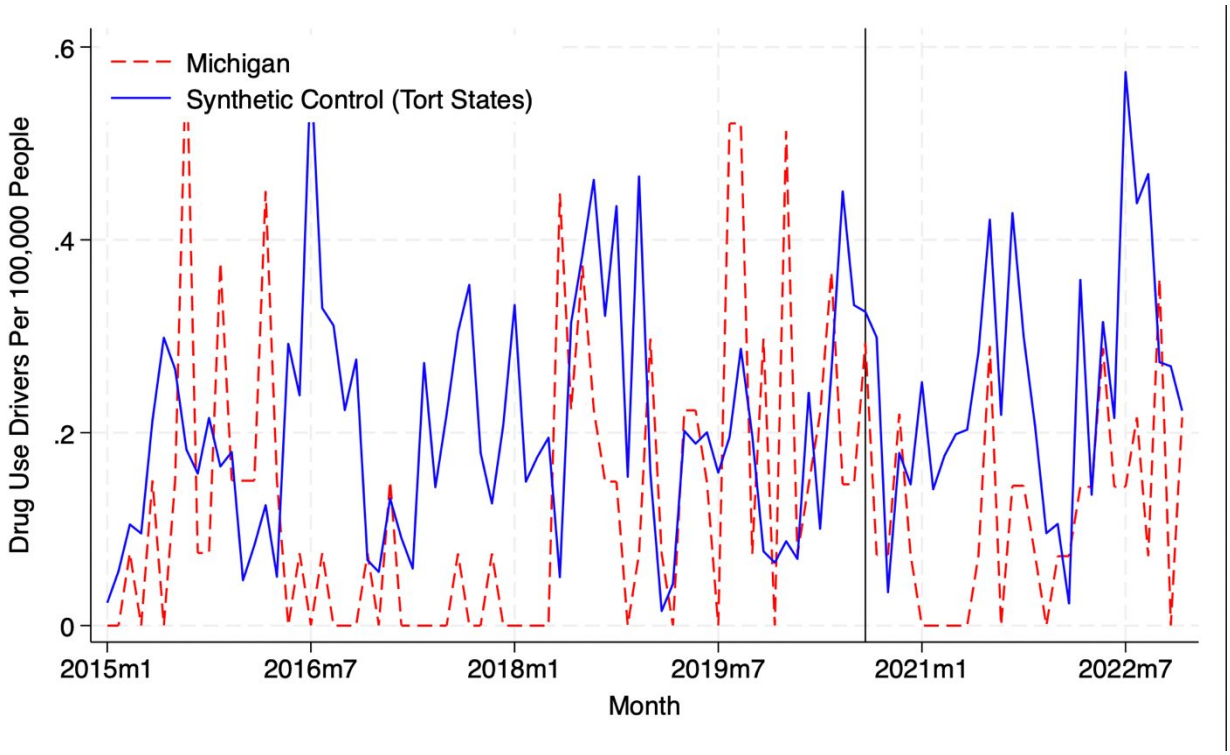


Figure 26. Michigan vs Synthetic Control Group of Tort States (Drug Use Drivers Per 100,000 People)

Seat Belt Misuse

Table 22. Seat Belt Misuse Per 100,000 People for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	-0.0574**	-0.0191	-0.00988	-0.0671***
	(0.0221)	(0.0164)	(0.0523)	(0.0240)
Light Condition	0.0685***	0.0170	0.0673	0.0725**
	(0.0249)	(0.0691)	(0.0535)	(0.0306)
Weather Condition	-0.0335**	-0.0335**	-0.0353*	-0.0300*
	(0.0137)	(0.00523)	(0.0193)	(0.0169)
Vision Obstruction	-0.0626	-0.144	-0.0376	-0.0611
	(0.0509)	(0.0885)	(0.0891)	(0.0616)
Ruralness of Accident	0.0229	0.125	-0.0348	0.0420
	(0.0325)	(0.137)	(0.0599)	(0.0372)
Constant	-0.0224	-0.0421	-0.00381	-0.0354
	(0.0397)	(0.109)	(0.0803)	(0.0442)
Observations	4,841	288	1,151	3,882
R-squared	0.418	0.885	0.424	0.432
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23. Seat Belt Misuse Per 100,000 People (Placebo/Permutation Test)

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
Jul 2020	0.358	0.163	0.000	-0.115	0.800	0.900	-0.559*	0.088	0.147
Aug 2020	0.128	0.651	0.326	-0.340	0.400	0.200	0.276	0.353	0.559
Sep 2020	0.052	0.860	0.721	-0.200	0.600	0.700	-0.130	0.676	0.706
Oct 2020	-0.005	0.977	0.977	-0.300	0.500	0.400	0.036	0.882	0.941
Nov 2020	0.059	0.791	0.488	-0.213	0.600	0.500	-0.002	1.000	1.000
Dec 2020	-0.023	0.884	0.860	-0.372	0.400	0.300	-0.350	0.147	0.118
Jan 2021	0.019	0.884	0.814	-0.317	0.500	0.300	-0.602**	0.029	0.059
Feb 2021	0.009	0.977	0.907	-0.242	0.500	0.500	-0.294***	0.000	0.088
Mar 2021	0.167	0.419	0.163	-0.260	0.600	0.600	-0.305	0.176	0.176
Apr 2021	0.134	0.535	0.349	-0.344	0.600	0.400	-0.273	0.265	0.382
May 2021	0.112	0.744	0.535	-0.357	0.500	0.600	0.203	0.588	0.765
Jun 2021	0.121	0.744	0.395	-0.244	0.600	0.300	-0.146	0.706	0.765
Jul 2021	0.220	0.419	0.116	-0.200	0.400	0.600	-0.425	0.176	0.206
Aug 2021	0.208	0.512	0.140	-0.289	0.400	0.400	0.584	0.118	0.176
Sep 2021	0.000	1.000	1.000	-0.423	0.200	0.100	-0.053	0.912	0.912
Oct 2021	-0.009	1.000	1.000	-0.600	0.300	0.200	0.432	0.265	0.382
Nov 2021	0.133	0.558	0.279	-0.078	0.600	0.400	-0.329	0.324	0.382
Dec 2021	-0.108	0.605	0.326	-0.363	0.400	0.200	0.042	0.853	0.882
Jan 2022	-0.068	0.767	0.395	-0.337	0.700	0.700	-0.034	0.882	0.941
Feb 2022	0.017	0.884	0.767	-0.224	0.600	0.600	0.156	0.471	0.559
Mar 2022	-0.137	0.512	0.256	-0.526	0.300	0.000	-0.250	0.324	0.412
Apr 2022	0.032	0.837	0.791	-0.341	0.300	0.300	0.026	0.912	0.941
May 2022	0.181	0.674	0.256	0.028	1.000	1.000	0.794	0.118	0.088
Jun 2022	0.139	0.721	0.372	-0.166	0.800	0.800	0.779*	0.088	0.000
Jul 2022	0.124	0.628	0.395	-0.178	0.600	0.800	-0.778*	0.059	0.000
Aug 2022	-0.028	0.953	0.884	-0.297	0.300	0.400	0.259	0.500	0.647
Sep 2022	0.212	0.488	0.047	-0.167	0.900	0.800	-0.648***	0.000	0.029
Oct 2022	-0.098	0.837	0.628	-0.365	0.200	0.100	0.068	0.794	0.912
Nov 2022	-0.059	0.744	0.581	-0.444	0.200	0.000	0.024	0.912	0.941
Dec 2022	-0.098	0.837	0.395	-0.296	0.500	0.400	0.296	0.265	0.382

*** p<0.01, ** p<0.05, * p<0.1

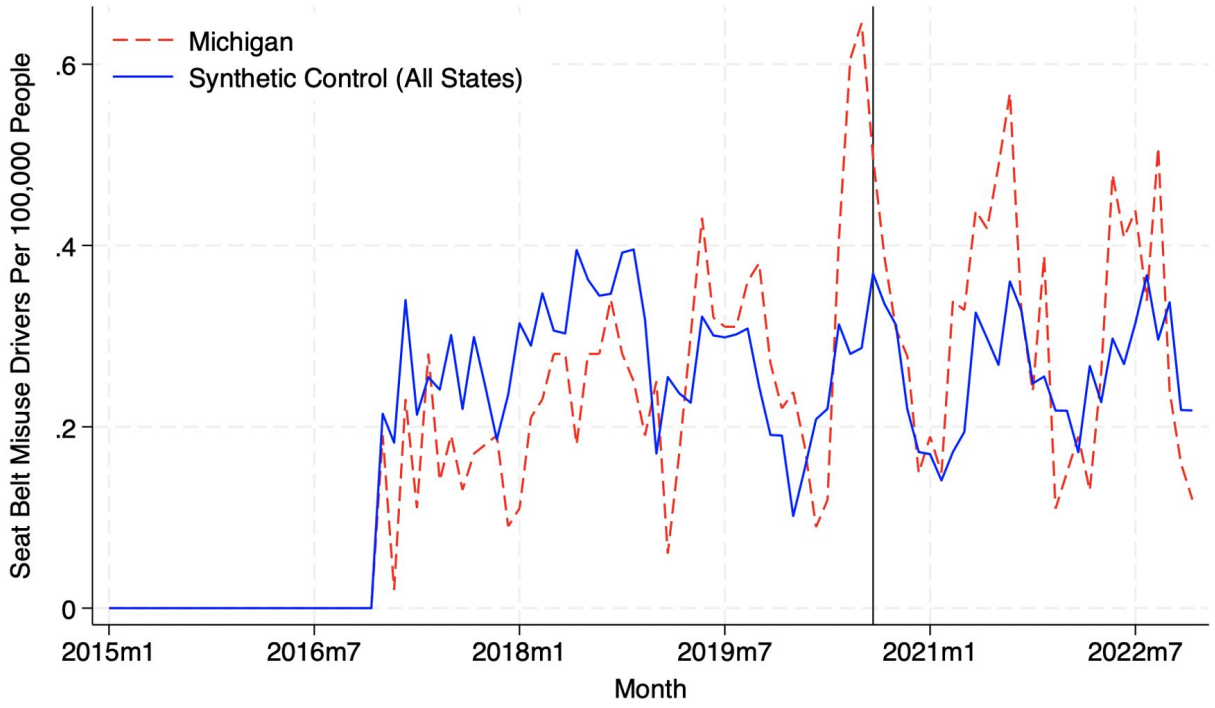


Figure 27. Michigan vs Synthetic Controls Group of All States (Seat Belt Use Per 100,000 People)

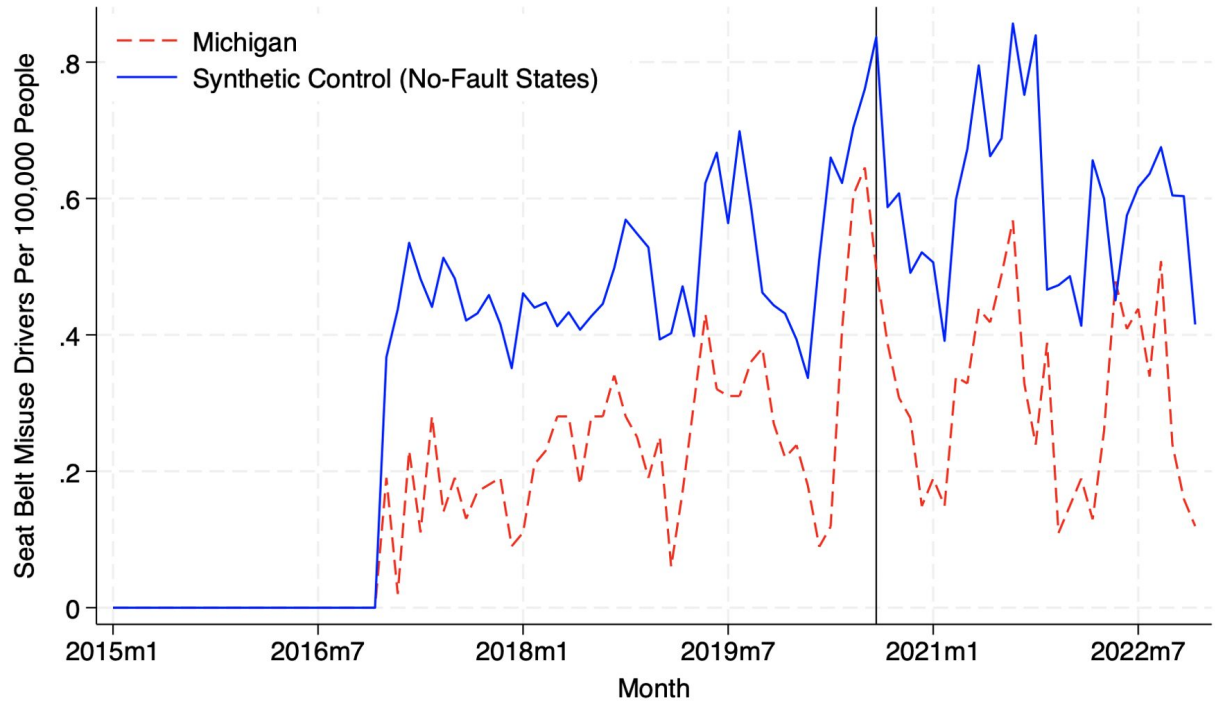


Figure 28. Michigan vs Synthetic Controls Group of No-Fault States (Seat Belt Use Per 100,000 People)

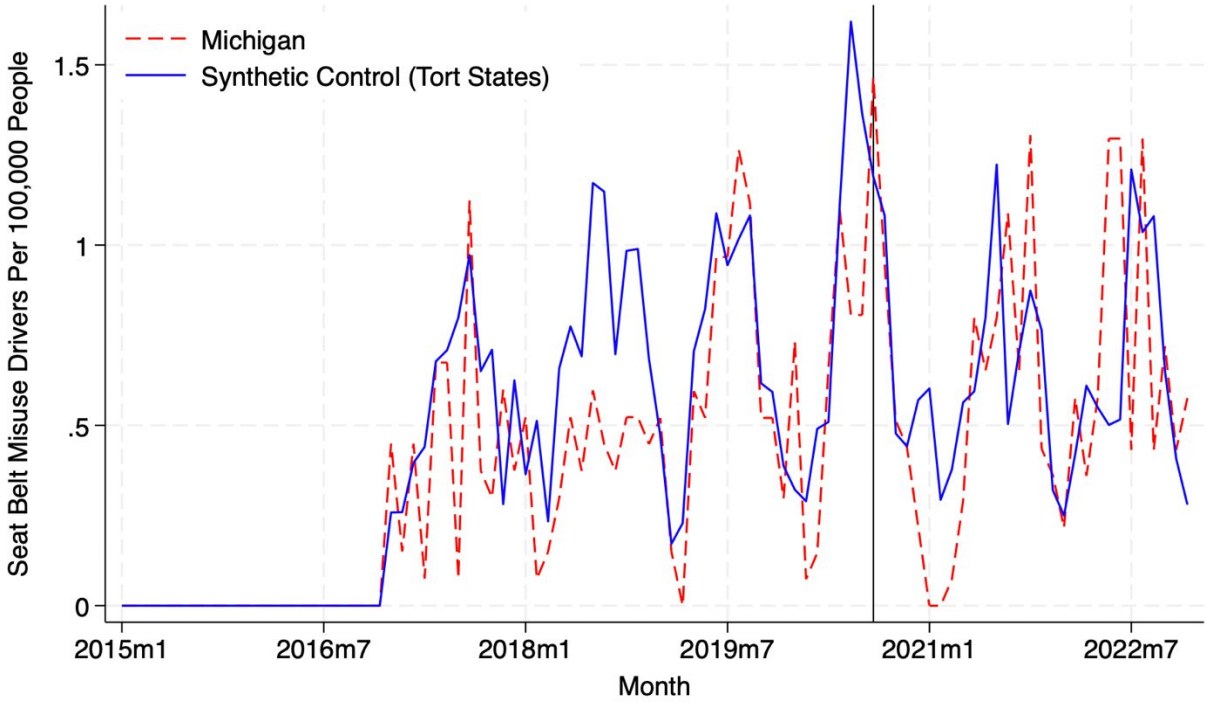


Figure 29. Michigan vs Synthetic Controls Group of Tort States (Seat Belt Use Per 100,000 People)

Outcome Variables Per 100 million VMT

Fatal Accidents

Table 24. Fatal Accidents Per 100 million VMT for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.121***	0.121***	0.129**	0.118***
	(0.0213)	(0.00266)	(0.0426)	(0.0243)
Light Condition	0.0409	-0.149**	0.0394	0.0375
	(0.0301)	(0.0295)	(0.0563)	(0.0350)
Weather Condition	-0.0435**	-0.0494*	-0.0653	-0.0346
	(0.0203)	(0.0120)	(0.0504)	(0.0206)
Vision Obstruction	-0.0768	-0.0675	-0.0555	-0.0735
	(0.0522)	(0.135)	(0.0833)	(0.0608)
Ruralness of Accident	-0.0675*	-0.156	-0.0372	-0.0726*
	(0.0345)	(0.128)	(0.0739)	(0.0393)
Constant	0.733***	0.802**	0.724***	0.720***
	(0.0551)	(0.144)	(0.0961)	(0.0633)
Observations	4,841	288	1,151	3,882
R-squared	0.122	0.727	0.204	0.122
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25. Fatal Accidents Per 100 million VMT

