Chapter 3

Rideshare and Motor-vehicle Crashes

1 Introduction

Chicago in 2011 became the second U.S. city to have access to ride share services. Rideshare company Uber was first to enter Chicago, this was followed by Lyft in 2013.[1] These rideshare services allow rides to be requested to any location within Chicago with a few clicks on a mobile application. Supply of these services increased steadily with the number of vehicles registered with the city of Chicago for ridesharing services going from 26,803 in March 2015 to 117,557 in December 2017.[2] Soon, rideshare entered other cities of Illinois. The rising popularity of rideshare combined with the ease at which rides can be summoned suggests that people planning to drink will order a ride back home instead of driving themselves, leading to lower alcohol related traffic fatalities and crashes. However, a more careful look at the possible mechanisms indicates the possibility of a null or positive relationship between the two variables under certain conditions. For example, if ride sharing simply replaces other safer means of transport (like public transportation or asking a friend to drop you home) a null relationship will be true. The primary motivation behind this paper is to test whether rideshare availability is associated with alcohol-related traffic accidents. However

[1]https://beta.techcrunch.com/2013/05/09/zimride-no-more-lyft-chicago/, https://www.uber.com/blog/chicago/chicago-ubers-biggest-launch-to-date/

[2]http://www.chicagotribune.com/news/columnists/wisniewski/ct-met-ride-hailing-numbers-20180201-story.html

the introduction of rideshare can potentially affect the total fatal crash rates by possibly bringing a certain type of drivers on the road and through its effect on traffic. Therefore I also find the effect the rideshare's introduction has on the total fatal crash rate. [3]

2 Background

Ride sharing services connect passengers with drivers. These services can be accessed via a mobile application or through their website. Drivers can use their personal car to provide a ride. To request a ride the passenger can either select the current location that has been auto-populated based on the GPS location of the phone or enter a specific location. Once the ride is requested the passenger can see the route the driver is taking on the map and knows the expected time of arrival.

Rideshare companies start rideshare on a city-by-city basis. Typically, rideshare companies start operating in a city without the permission of the local government or regulators.[4] If faced by regulations they take actions like garner public support through petitions, threaten