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
2020m7	0.555	0.116	0.000	-0.071	1.000	1.000	-0.054	0.853	0.912
2020m8	0.504	0.395	0.140	-0.044	1.000	1.000	0.673	0.147	0.147
2020m9	0.268	0.558	0.302	-0.042	1.000	1.000	-0.059	0.853	0.912
2020m10	0.256	0.605	0.372	-0.172	0.800	0.800	-0.035	0.912	0.912
2020m11	0.445	0.256	0.093	-0.010	0.900	0.900	0.508	0.206	0.206
2020m12	0.089	0.791	0.791	-0.468	0.700	0.500	-0.061	0.765	0.765
2021m1	0.066	0.884	0.884	-0.314	0.600	0.200	-0.309	0.471	0.500
2021m2	0.251	0.349	0.163	-0.349	0.700	0.600	-0.166	0.647	0.588
2021m3	0.264	0.395	0.186	-0.174	0.800	0.800	-0.277	0.382	0.500
2021m4	0.440	0.233	0.070	-0.076	1.000	1.000	-0.337	0.294	0.412
2021m5	0.396	0.419	0.163	-0.067	1.000	1.000	0.327	0.471	0.529
2021m6	0.309	0.349	0.209	-0.122	0.700	0.800	0.193	0.529	0.500
2021m7	0.469	0.326	0.070	-0.086	0.900	0.900	0.318	0.441	0.559
2021m8	0.383	0.419	0.233	-0.079	1.000	1.000	0.555	0.235	0.176
2021m9	0.347	0.302	0.163	-0.122	0.900	1.000	0.085	0.853	0.882
2021m10	0.350	0.512	0.395	-0.185	0.700	0.700	0.404	0.412	0.529
2021m11	0.281	0.535	0.349	-0.116	0.900	0.900	-0.039	0.971	0.971
2021m12	0.236	0.721	0.558	-0.155	0.700	0.600	0.328	0.471	0.588
2022m1	0.135	0.674	0.581	-0.230	0.600	0.600	0.647***	0.000	0.059
2022m2	-0.027	0.953	0.930	-0.410	0.600	0.200	0.713***	0.000	0.000
2022m3	-0.020	0.977	0.930	-0.366	0.500	0.100	-0.319	0.382	0.382
2022m4	0.109	0.814	0.814	-0.263	0.600	0.600	0.265	0.529	0.500
2022m5	0.284	0.512	0.256	0.066	0.900	0.900	0.755***	0.000	0.029
2022m6	0.368	0.302	0.047	0.067	0.900	0.900	0.708*	0.059	0.000
2022m7	0.299	0.349	0.209	-0.064	0.800	0.800	-0.129	0.676	0.706
2022m8	0.091	0.860	0.837	-0.178	0.600	0.400	0.233	0.588	0.676
2022m9	0.411	0.302	0.070	-0.022	1.000	1.000	-0.210	0.529	0.529
2022m10	0.081	0.953	0.930	-0.236	0.700	0.600	0.438	0.235	0.176
2022m11	0.123	0.884	0.721	-0.375	0.600	0.400	0.578**	0.029	0.000
2022m12	0.100	0.860	0.837	-0.173	0.700	0.700	0.592	0.147	0.147

*** p<0.01, ** p<0.05, * p<0.1

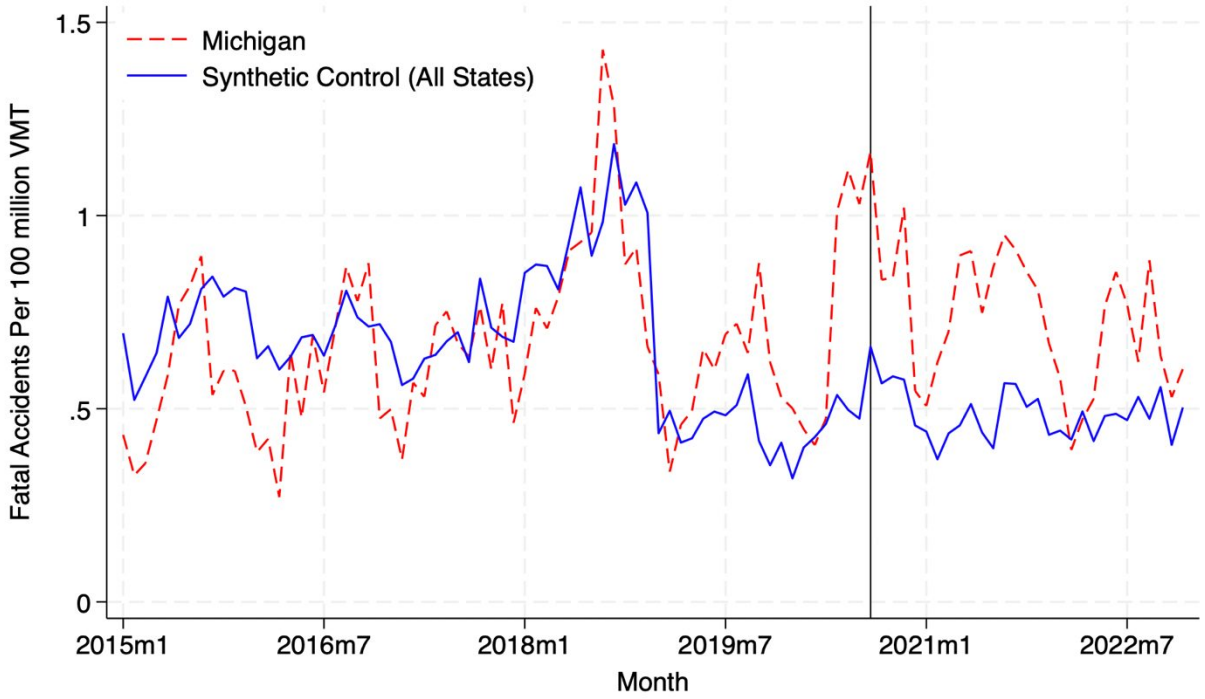


Figure 30. Michigan vs Synthetic Controls Group of All States (Fatal Accidents Per 100 million VMT)

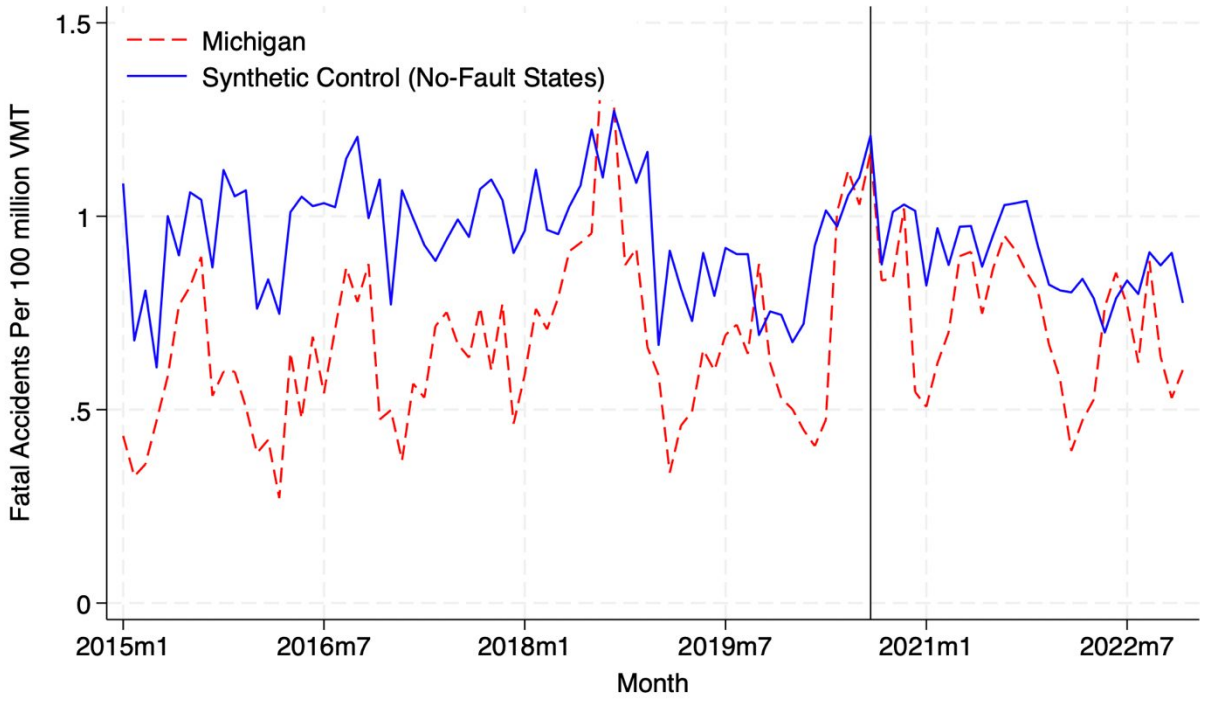


Figure 31. Michigan vs Synthetic Controls Group of No-Fault (Fatal Accidents Per 100 million VMT)

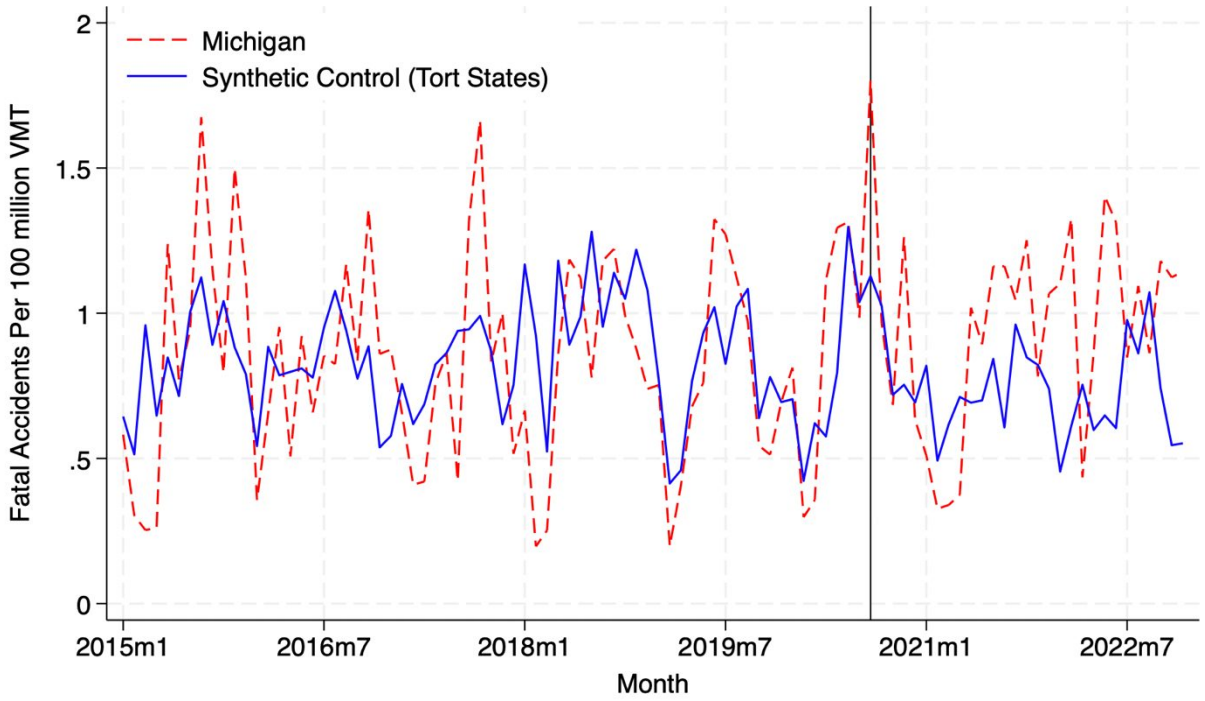


Figure 32. Michigan vs Synthetic Controls Group of Tort States (Fatal Accidents Per 100 million VMT)

Fatalities

Table 26. Fatalities Per 100 million VMT for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.123***	0.123***	0.141**	0.117***
	(0.0233)	(0.00359)	(0.0455)	(0.0266)
Light Condition	0.0575*	-0.126*	0.0307	0.0590
	(0.0320)	(0.0420)	(0.0580)	(0.0375)
Weather Condition	-0.0481**	-0.0651*	-0.0713	-0.0382*
	(0.0216)	(0.0161)	(0.0531)	(0.0220)
Vision Obstruction	-0.0780	-0.0427	-0.103	-0.0619
	(0.0555)	(0.174)	(0.0819)	(0.0682)
Ruralness of Accident	-0.0511	-0.186	-0.0321	-0.0533
	(0.0412)	(0.130)	(0.0810)	(0.0479)
Constant	0.775***	0.856**	0.791***	0.755***
	(0.0614)	(0.172)	(0.105)	(0.0702)
Observations	4,841	288	1,151	3,882
R-squared	0.114	0.710	0.204	0.113
Number of state	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 27. Fatalities Per 100 million VMT

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
2020m7	0.558	0.163	0.023	-0.099	1.000	1.000	-0.056	0.882	0.882
2020m8	0.549	0.395	0.093	-0.052	0.800	0.800	0.774	0.118	0.147
2020m9	0.261	0.628	0.326	-0.091	1.000	1.000	-0.007	0.971	0.971
2020m10	0.240	0.605	0.372	-0.214	0.800	0.800	-0.050	0.912	0.912
2020m11	0.551	0.209	0.023	0.074	0.800	0.800	0.546	0.265	0.176
2020m12	0.112	0.767	0.837	-0.460	0.700	0.500	-0.267	0.559	0.588
2021m1	0.049	0.977	0.907	-0.366	0.300	0.200	-0.255	0.471	0.500
2021m2	0.224	0.488	0.302	-0.433	0.600	0.600	-0.166	0.588	0.647
2021m3	0.273	0.465	0.279	-0.193	0.800	0.800	-0.395	0.235	0.294
2021m4	0.464	0.233	0.093	-0.107	1.000	1.000	-0.374	0.265	0.324
2021m5	0.396	0.419	0.186	-0.086	1.000	1.000	0.725	0.235	0.147
2021m6	0.352	0.326	0.209	-0.199	0.800	0.800	0.107	0.735	0.794
2021m7	0.471	0.326	0.093	-0.108	0.900	0.900	0.288	0.618	0.676
2021m8	0.385	0.419	0.233	-0.142	0.900	0.900	0.519	0.294	0.147
2021m9	0.352	0.326	0.140	-0.132	0.800	0.700	0.106	0.824	0.853
2021m10	0.344	0.558	0.419	-0.230	0.700	0.700	0.535	0.353	0.441
2021m11	0.278	0.581	0.442	-0.134	0.900	0.900	0.023	0.971	0.971
2021m12	0.235	0.744	0.558	-0.175	0.600	0.600	0.245	0.706	0.676
2022m1	0.134	0.767	0.605	-0.265	0.600	0.600	0.629*	0.059	0.088
2022m2	0.002	1.000	1.000	-0.403	0.600	0.200	0.659*	0.088	0.088
2022m3	-0.025	0.907	0.907	-0.404	0.600	0.000	-0.370	0.294	0.265
2022m4	0.077	0.860	0.860	-0.305	0.500	0.500	0.200	0.618	0.647
2022m5	0.273	0.605	0.279	0.053	0.900	0.900	0.774***	0.000	0.029
2022m6	0.448	0.279	0.000	0.115	0.800	0.800	0.612	0.118	0.000
2022m7	0.308	0.372	0.256	-0.091	0.900	0.900	-0.362	0.324	0.353
2022m8	0.064	0.907	0.907	-0.185	0.600	0.500	0.348	0.412	0.441
2022m9	0.423	0.326	0.116	-0.019	1.000	1.000	-0.361	0.324	0.353
2022m10	0.082	0.930	0.907	-0.235	0.800	0.600	0.396	0.441	0.353
2022m11	0.133	0.884	0.791	-0.392	0.600	0.400	0.637	0.147	0.029
2022m12	0.120	0.791	0.767	-0.164	0.700	0.700	0.856	0.147	0.088

*** p<0.01, ** p<0.05, * p<0.1

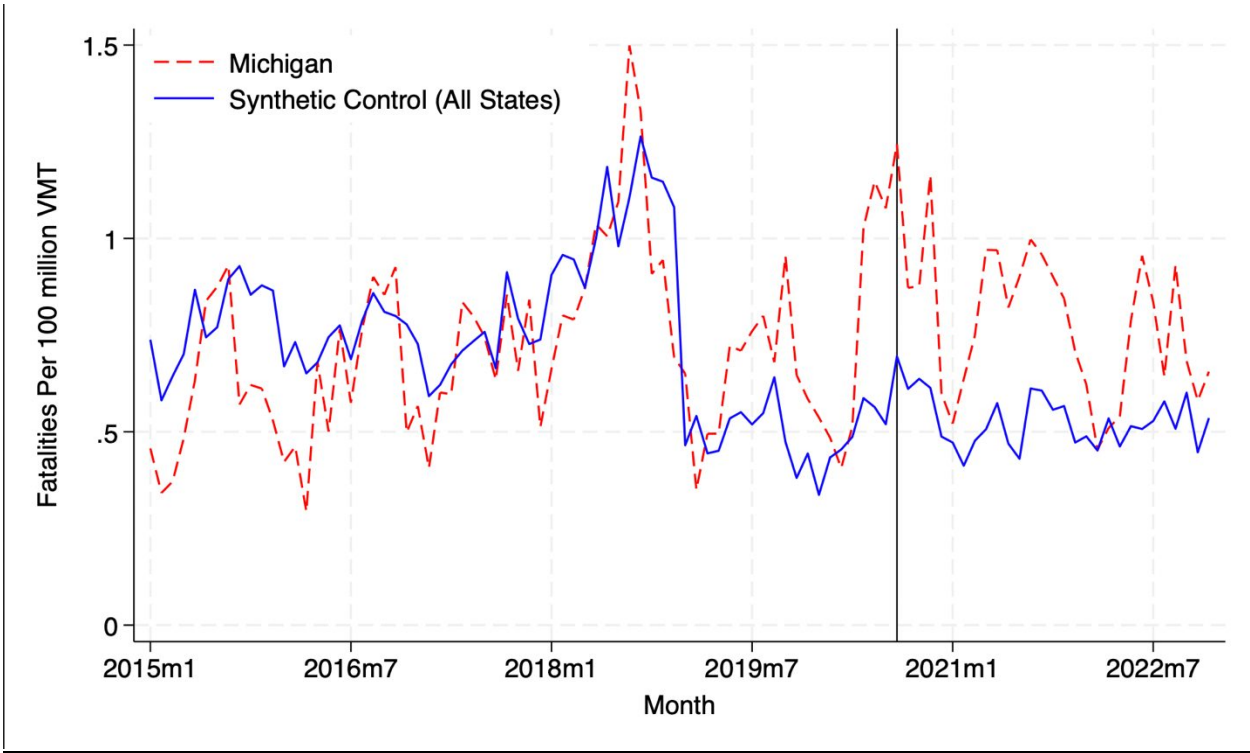


Figure 33. Michigan vs Synthetic Controls Group of All States (Fatalities Per 100 million VMT)

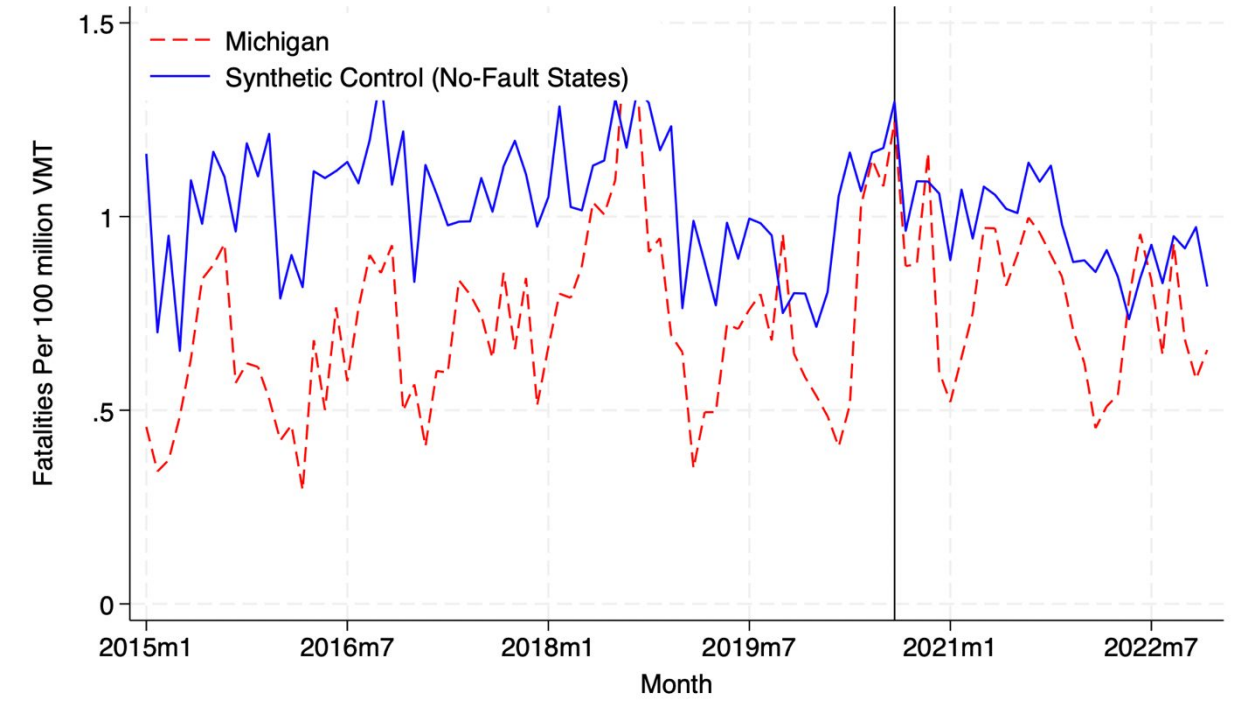


Figure 34. Michigan vs Synthetic Controls Group of No-Fault (Fatal Accidents Per 100 million VMT)

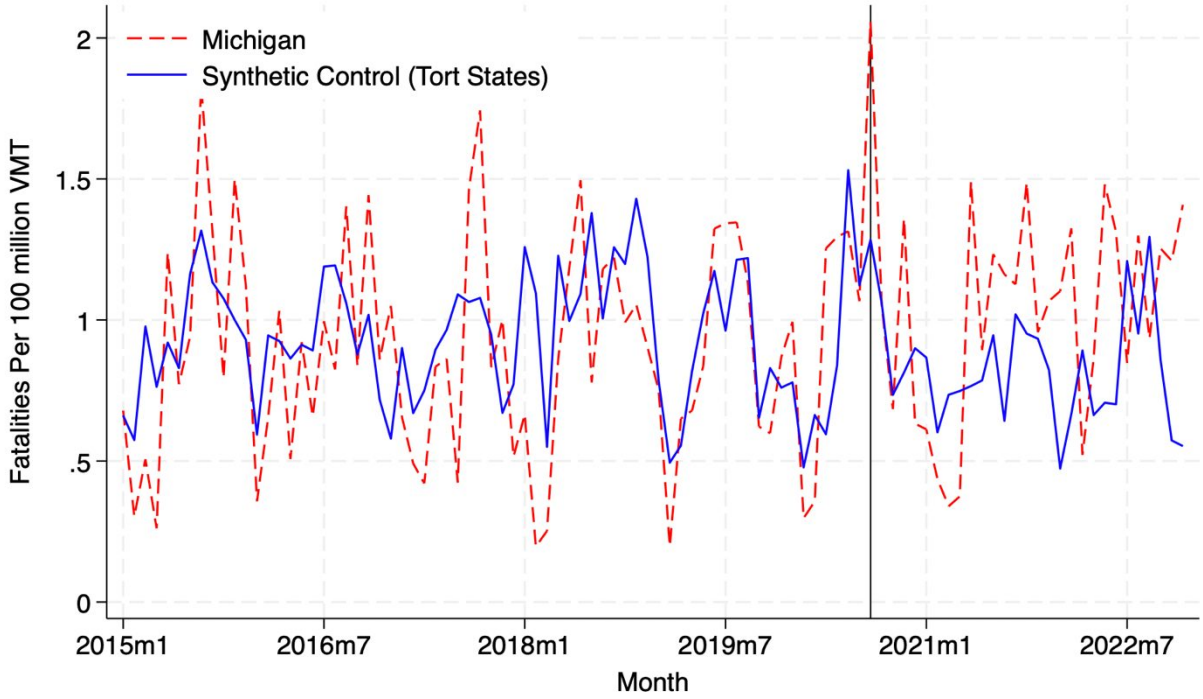


Figure 35. Michigan vs Synthetic Controls Group of Tort States (Fatal Accidents Per 100 million VMT)

Adjusted Accidents

Table 28. Adjusted Accidents Per 100 million VMT for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.215***	0.197**	0.213**	0.213***
	(0.0363)	(0.0209)	(0.0766)	(0.0412)
Light Condition	-0.00449	-0.242	-0.0125	-0.00802
	(0.0572)	(0.0948)	(0.117)	(0.0667)
Weather Condition	-0.0562**	-0.0904	-0.0592*	-0.0520*
	(0.0219)	(0.0340)	(0.0300)	(0.0277)
Vision Obstruction	-0.116	-0.0177	-0.165	-0.0910
	(0.0993)	(0.100)	(0.148)	(0.125)
Ruralness of Accident	-0.0760	-0.166	-0.117	-0.0616
	(0.0506)	(0.173)	(0.131)	(0.0529)
Constant	1.092***	1.130**	1.114***	1.064***
	(0.0789)	(0.194)	(0.125)	(0.0913)
Observations	4,835	288	1,151	3,876
R-squared	0.258	0.731	0.338	0.252
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 29. Adjusted Accidents Per 100 million VMT

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
2020m7	0.661	0.256	0.070	-0.355	0.800	0.800	-0.123	0.794	0.853
2020m8	0.606	0.395	0.163	-0.242	0.700	0.700	1.395***	0.000	0.029
2020m9	0.453	0.419	0.186	-0.062	1.000	1.000	-0.030	0.941	1.000
2020m10	0.247	0.721	0.465	-0.367	0.600	0.700	0.147	0.853	0.882
2020m11	0.736	0.233	0.000	-0.055	0.800	0.800	0.732	0.235	0.324
2020m12	0.082	0.884	0.837	-0.849	0.600	0.500	0.042	0.912	0.912
2021m1	0.124	0.837	0.814	-0.446	0.500	0.400	-0.477	0.500	0.529
2021m2	0.434	0.256	0.116	-0.496	0.600	0.600	-0.312	0.471	0.647
2021m3	0.425	0.419	0.186	-0.291	0.800	0.900	-0.214	0.706	0.735
2021m4	0.627	0.233	0.023	-0.185	1.000	1.000	-0.436	0.382	0.441
2021m5	0.521	0.442	0.209	-0.118	1.000	1.000	0.713	0.265	0.382
2021m6	0.395	0.395	0.326	-0.258	0.700	0.700	0.265	0.529	0.647
2021m7	0.586	0.395	0.116	-0.262	0.900	0.900	0.663	0.324	0.294
2021m8	0.452	0.442	0.326	-0.264	0.800	0.900	0.899	0.176	0.206
2021m9	0.484	0.326	0.140	-0.252	0.900	0.900	0.103	0.912	0.971
2021m10	0.534	0.465	0.372	-0.311	0.800	0.700	0.764	0.324	0.441
2021m11	0.463	0.465	0.302	-0.144	0.900	0.900	0.001	1.000	1.000
2021m12	0.400	0.698	0.442	-0.241	0.800	0.800	0.417	0.618	0.794
2022m1	0.215	0.674	0.535	-0.324	0.700	0.700	1.207***	0.000	0.029
2022m2	-0.069	0.930	0.930	-0.716	0.700	0.200	1.171***	0.000	0.000
2022m3	-0.068	0.791	0.744	-0.605	0.500	0.100	-0.335	0.529	0.588
2022m4	0.115	0.791	0.791	-0.490	0.500	0.400	0.443	0.382	0.412
2022m5	0.281	0.791	0.488	-0.057	0.900	0.900	1.379***	0.000	0.029
2022m6	0.456	0.326	0.116	-0.093	0.900	0.900	1.187**	0.029	0.000
2022m7	0.414	0.326	0.163	-0.183	0.800	0.800	-0.105	0.794	0.824
2022m8	0.129	0.907	0.837	-0.319	0.400	0.300	0.209	0.706	0.824
2022m9	0.545	0.302	0.047	-0.193	0.800	0.900	-0.335	0.471	0.588
2022m10	0.162	0.860	0.860	-0.407	0.800	0.600	0.941	0.147	0.029
2022m11	0.167	0.860	0.744	-0.654	0.600	0.400	1.276***	0.000	0.000
2022m12	0.137	0.907	0.860	-0.328	0.500	0.700	1.221	0.118	0.118

*** p<0.01, ** p<0.05, * p<0.1

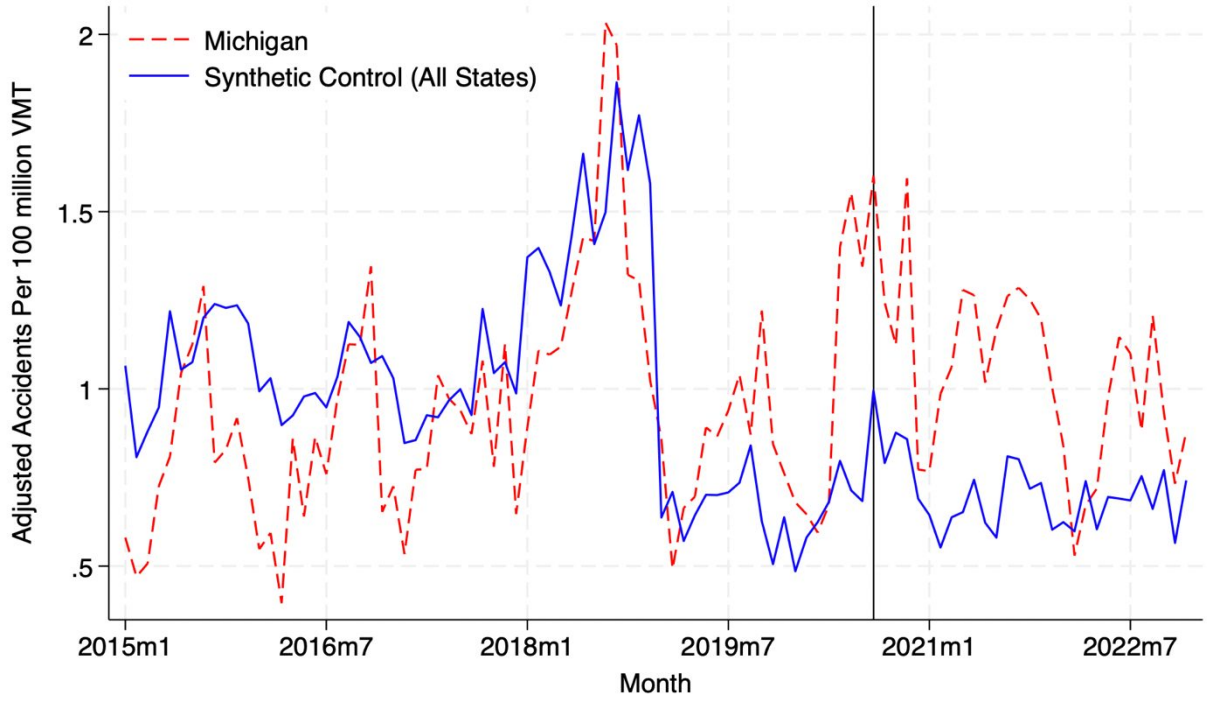


Figure 36. Michigan vs Synthetic Controls Group of All States (Adjusted Accidents Per 100 million VMT)

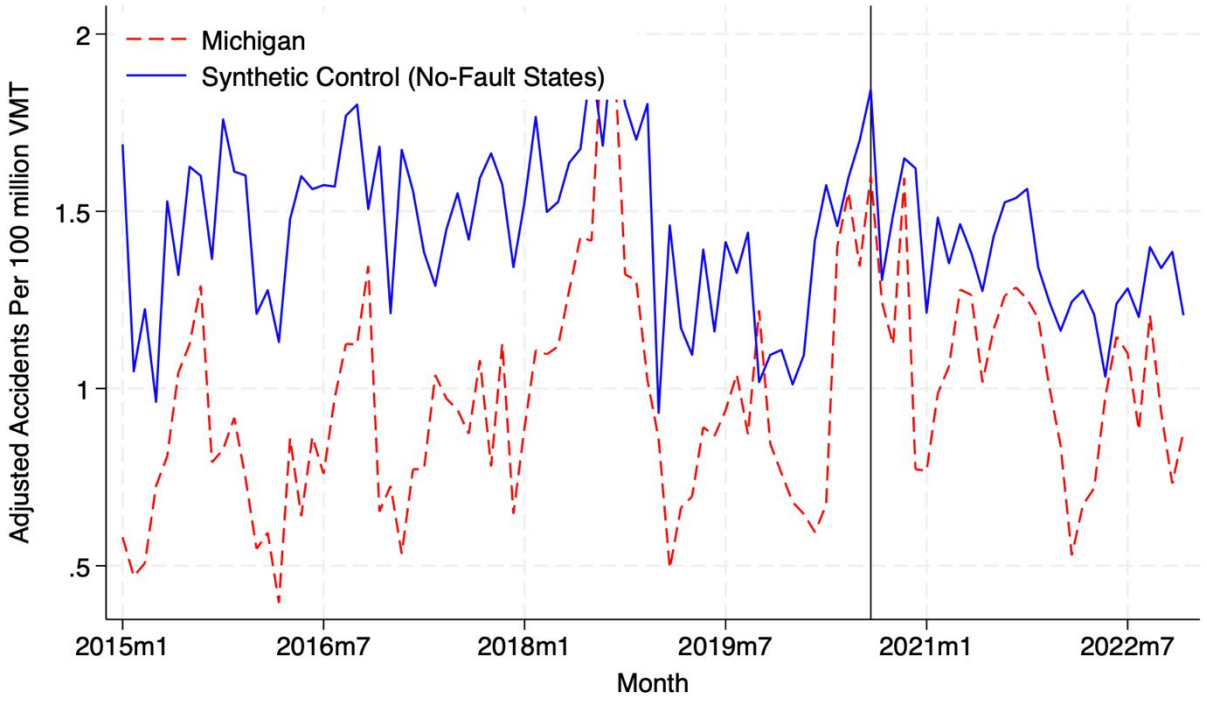


Figure 37. Michigan vs Synthetic Controls Group of No-Fault (Adjusted Accidents Per 100 million VMT)

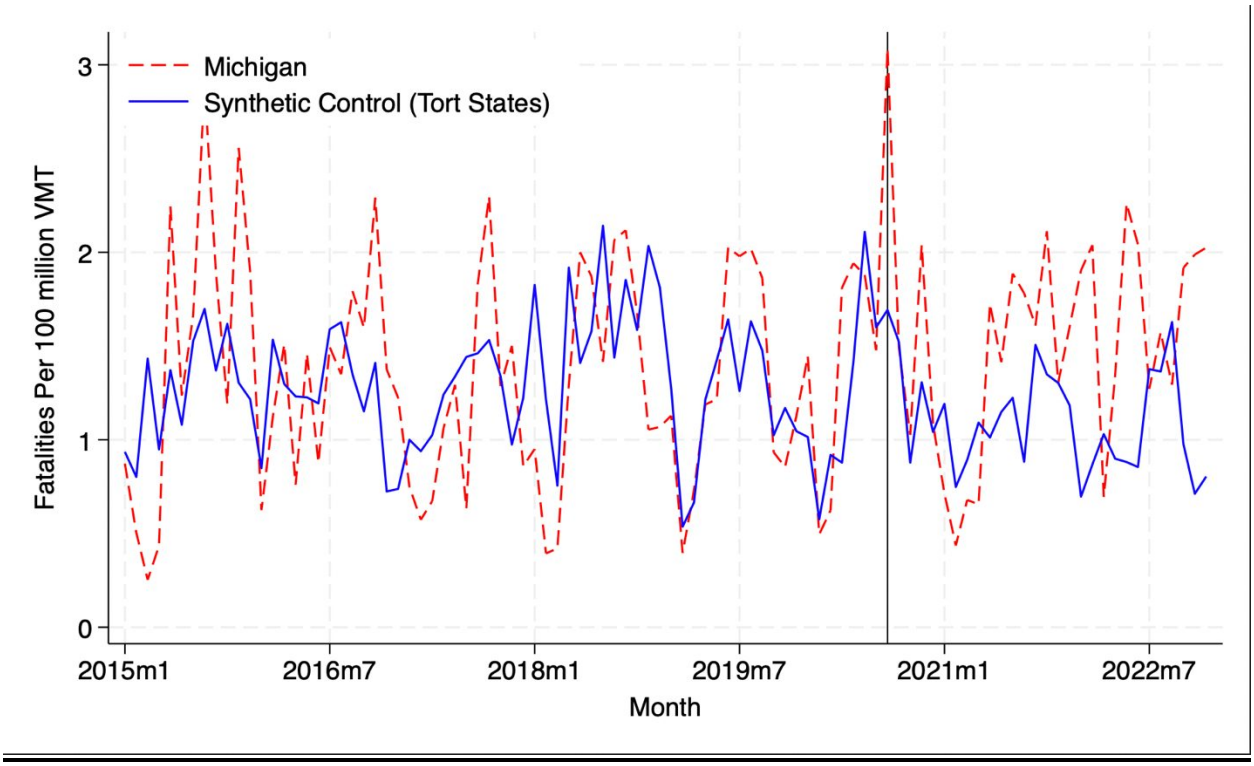


Figure 38. Michigan vs Synthetic Controls Group of Tort (Adjusted Accidents Per 100 million VMT)

Distracted Drivers

Table 30. Distracted Drivers Per 100 million VMT for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0305***	0.0600***	0.0359**	0.0298***
	(0.00873)	(0.00256)	(0.0160)	(0.0102)
Light Condition	-0.0577***	-0.149**	-0.0472*	-0.0621***
	(0.0159)	(0.0319)	(0.0232)	(0.0190)
Weather Condition	-0.0244***	-0.0147	-0.0167	-0.0276***
	(0.00792)	(0.0195)	(0.0114)	(0.00975)
Vision Obstruction	-0.117***	0.00742	-0.0899**	-0.120***
	(0.0347)	(0.0432)	(0.0388)	(0.0445)
Ruralness of Accident	0.00612	-0.125	-0.0293	0.0140
	(0.0187)	(0.0923)	(0.0207)	(0.0228)
Constant	0.245***	0.273***	0.197***	0.256***
	(0.0222)	(0.0207)	(0.0396)	(0.0266)
Observations	4,841	288	1,151	3,882
R-squared	0.094	0.590	0.162	0.096
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 31. Distracted Drivers Per 100 million VMT

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
Jul 2020	-0.005	0.930	0.884	-0.060	0.600	0.400	0.002	0.941	0.971
Aug 2020	0.013	0.791	0.767	-0.056	0.600	0.700	0.209*	0.088	0.029
Sep 2020	0.041	0.512	0.302	-0.041	0.700	0.600	0.066	0.353	0.353
Oct 2020	0.017	0.767	0.674	-0.121	0.500	0.300	0.083	0.265	0.353
Nov 2020	-0.029	0.605	0.326	-0.052	0.700	0.800	-0.095*	0.088	0.059
Dec 2020	0.017	0.605	0.372	-0.082	0.400	0.300	-0.026	0.618	0.647
Jan 2021	-0.040	0.535	0.256	-0.150	0.400	0.000	0.165*	0.059	0.000
Feb 2021	0.016	0.767	0.698	-0.143	0.400	0.300	-0.035*	0.559	0.676
Mar 2021	-0.001	0.930	0.930	-0.088	0.600	0.500	-0.074	0.353	0.382
Apr 2021	0.054	0.372	0.070	-0.032	0.900	0.900	-0.013	0.912	0.912
May 2021	-0.022	0.744	0.605	-0.097	0.700	0.400	0.000	1.000	1.000
Jun 2021	0.066	0.326	0.000	0.001	1.000	1.000	0.040	0.618	0.618
Jul 2021	0.008	0.930	0.907	-0.066	0.600	0.600	-0.021	0.647	0.676
Aug 2021	0.074	0.349	0.047	0.000	1.000	1.000	0.053	0.529	0.500
Sep 2021	0.025	0.628	0.512	-0.076	0.500	0.500	0.054	0.353	0.441
Oct 2021	0.049	0.512	0.279	-0.099	0.700	0.600	0.113	0.353	0.324
Nov 2021	0.012	0.860	0.791	-0.095	0.300	0.500	0.061	0.500	0.500
Dec 2021	0.041	0.465	0.279	-0.047	0.800	0.900	-0.098	0.265	0.324
Jan 2022	0.025	0.721	0.512	-0.087	0.500	0.700	-0.125	0.176	0.059
Feb 2022	0.006	0.953	0.907	-0.049	0.700	0.600	0.029	0.647	0.794
Mar 2022	-0.022	0.628	0.419	-0.103	0.200	0.000	-0.030	0.618	0.735
Apr 2022	0.057	0.419	0.070	-0.017	1.000	1.000	-0.092	0.235	0.235
May 2022	0.013	0.767	0.674	-0.068	0.700	0.800	0.136	0.206	0.176
Jun 2022	0.003	0.953	0.930	-0.078	0.700	0.400	0.034	0.735	0.735
Jul 2022	0.019	0.698	0.605	-0.076	0.700	0.800	0.043	0.471	0.647
Aug 2022	0.011	0.791	0.651	-0.067	0.500	0.400	-0.099	0.118	0.147
Sep 2022	-0.014	0.814	0.674	-0.080	0.600	0.400	0.015	0.794	0.824
Oct 2022	0.035	0.581	0.349	-0.023	0.900	1.000	0.147	0.206	0.088
Nov 2022	0.008	0.860	0.744	-0.065	0.700	0.600	-0.038	0.412	0.588
Dec 2022	-0.029	0.581	0.349	-0.119	0.500	0.300	-0.016	0.824	0.853

*** p<0.01, ** p<0.05, * p<0.1

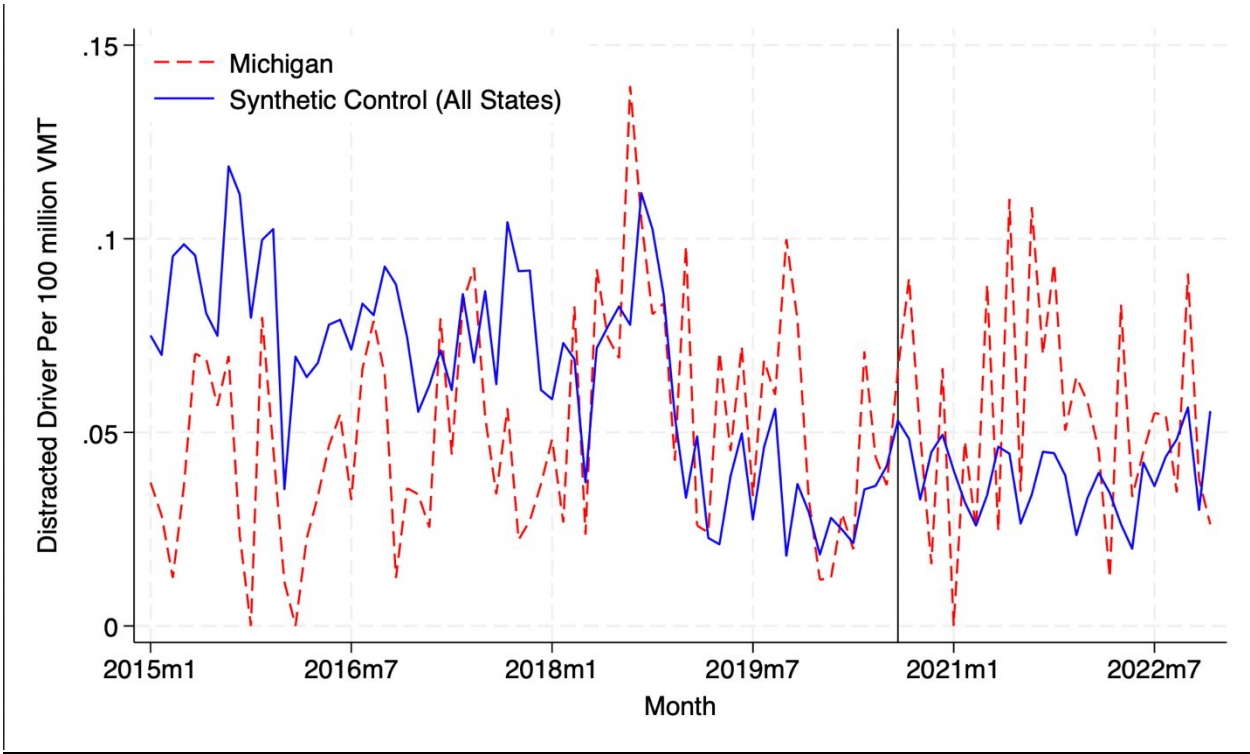


Figure 39. Michigan vs Synthetic Controls Group of All States (Distracted Drivers Per 100 million VMT)

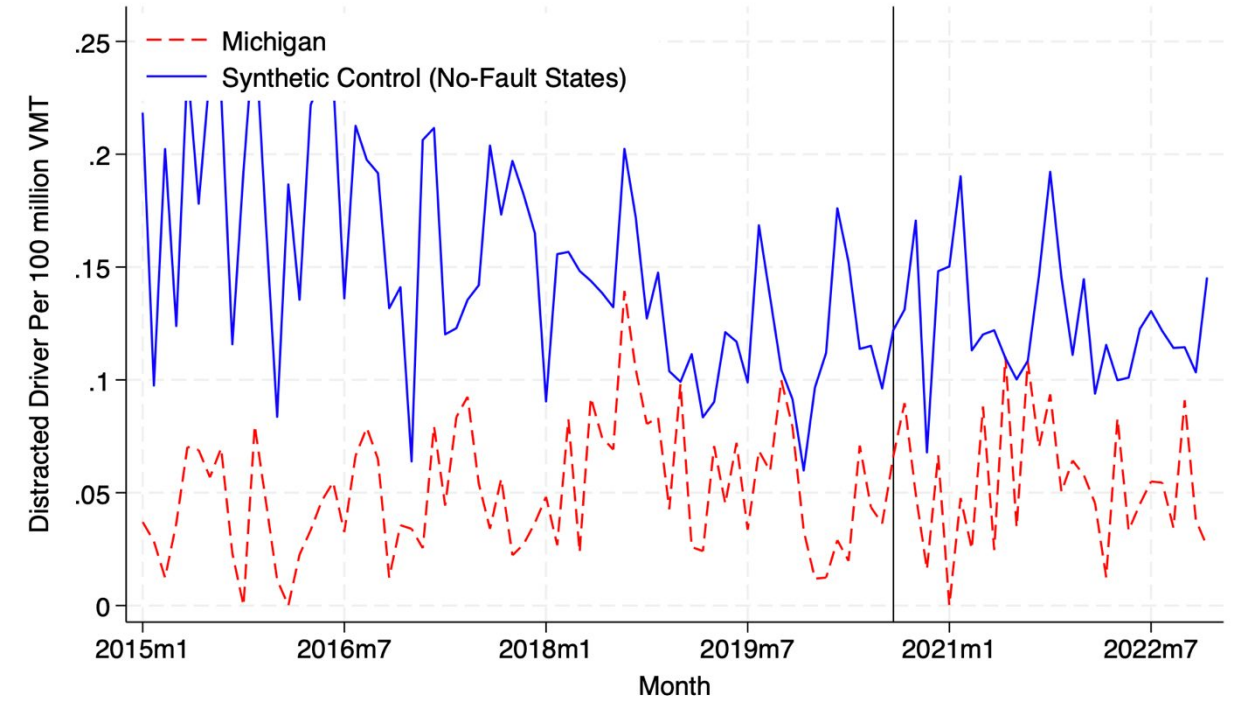


Figure 40. Michigan vs Synthetic Controls Group of No-Fault (Distracted Drivers Per 100 million VMT)

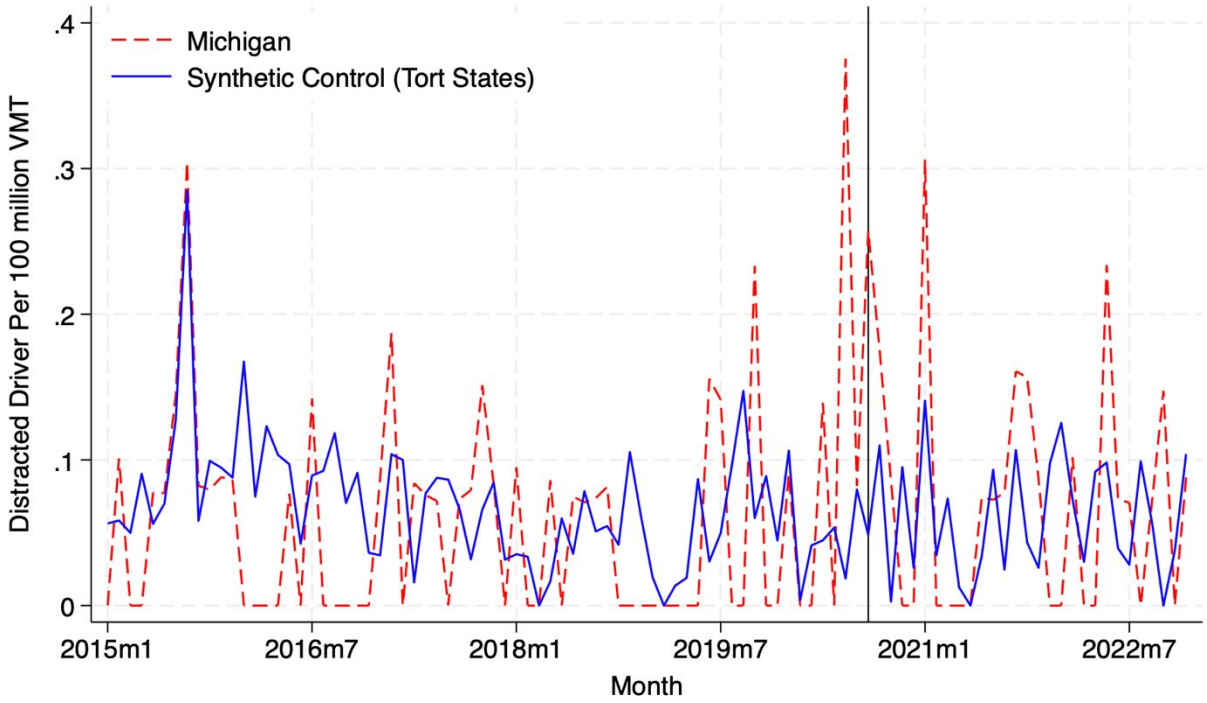


Figure 41. Michigan vs Synthetic Controls Group of Tort (Distracted Drivers Per 100 million VMT)

Drunk Drivers

Table 32. Drunk Drivers Per 100 million VMT for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0107**	-0.0437	0.0212**	0.00806
	(0.00449)	(0.0229)	(0.00721)	(0.00519)
Light Condition	-0.0104	-0.00796	-0.0161	-0.00884
	(0.0110)	(0.0371)	(0.0183)	(0.0131)
Weather Condition	-0.00674	0.00684	-0.0124**	-0.00457
	(0.00495)	(0.0166)	(0.00430)	(0.00660)
Vision Obstruction	-0.0597**	-0.137***	-0.0418	-0.0613*
	(0.0296)	(0.00704)	(0.0319)	(0.0342)
Ruralness of Accident	-0.0207*	-0.0919*	-0.0252	-0.0236*
	(0.0111)	(0.0288)	(0.0168)	(0.0135)
Constant	0.0887***	0.0688*	0.0917***	0.0856***
	(0.0120)	(0.0221)	(0.0194)	(0.0140)
Observations	4,841	288	1,151	3,882
R-squared	0.052	0.620	0.149	0.054
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 33. Drunk Drivers Per 100 million VMT

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
2020m7	0.048	0.395	0.349	0.033	0.500	0.400	0.361**	0.029	0.059
2020m8	-0.015	0.907	0.837	-0.060	0.700	0.400	0.018	0.853	0.971
2020m9	-0.005	0.977	0.977	-0.010	1.000	1.000	-0.236	0.118	0.235
2020m10	0.008	0.860	0.837	-0.013	0.900	0.800	-0.198*	0.088	0.147
2020m11	0.024	0.744	0.698	-0.046	0.600	0.600	-0.019	0.882	1.000
2020m12	0.021	0.744	0.721	0.006	0.900	0.900	0.011	0.735	0.853
2021m1	0.002	0.977	0.977	0.018	0.700	0.600	-0.059	0.412	0.647
2021m2	0.024	0.814	0.767	-0.003	0.900	0.900	0.000	1.000	1.000
2021m3	-0.021	0.721	0.698	-0.011	0.900	0.600	-0.026	0.706	0.765
2021m4	0.003	0.884	0.860	-0.060	0.500	0.300	-0.013	0.706	0.794
2021m5	-0.055	0.488	0.372	-0.008	1.000	1.000	0.109	0.206	0.529
2021m6	0.016	0.791	0.767	-0.013	0.700	0.600	0.223***	0.000	0.088
2021m7	0.012	0.837	0.744	-0.035	0.600	0.400	0.092	0.324	0.676
2021m8	-0.037	0.744	0.674	-0.049	0.900	0.600	0.387***	0.000	0.000
2021m9	-0.032	0.674	0.558	-0.031	0.800	0.800	0.089	0.235	0.471
2021m10	0.056	0.326	0.302	0.049	0.700	0.400	0.078	0.294	0.676
2021m11	-0.042	0.605	0.512	-0.024	0.600	0.600	0.002	1.000	1.000
2021m12	-0.039	0.628	0.512	-0.020	0.800	0.700	0.073	0.324	0.618
2022m1	-0.116	0.302	0.163	-0.098	0.200	0.000	0.361***	0.000	0.088
2022m2	-0.030	0.628	0.605	-0.036	0.500	0.200	0.408***	0.000	0.029
2022m3	-0.067	0.465	0.395	-0.075	0.300	0.200	0.019	0.912	0.941
2022m4	-0.008	0.814	0.791	-0.020	0.500	0.500	-0.014	0.794	0.882
2022m5	-0.002	0.977	0.977	-0.008	0.900	0.900	0.219**	0.029	0.265
2022m6	-0.001	1.000	1.000	-0.028	0.600	0.500	0.131	0.176	0.500
2022m7	-0.028	0.767	0.628	-0.044	0.400	0.100	-0.009	0.882	0.971
2022m8	-0.056	0.395	0.349	-0.023	0.900	0.800	0.192	0.118	0.206
2022m9	0.008	0.977	0.977	0.031	0.600	0.300	0.007	0.971	1.000
2022m10	-0.049	0.535	0.372	-0.015	0.800	0.800	0.059	0.471	0.676
2022m11	-0.022	0.791	0.721	-0.026	0.600	0.200	-0.007	0.971	0.971
2022m12	-0.007	0.977	0.953	-0.019	0.600	0.500	0.399***	0.000	0.000

*** p<0.01, ** p<0.05, * p<0.1

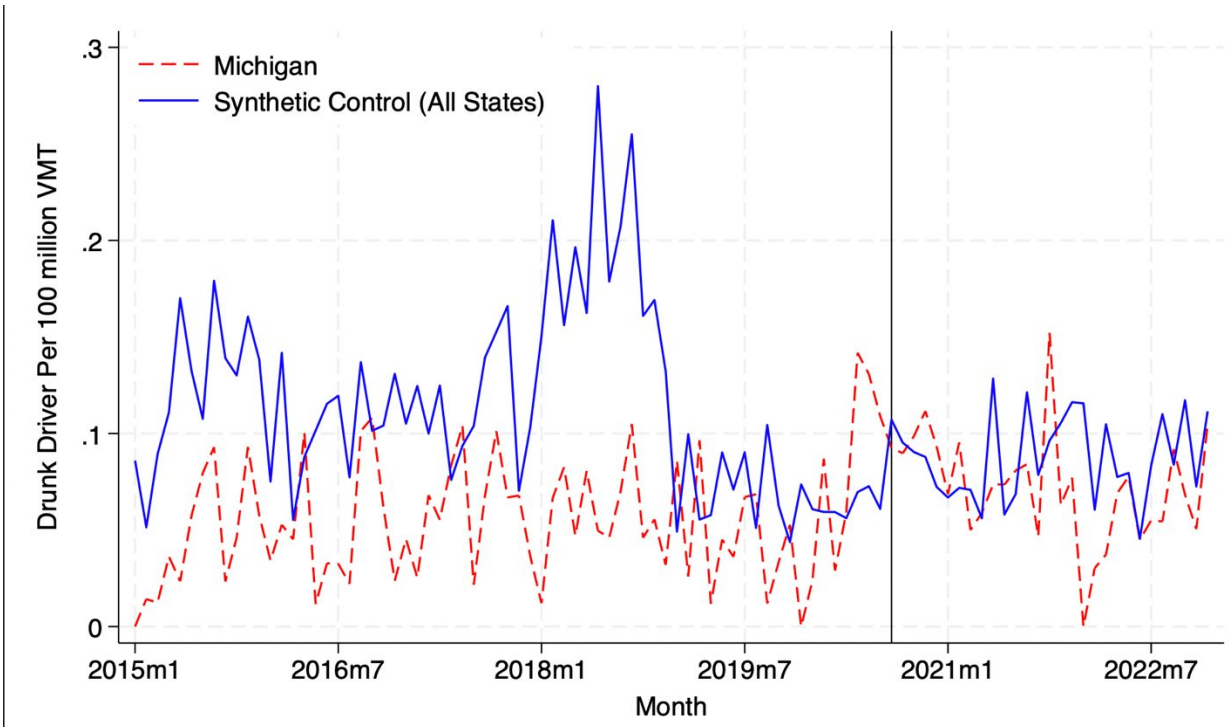


Figure 42. Michigan vs Synthetic Controls Group of All States (Drunk Drivers Per 100 million VMT)

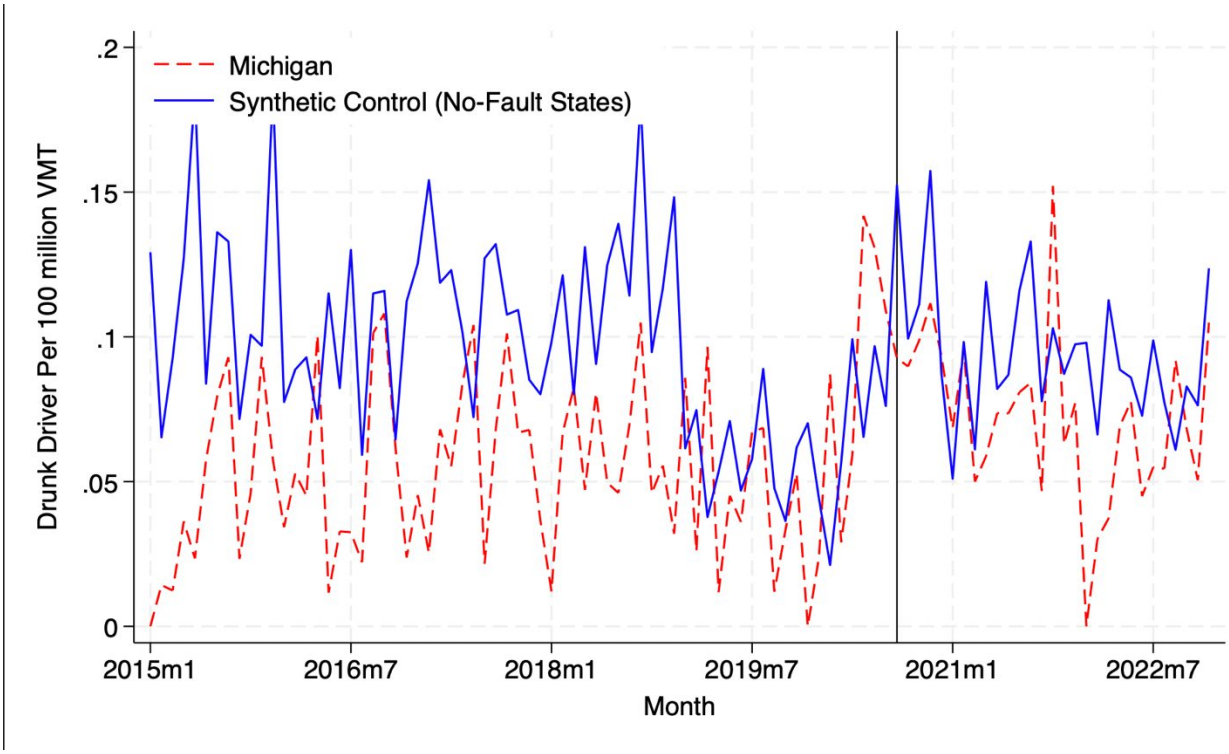


Figure 43. Michigan vs Synthetic Controls Group of No-Fault (Drunk Drivers Per 100 million VMT)

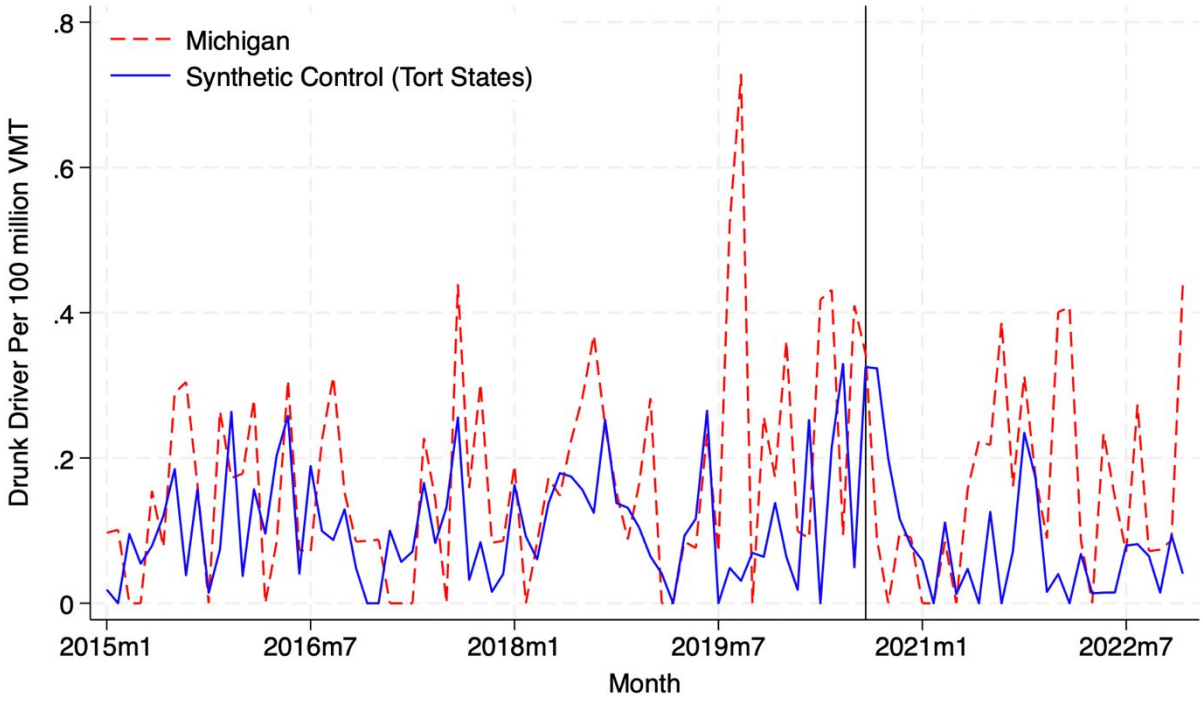


Figure 44. Michigan vs Synthetic Controls Group of Tort States (Drunk Drivers Per 100 million VMT)

Impaired Drivers

Table 34. Impaired Drivers Per 100 million VMT for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0305***	0.0600***	0.0359**	0.0298***
	(0.00873)	(0.00256)	(0.0160)	(0.0102)
Light Condition	-0.0577***	-0.149**	-0.0472*	-0.0621***
	(0.0159)	(0.0319)	(0.0232)	(0.0190)
Weather Condition	-0.0244***	-0.0147	-0.0167	-0.0276***
	(0.00792)	(0.0195)	(0.0114)	(0.00975)
Vision Obstruction	-0.117***	0.00742	-0.0899**	-0.120***
	(0.0347)	(0.0432)	(0.0388)	(0.0445)
Ruralness of Accident	0.00612	-0.125	-0.0293	0.0140
	(0.0187)	(0.0923)	(0.0207)	(0.0228)
Constant	0.245***	0.273***	0.197***	0.256***
	(0.0222)	(0.0207)	(0.0396)	(0.0266)
Observations	4,841	288	1,151	3,882
R-squared	0.094	0.590	0.162	0.096
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 35. Impaired Drivers Per 100 million VMT

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
2020m7	0.359**	0.023	0.000	0.272***	0.000	0.000	-0.242	0.118	0.265
2020m8	0.206	0.233	0.233	0.141	0.400	0.300	0.409***	0.000	0.147
2020m9	0.093	0.419	0.535	0.028	0.800	0.800	-0.302*	0.088	0.088
2020m10	0.051	0.581	0.605	-0.034	0.900	0.900	0.194	0.118	0.324
2020m11	0.301*	0.093	0.000	0.269***	0.000	0.000	0.194	0.353	0.559
2020m12	0.042	0.814	0.744	-0.110	0.800	0.800	0.102	0.500	0.647
2021m1	0.075	0.674	0.674	-0.050	0.900	0.900	-0.606***	0.000	0.000
2021m2	0.193	0.116	0.070	0.086	0.600	0.400	-0.031	0.853	0.882
2021m3	0.149	0.209	0.093	0.021	1.000	1.000	-0.202	0.147	0.206
2021m4	0.199*	0.093	0.023	0.082	0.800	0.600	-0.247*	0.059	0.176
2021m5	0.161	0.279	0.256	0.113	0.600	0.600	0.130	0.471	0.676
2021m6	0.160	0.302	0.326	0.053	0.800	0.600	-0.065	0.794	0.941
2021m7	0.266**	0.047	0.000	0.112	0.600	0.600	0.031	0.882	0.912
2021m8	0.132	0.326	0.302	0.050	0.700	0.700	0.143	0.324	0.529
2021m9	0.161	0.326	0.279	0.104	0.300	0.400	-0.194	0.324	0.529
2021m10	0.187	0.302	0.233	0.035	1.000	0.900	-0.168	0.500	0.559
2021m11	0.084	0.628	0.651	0.030	0.900	0.800	-0.079	0.735	0.882
2021m12	0.095	0.558	0.465	0.008	1.000	1.000	0.100	0.412	0.588
2022m1	-0.094	0.465	0.465	-0.148	0.400	0.100	0.143	0.265	0.324
2022m2	-0.002	0.977	0.977	-0.118	0.600	0.400	0.177	0.235	0.412
2022m3	-0.067	0.767	0.674	-0.155	0.600	0.400	-0.043	0.735	0.824
2022m4	-0.005	0.977	1.000	-0.110	0.500	0.500	0.105	0.412	0.618
2022m5	-0.013	0.930	0.907	-0.025	1.000	1.000	0.332**	0.029	0.176
2022m6	0.001	1.000	1.000	-0.052	0.500	0.500	0.131	0.559	0.618
2022m7	0.029	0.907	0.884	-0.040	0.900	0.800	-0.196	0.176	0.441
2022m8	-0.080	0.581	0.698	-0.109	0.500	0.500	-0.149	0.441	0.441
2022m9	-0.018	0.930	0.907	-0.059	0.400	0.300	-0.477*	0.059	0.000
2022m10	-0.011	0.953	0.977	0.026	1.000	0.900	0.168	0.235	0.441
2022m11	-0.033	0.814	0.814	-0.086	0.500	0.400	0.154	0.353	0.500
2022m12	-0.070	0.512	0.558	-0.058	0.600	0.400	0.019	0.912	0.912

*** p<0.01, ** p<0.05, * p<0.1

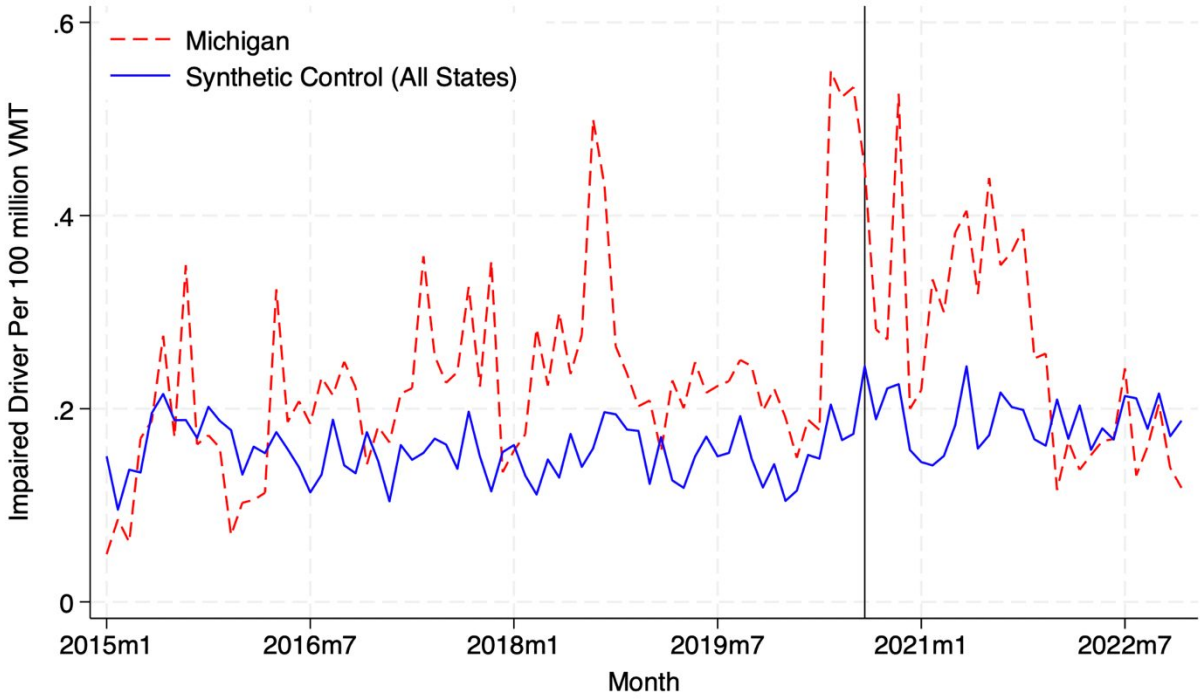


Figure 45. Michigan vs Synthetic Controls Group of All States (Impaired Drivers Per 100 million VMT)

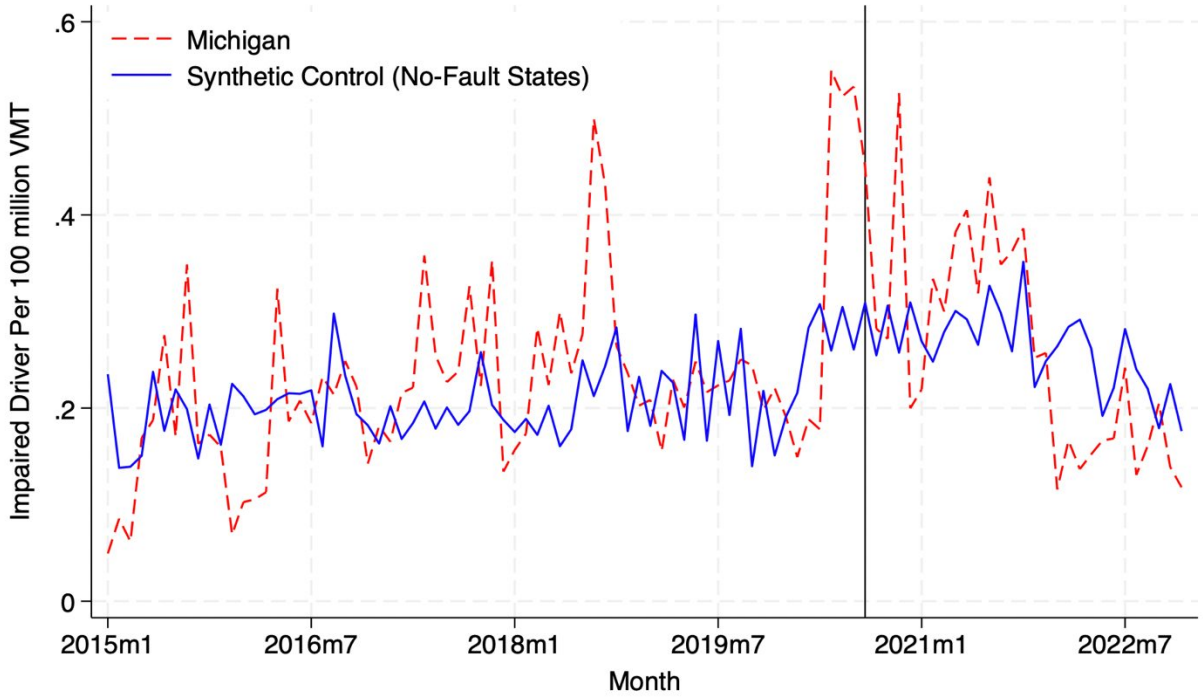


Figure 46. Michigan vs Synthetic Controls Group of No-Fault (Drunk Drivers Per 100 million VMT)

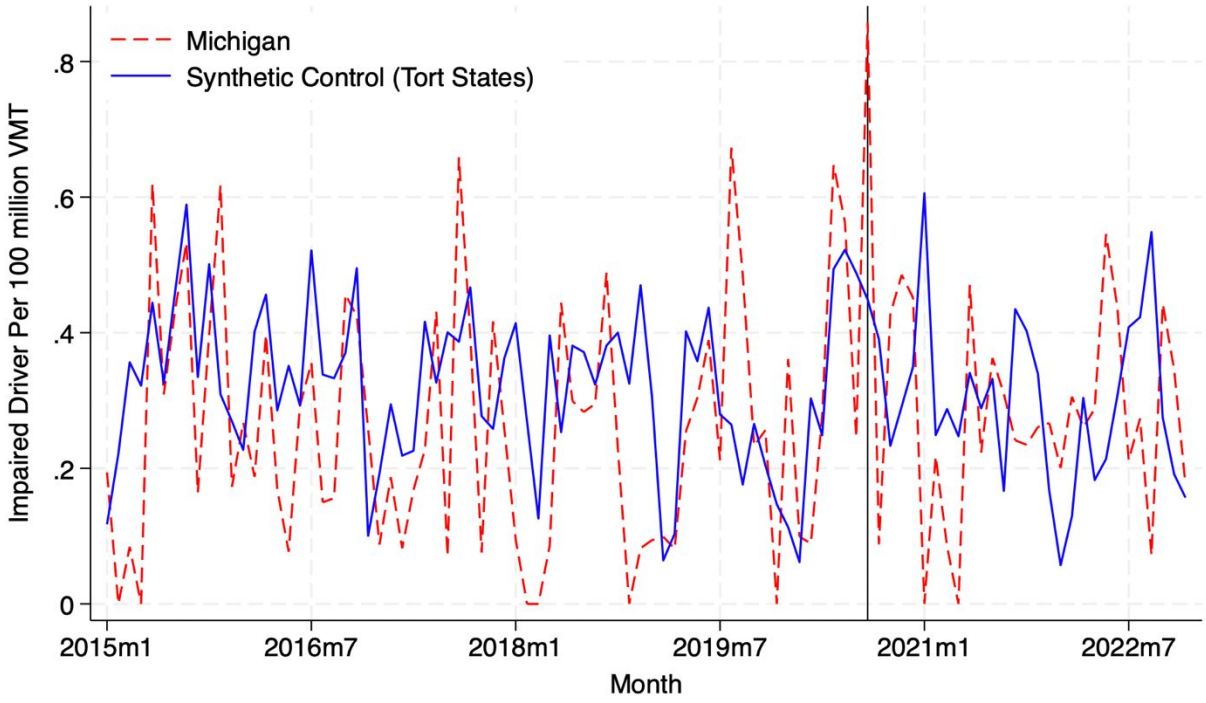


Figure 47. Michigan vs Synthetic Controls Group of Tort States (Impaired Drivers Per 100 million VMT)

Drug Use Drivers

Table 36. Drug Use Drivers Per 100 million VMT for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0207*	0.0640*	0.0171	0.0201
	(0.0113)	(0.0209)	(0.0210)	(0.0133)
Light Condition	-0.0425**	-0.0456	-0.0626	-0.0422**
	(0.0170)	(0.0298)	(0.0407)	(0.0192)
Weather Conditions	-0.00673	-0.0263*	-0.00988	-0.00615
	(0.00698)	(0.00827)	(0.0114)	(0.00862)
Vision Obstruction	-0.0211	0.0400	0.0444	-0.0347
	(0.0361)	(0.0804)	(0.0549)	(0.0444)
Ruralness of Accident	-0.0201	-0.0565	0.00992	-0.0261*
	(0.0138)	(0.0415)	(0.0304)	(0.0141)
Constant	0.140***	0.131*	0.117***	0.151***
	(0.0231)	(0.0369)	(0.0270)	(0.0281)
Observations	4,841	288	1,151	3,882
R-squared	0.061	0.549	0.160	0.067
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 37. Drug Use Drivers Per 100 million VMT

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
Jul 2020	0.221	0.140	0.023	0.173	0.400	0.000	-0.133	0.471	0.676
Aug 2020	0.149	0.419	0.163	0.099	0.400	0.100	0.055	0.912	0.912
Sep 2020	0.068	0.628	0.535	0.013	0.900	0.800	-0.203	0.382	0.529
Oct 2020	0.112	0.372	0.093	0.032	0.900	0.900	0.047	0.735	0.853
Nov 2020	0.222	0.116	0.000	0.206	0.300	0.000	0.067	0.765	0.882
Dec 2020	-0.060	0.744	0.605	-0.130	0.400	0.000	-0.099	0.735	0.824
Jan 2021	0.017	0.907	0.884	-0.010	1.000	0.900	-0.359*	0.059	0.000
Feb 2021	0.081	0.605	0.326	0.042	0.900	0.900	-0.202	0.147	0.324
Mar 2021	0.070	0.581	0.442	-0.020	0.900	0.900	-0.201	0.235	0.324
Apr 2021	0.137	0.349	0.140	0.105	0.400	0.100	-0.225	0.206	0.353
May 2021	0.133	0.372	0.186	0.049	1.000	1.000	-0.207	0.265	0.500
Jun 2021	0.112	0.558	0.233	0.065	0.900	0.400	-0.162	0.294	0.588
Jul 2021	0.182	0.186	0.000	0.132	0.300	0.000	-0.024	0.853	0.941
Aug 2021	0.167	0.302	0.116	0.121	0.700	0.400	-0.205	0.206	0.412
Sep 2021	0.029	0.837	0.814	0.001	1.000	1.000	-0.242	0.235	0.382
Oct 2021	0.178	0.302	0.140	0.081	0.500	0.300	-0.136	0.559	0.706
Nov 2021	0.152	0.419	0.186	0.122	0.500	0.100	-0.141	0.441	0.647
Dec 2021	0.085	0.512	0.349	0.029	1.000	0.700	-0.113	0.382	0.588
Jan 2022	-0.006	0.907	0.907	-0.053	0.900	0.700	-0.032	0.882	0.941
Feb 2022	0.005	0.977	0.977	-0.088	0.600	0.200	0.069	0.618	0.676
Mar 2022	0.024	0.837	0.814	-0.036	1.000	0.700	-0.207	0.118	0.324
Apr 2022	0.034	0.767	0.744	-0.005	1.000	1.000	0.043	0.794	0.912
May 2022	0.071	0.721	0.651	0.055	0.800	0.400	-0.004	1.000	1.000
Jun 2022	0.075	0.651	0.535	0.061	0.900	0.800	-0.058	0.676	0.824
Jul 2022	0.039	0.791	0.767	-0.012	1.000	0.900	-0.341	0.176	0.176
Aug 2022	-0.040	0.860	0.767	-0.095	0.700	0.600	-0.171	0.235	0.471
Sep 2022	0.041	0.860	0.721	0.024	1.000	0.700	-0.359	0.118	0.147
Oct 2022	0.041	0.907	0.884	0.014	0.900	0.900	0.094	0.735	0.882
Nov 2022	0.120	0.465	0.163	0.066	0.700	0.600	-0.324	0.147	0.206
Dec 2022	0.015	0.907	0.837	0.004	1.000	1.000	-0.017	0.912	0.941

*** p<0.01, ** p<0.05, * p<0.1

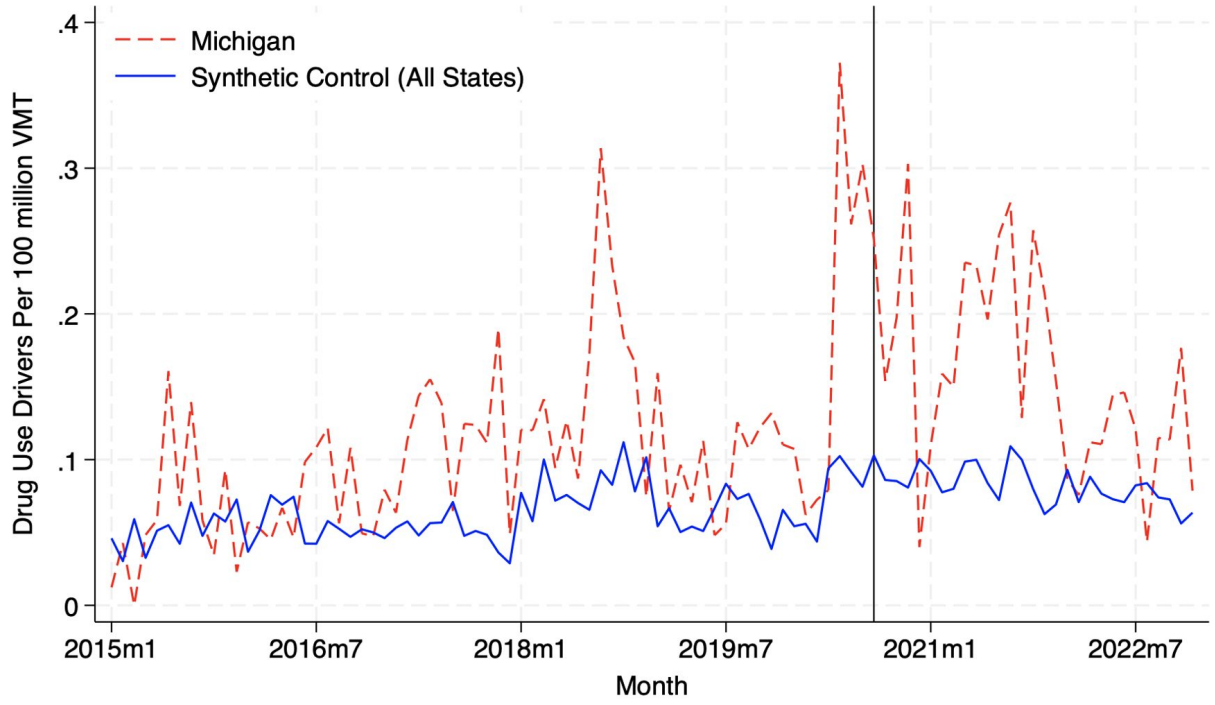


Figure 48. Michigan vs Synthetic Controls Group of All States (Drug Use Drivers Per 100 million VMT)

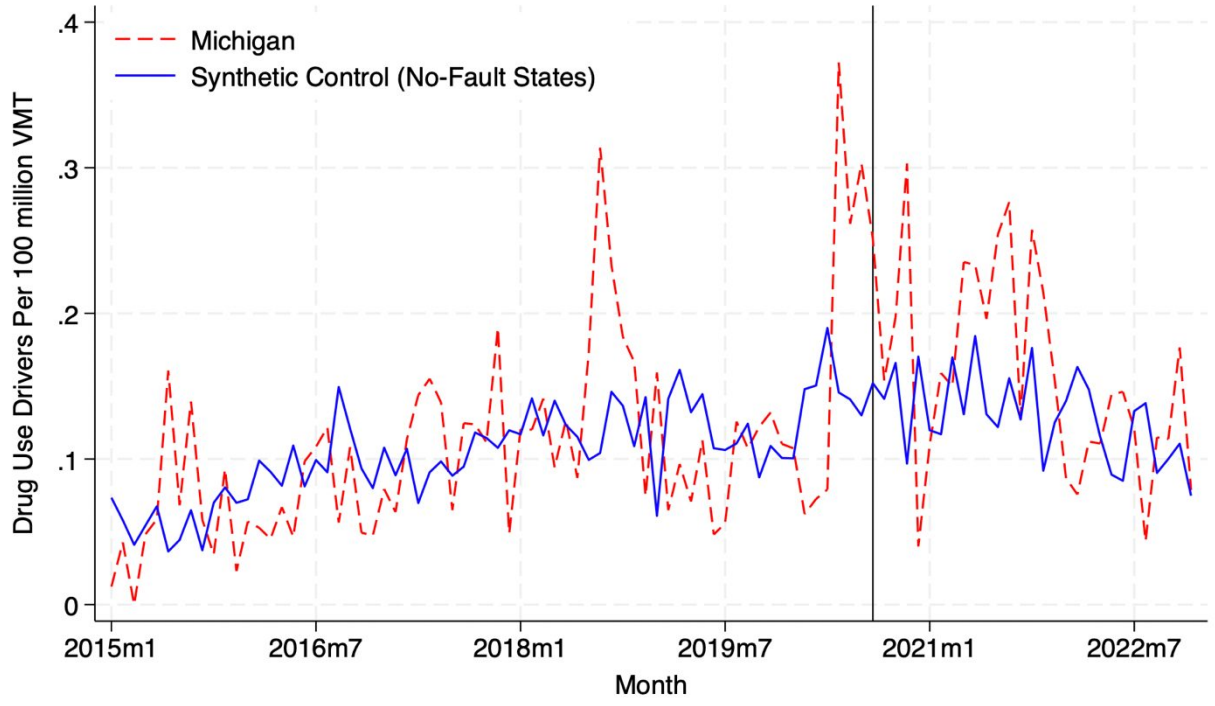


Figure 49. Michigan vs Synthetic Controls Group of No-Fault (Drug Use Drivers Per 100 million VMT)

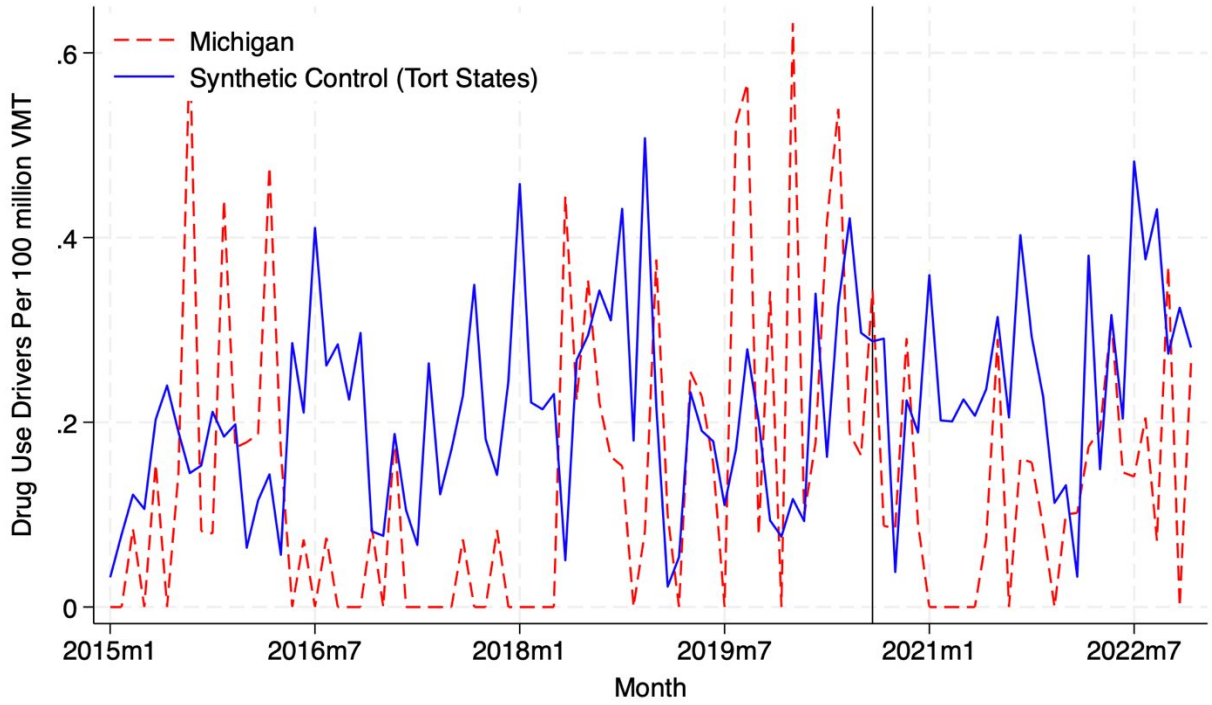


Figure 50. Michigan vs Synthetic Controls Group of Tort States (Drug Use Drivers Per 100 million VMT)

Seat Belt Misuse

Table 38. Seat Belt Misuse Per 100 million VMT for State Month Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	-0.0399*	-0.0192	-0.00989	-0.0456**
	(0.0215)	(0.0456)	(0.0571)	(0.0225)
Light Condition	0.0537**	0.0427	0.0508	0.0566*
	(0.0236)	(0.0966)	(0.0575)	(0.0292)
Weather Condition	-0.0351**	-0.0428*	-0.0427	-0.0294
	(0.0152)	(0.0105)	(0.0257)	(0.0175)
Vision Obstruction	-0.0943*	-0.216	-0.0847	-0.0867
	(0.0472)	(0.0749)	(0.0944)	(0.0518)
Ruralness of Accident	0.0193	0.152	-0.0273	0.0361
	(0.0354)	(0.174)	(0.0763)	(0.0394)
Constant	-0.00712	-0.0625	0.0120	-0.0201
	(0.0358)	(0.162)	(0.0844)	(0.0382)
Observations	4,841	288	1,151	3,882
R-squared	0.454	0.874	0.464	0.466
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 39. Seat Belt Misuse Per 100 million VMT

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
Jul 2020	0.464	0.209	0.000	-0.157	0.900	0.900	-0.313	0.500	0.529
Aug 2020	0.208	0.581	0.326	-0.346	0.400	0.300	0.643	0.118	0.088
Sep 2020	0.044	0.837	0.791	-0.250	0.600	0.700	0.020	0.941	1.000
Oct 2020	-0.010	1.000	1.000	-0.343	0.500	0.400	0.070	0.824	0.882
Nov 2020	0.135	0.651	0.302	-0.238	0.700	0.600	0.028	0.882	0.882
Dec 2020	-0.015	0.977	0.930	-0.465	0.400	0.300	-0.429	0.147	0.088
Jan 2021	0.030	0.930	0.930	-0.394	0.500	0.300	-0.841**	0.029	0.000
Feb 2021	0.010	1.000	0.953	-0.414	0.500	0.400	-0.410*	0.088	0.147
Mar 2021	0.218	0.302	0.140	-0.281	0.500	0.600	-0.341	0.206	0.176
Apr 2021	0.235	0.419	0.233	-0.308	0.500	0.500	-0.249	0.353	0.441
May 2021	0.157	0.651	0.488	-0.340	0.700	0.800	0.265	0.471	0.618
Jun 2021	0.189	0.581	0.256	-0.204	0.500	0.300	-0.016	0.971	0.971
Jul 2021	0.280	0.349	0.093	-0.237	0.500	0.600	-0.154	0.706	0.853
Aug 2021	0.248	0.419	0.209	-0.279	0.300	0.400	0.681	0.118	0.147
Sep 2021	-0.022	0.977	0.977	-0.478	0.200	0.100	0.074	0.941	0.912
Oct 2021	-0.019	0.930	0.930	-0.635	0.200	0.200	0.566	0.206	0.294
Nov 2021	0.191	0.512	0.256	-0.038	0.900	0.800	-0.307	0.294	0.471
Dec 2021	-0.119	0.698	0.488	-0.380	0.400	0.200	0.071	0.853	0.794
Jan 2022	-0.077	0.744	0.535	-0.397	0.700	0.700	-0.024	0.824	0.853
Feb 2022	0.054	0.814	0.744	-0.249	0.700	0.600	0.239	0.471	0.412
Mar 2022	-0.159	0.512	0.302	-0.529	0.300	0.000	-0.242	0.382	0.382
Apr 2022	0.084	0.791	0.628	-0.323	0.300	0.400	0.155	0.618	0.706
May 2022	0.191	0.628	0.372	0.041	1.000	0.900	0.867**	0.029	0.029
Jun 2022	0.146	0.744	0.419	-0.152	0.800	0.800	0.787***	0.000	0.000
Jul 2022	0.121	0.674	0.512	-0.181	0.500	0.600	-0.630	0.147	0.059
Aug 2022	-0.048	0.930	0.837	-0.293	0.400	0.400	0.339	0.353	0.412
Sep 2022	0.248	0.488	0.116	-0.118	0.900	1.000	-0.618*	0.059	0.029
Oct 2022	-0.118	0.674	0.535	-0.341	0.100	0.100	0.069	0.765	0.794
Nov 2022	-0.070	0.814	0.651	-0.473	0.200	0.000	0.028	0.941	0.971
Dec 2022	-0.121	0.814	0.465	-0.354	0.400	0.300	0.353	0.147	0.265

*** p<0.01, ** p<0.05, * p<0.1

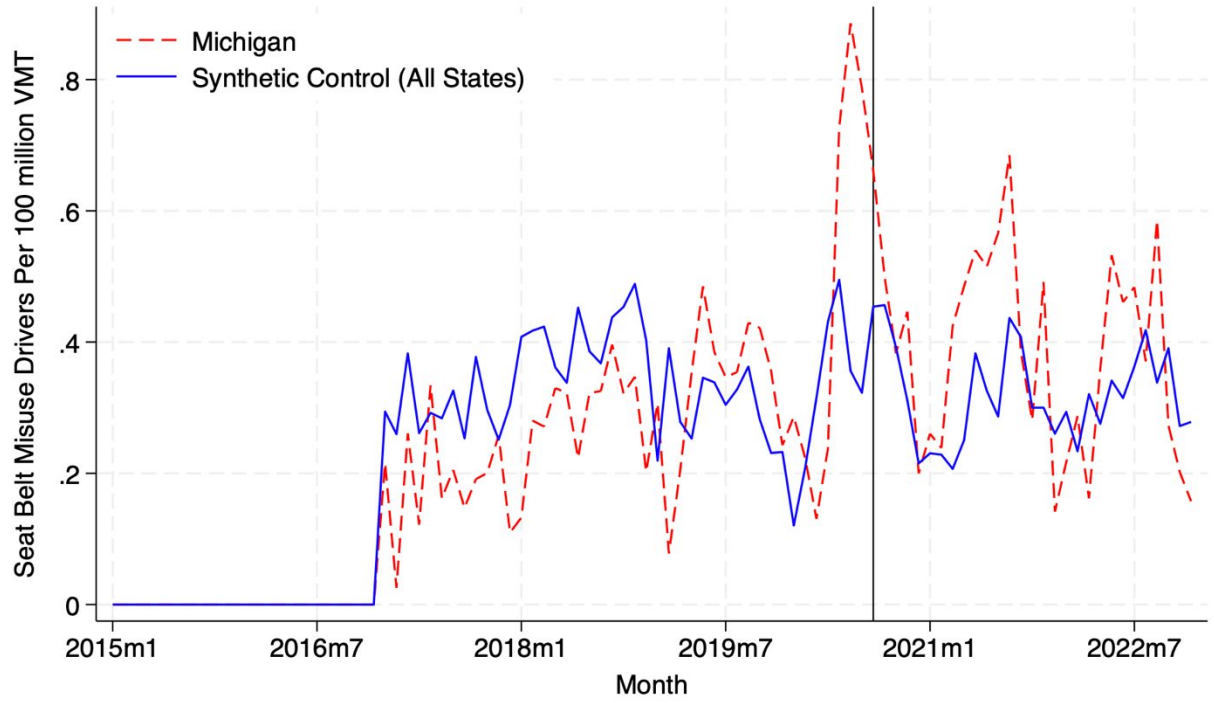


Figure 51. Michigan vs Synthetic Controls Group of All (Seat Belt Misuse Per 100 million VMT)

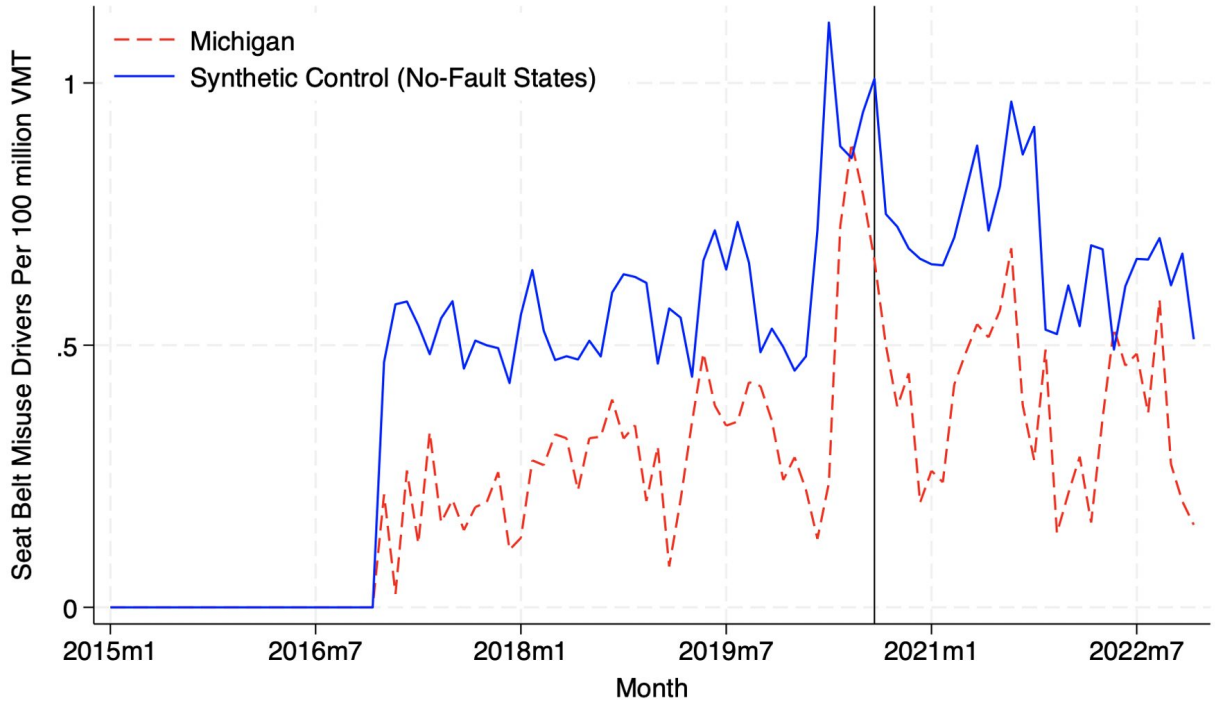


Figure 52. Michigan vs Synthetic Controls Group of No-Fault (Seat Belt Misuse Per 100 million VMT)

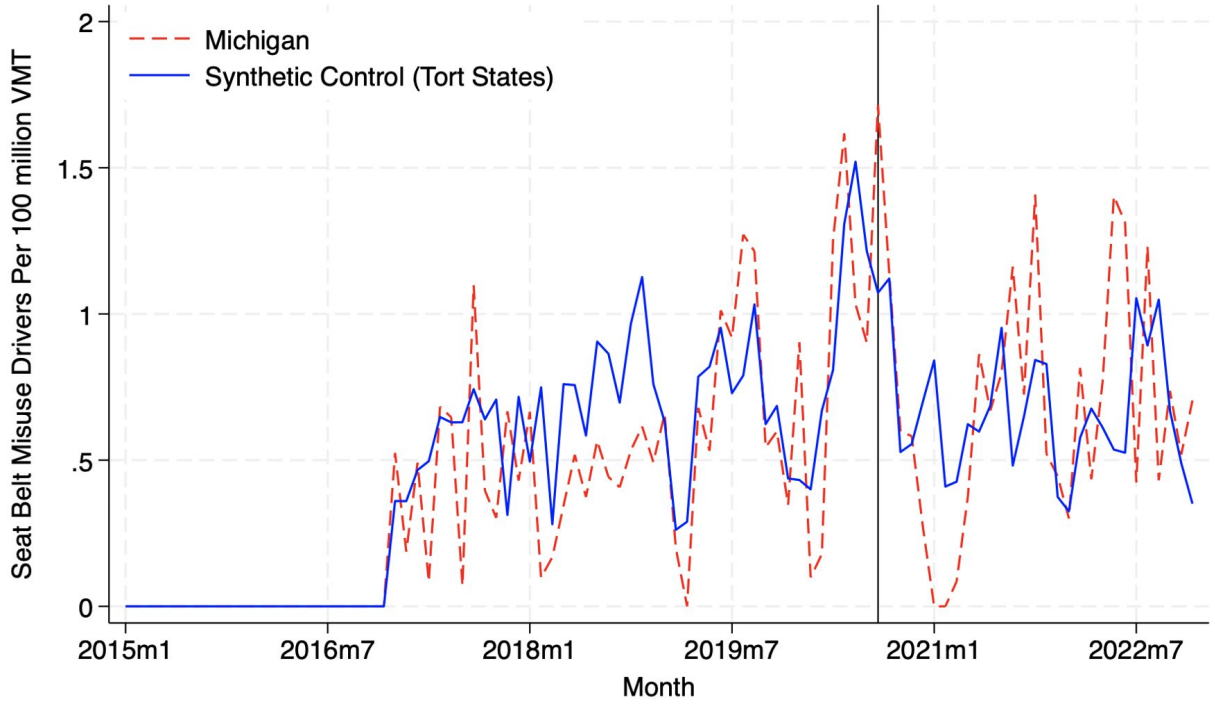


Figure 53. Michigan vs Synthetic Controls Group of Tort (Seat Belt Misuse Per 100 million VMT)

Overall Risky Driver Behaviors

Table 40. Overall Risky Driver Behaviors Per 100 million VMT for Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0673***	0.0560	0.0775*	0.0651***
	(0.0162)	(0.0370)	(0.0368)	(0.0179)
Light Condition	-0.0106	-0.0322	0.0191	-0.0215
	(0.0223)	(0.0853)	(0.0375)	(0.0265)
Weather Condition	-0.0359**	-0.0401*	-0.0473	-0.0313**
	(0.0138)	(0.0106)	(0.0311)	(0.0152)
Vision Obstruction	-0.0970***	-0.250***	-0.0196	-0.111**
	(0.0357)	(0.0147)	(0.0358)	(0.0436)
Ruralness of Accident	-0.0249	-0.0462	-0.0334	-0.0222
	(0.0283)	(0.156)	(0.0532)	(0.0324)
Constant	0.366***	0.262	0.308***	0.375***
	(0.0367)	(0.108)	(0.0704)	(0.0424)
Observations	4,841	288	1,151	3,882
R-squared	0.208	0.768	0.264	0.216
Number of States	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 41. Risky Driver Behaviors Per 100 million VMT

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
2020m7	0.488	0.116	0.000	-0.032	1.000	1.000	-0.172	0.647	0.735
2020m8	0.409	0.302	0.093	-0.023	1.000	1.000	0.891***	0.000	0.029
2020m9	0.144	0.512	0.465	-0.106	0.900	0.900	-0.297	0.206	0.324
2020m10	0.091	0.698	0.651	-0.205	0.800	0.800	0.209	0.471	0.588
2020m11	0.300	0.233	0.116	-0.013	1.000	1.000	0.410	0.118	0.176
2020m12	0.008	0.953	0.977	-0.415	0.600	0.300	0.048	0.824	0.912
2021m1	0.078	0.698	0.698	-0.231	0.600	0.600	-0.413	0.118	0.147
2021m2	0.149	0.372	0.279	-0.261	0.600	0.700	-0.184	0.412	0.529
2021m3	0.217	0.372	0.140	-0.166	0.700	0.800	-0.354	0.118	0.029
2021m4	0.313	0.256	0.070	-0.093	0.800	0.800	-0.267	0.265	0.382
2021m5	0.335	0.419	0.186	-0.012	1.000	1.000	0.447	0.235	0.324
2021m6	0.250	0.233	0.140	-0.115	0.900	0.800	0.084	0.618	0.765
2021m7	0.374	0.209	0.023	-0.092	0.800	0.800	0.268	0.294	0.471
2021m8	0.288	0.465	0.209	-0.018	0.900	0.900	0.594*	0.059	0.088
2021m9	0.180	0.535	0.419	-0.158	0.800	0.400	-0.074	0.853	0.882
2021m10	0.203	0.558	0.465	-0.235	0.500	0.200	0.436	0.294	0.382
2021m11	0.189	0.581	0.419	-0.100	0.800	0.700	-0.124	0.618	0.706
2021m12	0.042	0.884	0.907	-0.229	0.600	0.400	0.226	0.265	0.529
2022m1	-0.010	1.000	0.953	-0.248	0.500	0.500	0.470**	0.029	0.088
2022m2	-0.003	1.000	1.000	-0.321	0.700	0.200	0.672***	0.000	0.000
2022m3	-0.115	0.512	0.488	-0.374	0.400	0.000	-0.224	0.324	0.412
2022m4	0.060	0.907	0.860	-0.246	0.500	0.500	0.177	0.500	0.647
2022m5	0.180	0.535	0.395	0.002	1.000	1.000	0.642***	0.000	0.059
2022m6	0.192	0.465	0.326	-0.070	0.800	0.800	0.581*	0.059	0.029
2022m7	0.233	0.372	0.256	-0.054	0.900	0.900	-0.385	0.206	0.265
2022m8	0.020	0.953	0.953	-0.187	0.300	0.200	0.258	0.353	0.559
2022m9	0.249	0.488	0.302	-0.081	0.800	0.700	-0.351	0.206	0.324
2022m10	-0.041	0.907	0.907	-0.237	0.500	0.300	0.205	0.412	0.559
2022m11	-0.037	0.953	0.930	-0.350	0.500	0.000	0.240	0.294	0.412
2022m12	-0.010	1.000	0.953	-0.206	0.500	0.300	0.314	0.235	0.353

*** p<0.01, ** p<0.05, * p<0.1

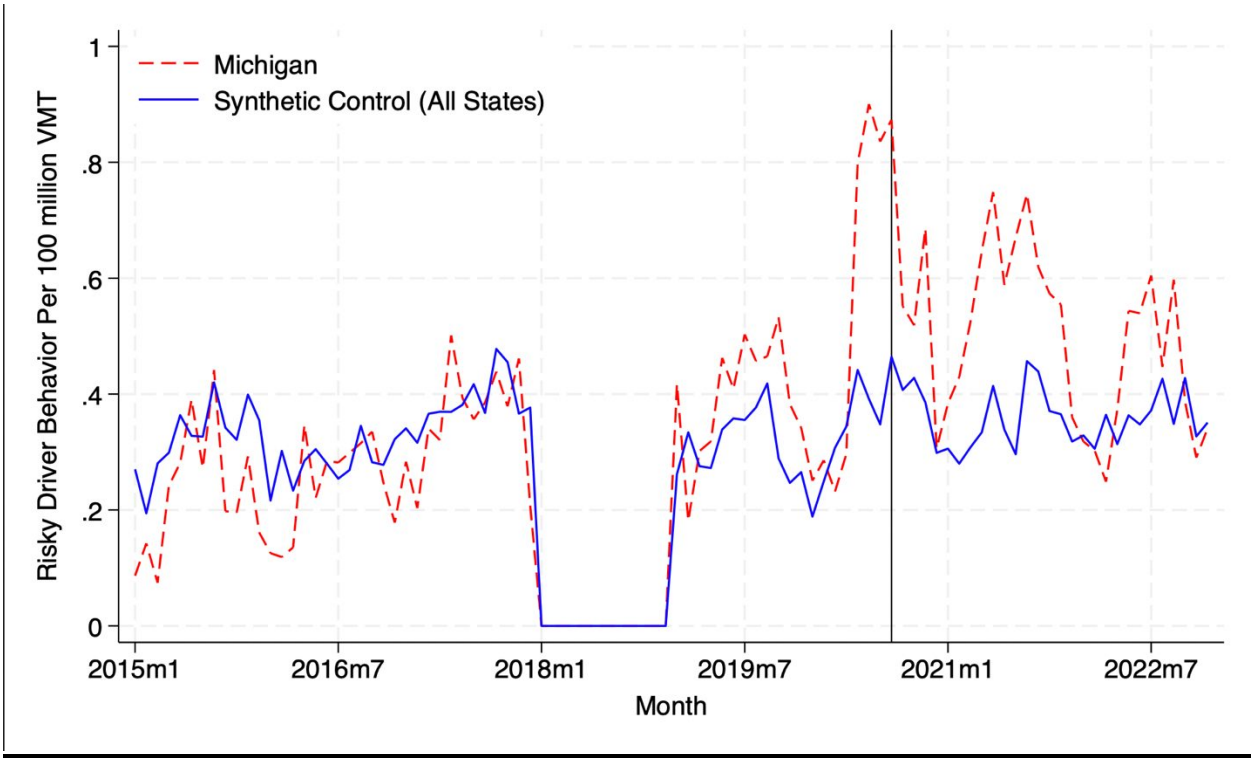


Figure 54. Michigan vs Synthetic Controls Group of All (Risky Driver Behaviors Per 100 million VMT)

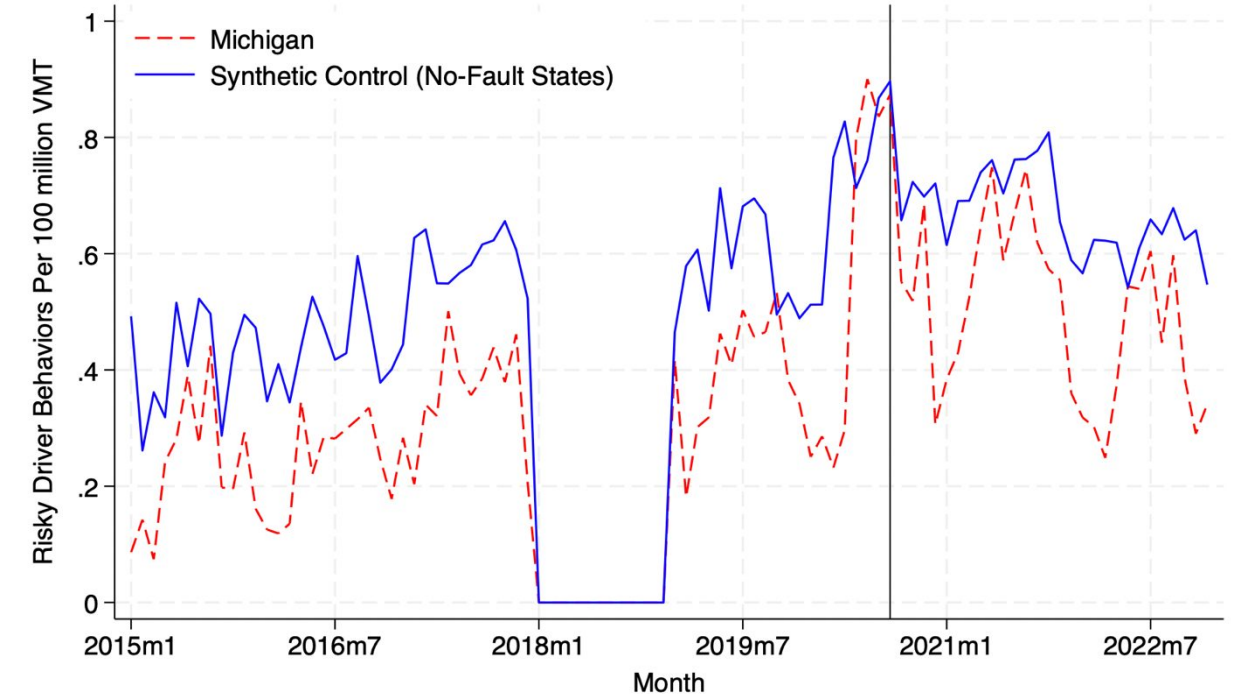


Figure 55. Michigan vs Synthetic Controls of No-Fault (Risky Driver Behaviors Per 100 million VMT)

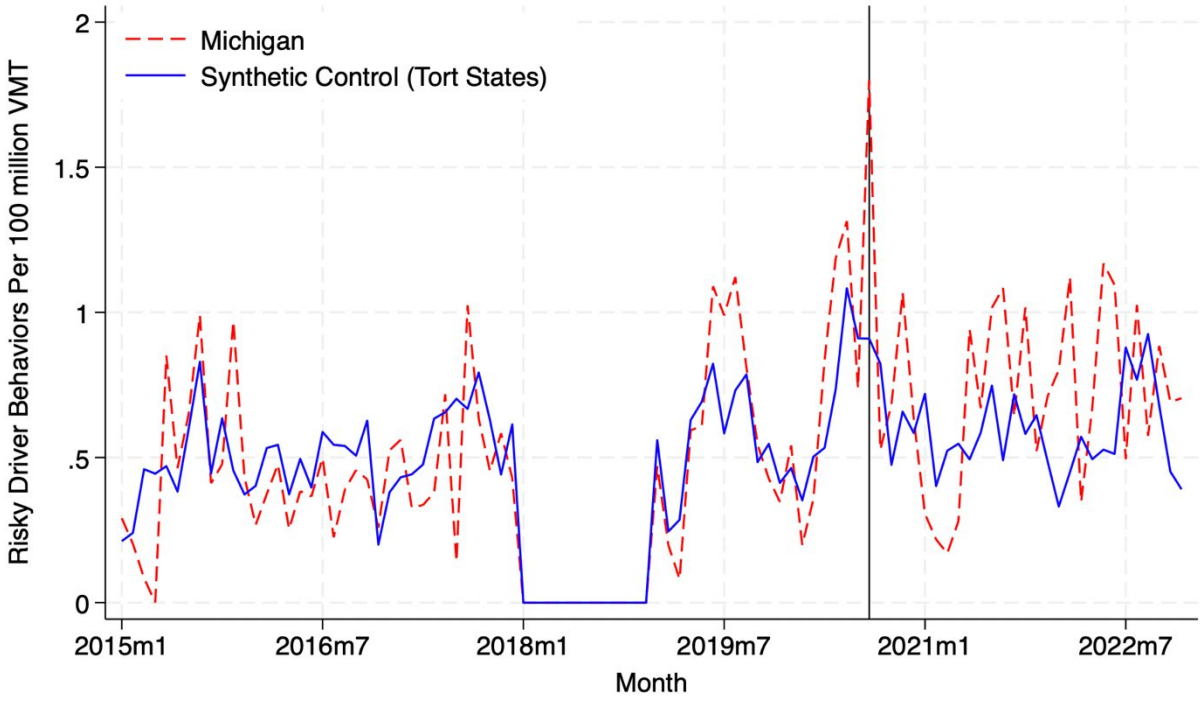


Figure 56. Michigan vs Synthetic Controls Group of Tort (Risky Driver Behaviors Per 100 million VMT)

Speeding

Table 42. Speeding Per 100 million VMT for Diff-in-Diff Model

VARIABLES	(1) MI vs All States	(2) MI vs Neighboring States	(3) MI vs Other No-Fault States	(4) MI vs Tort Liability States
Diff-in-Diff Estimator	0.0534***	0.0562***	0.0582***	0.0519***
	(0.00778)	(0.00322)	(0.0159)	(0.00891)
Light Condition	0.0240	0.129***	0.0248	0.0207
	(0.0157)	(0.00892)	(0.0162)	(0.0200)
Weather Condition	-0.00487	-0.0111	-0.0113	-0.00238
	(0.00753)	(0.00750)	(0.0176)	(0.00882)
Vision Obstruction	-0.0448	-0.0423	0.00467	-0.0557
	(0.0312)	(0.106)	(0.0236)	(0.0370)
Ruralness of Accident	0.0144	-0.0701	0.0151	0.0158
	(0.0249)	(0.0317)	(0.0293)	(0.0305)
Constant	0.171***	0.0836	0.166***	0.171***
	(0.0297)	(0.0337)	(0.0471)	(0.0352)
Observations	4,835	288	1,151	3,876
R-squared	0.262	0.682	0.294	0.272
Number of state	51	3	12	41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 43. Speeding Per 100 million VMT

Model	MI vs All States			MI vs No-Fault States			MI vs Tort Liability States		
	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev	Coefficients	P-Value	P-Value Std Dev
2020m7	0.244***	0.000	0.000	0.191	0.300	0.000	-0.119	0.324	0.471
2020m8	0.078	0.512	0.395	0.060	0.700	0.600	0.287**	0.029	0.147
2020m9	0.041	0.721	0.605	0.044	0.700	0.600	-0.017	0.882	0.941
2020m10	-0.003	0.953	0.930	0.052	0.500	0.400	-0.102	0.412	0.559
2020m11	0.160*	0.093	0.000	0.141***	0.000	0.000	-0.059	0.588	0.618
2020m12	0.045	0.674	0.581	-0.014	0.900	0.900	0.038	0.676	0.706
2021m1	0.021	0.884	0.814	0.048	0.600	0.600	-0.132	0.353	0.559
2021m2	0.127	0.302	0.163	0.092	0.800	0.500	-0.267*	0.059	0.206
2021m3	0.180	0.140	0.023	0.176	0.200	0.000	0.044	0.647	0.676
2021m4	0.207	0.116	0.023	0.161	0.400	0.100	-0.168	0.235	0.294
2021m5	0.107	0.535	0.395	0.080	1.000	1.000	-0.201	0.235	0.500
2021m6	0.070	0.512	0.442	0.092	0.700	0.500	-0.073	0.382	0.588
2021m7	0.151	0.209	0.047	0.106	0.100	0.100	0.111	0.294	0.382
2021m8	0.059	0.721	0.581	0.058	0.800	0.900	-0.032	0.735	0.912
2021m9	0.059	0.558	0.395	0.070	0.400	0.200	-0.041	0.735	0.824
2021m10	0.093	0.419	0.302	0.108	0.300	0.000	0.016	0.912	1.000
2021m11	0.020	0.884	0.791	-0.016	0.900	0.800	0.049	0.765	0.853
2021m12	-0.041	0.674	0.581	-0.032	0.500	0.400	-0.117	0.294	0.441
2022m1	0.019	0.884	0.837	0.063	0.700	0.700	0.418***	0.000	0.029
2022m2	0.009	0.953	0.907	0.013	1.000	1.000	0.266*	0.059	0.088
2022m3	-0.014	1.000	0.930	-0.003	1.000	1.000	0.012	0.882	0.941
2022m4	0.037	0.628	0.488	0.053	0.400	0.300	0.105	0.265	0.412
2022m5	0.046	0.814	0.744	0.083	0.500	0.200	0.204	0.206	0.324
2022m6	0.031	0.860	0.791	0.055	0.800	0.500	0.176	0.147	0.265
2022m7	-0.003	0.953	0.953	-0.002	1.000	1.000	-0.086	0.529	0.676
2022m8	-0.009	0.930	0.907	0.022	0.900	0.900	-0.134	0.353	0.500
2022m9	0.119	0.372	0.116	0.130	0.000	0.000	0.136	0.206	0.412
2022m10	-0.074	0.535	0.465	0.013	1.000	0.900	0.206	0.176	0.382
2022m11	-0.024	0.814	0.767	-0.015	0.900	0.900	0.146	0.294	0.441
2022m12	-0.077	0.674	0.488	-0.065	0.700	0.500	0.068	0.735	0.882

*** p<0.01, ** p<0.05, * p<0.1

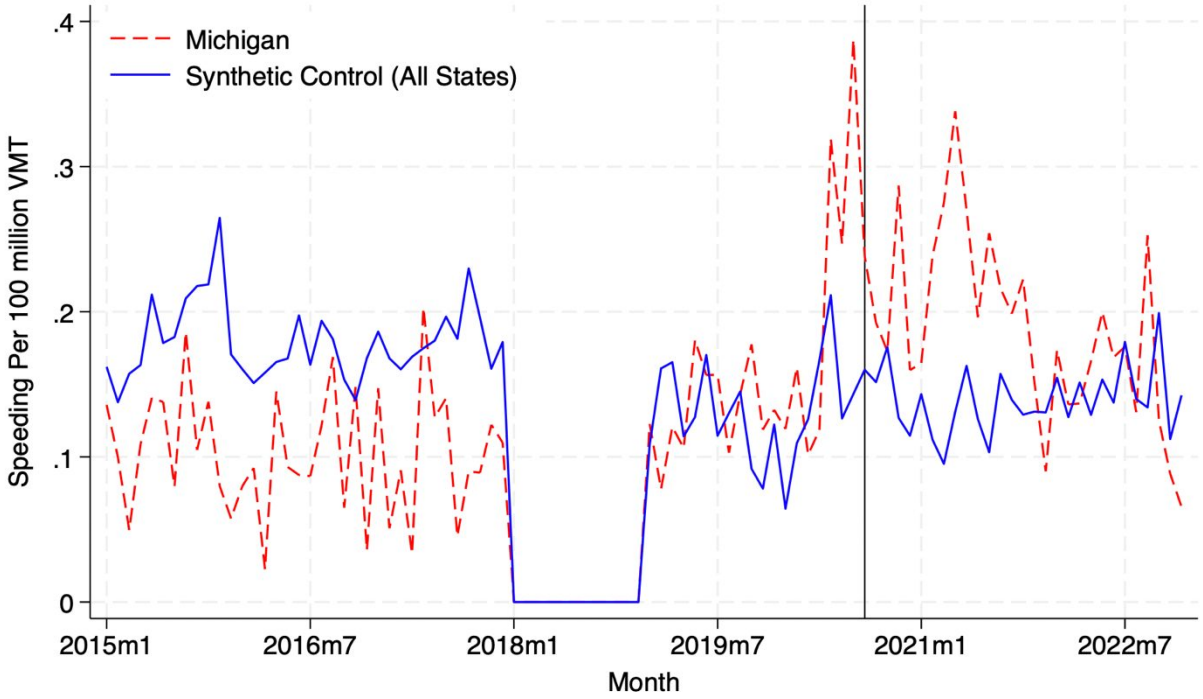


Figure 57. Michigan vs Synthetic Controls Group of All (Speeding Per 100 million VMT)

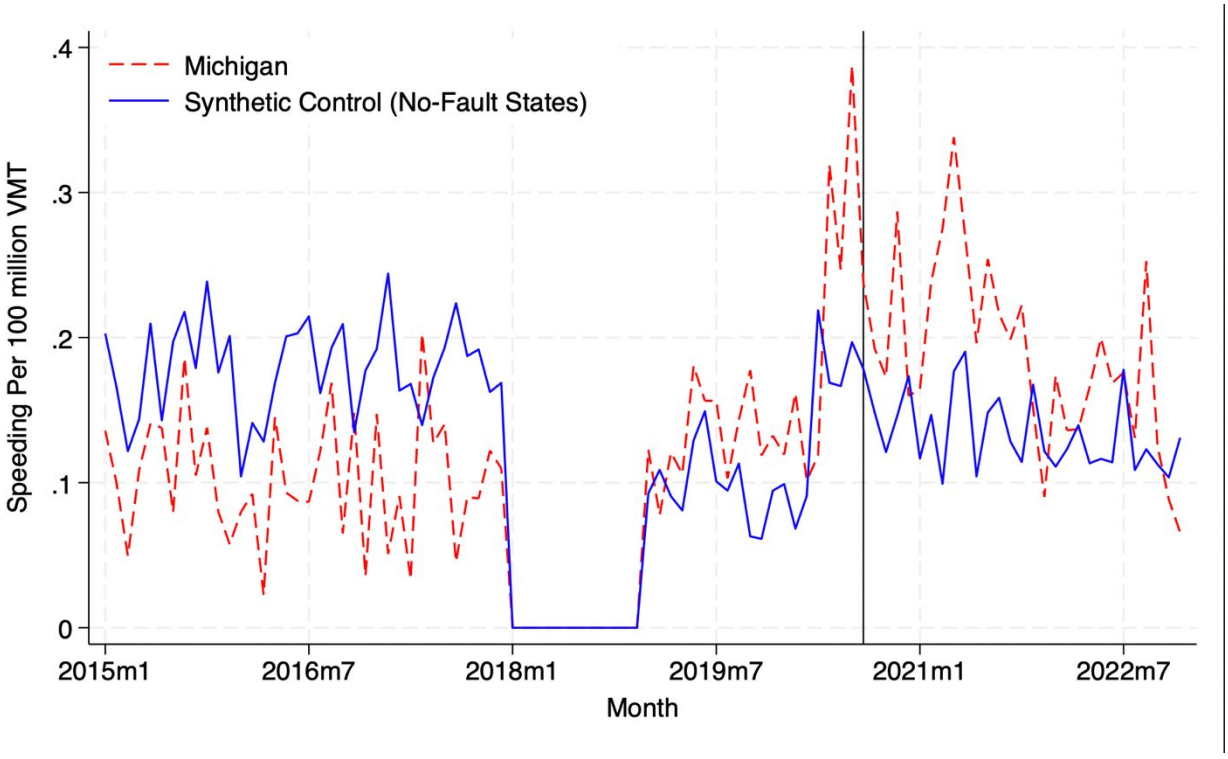


Figure 58. Michigan vs Synthetic Controls Group of No-Fault (Speeding Per 100 million VMT)

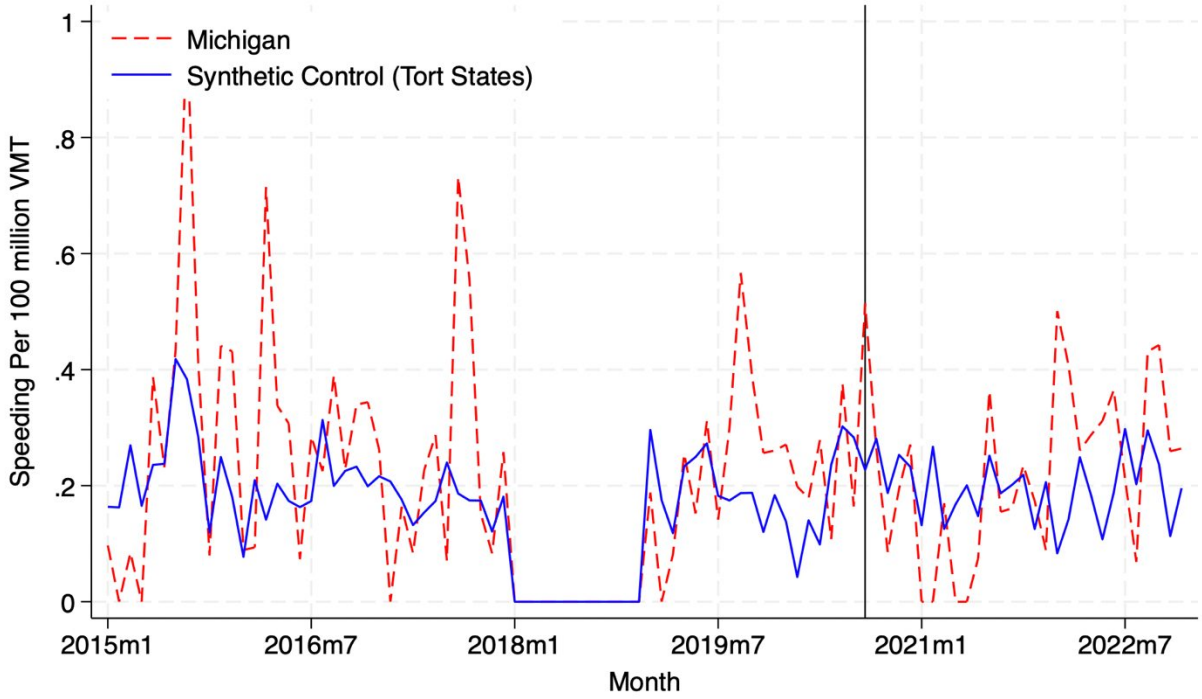


Figure 59. Michigan vs Synthetic Controls Group of Tort (Speeding Per 100 million VMT)

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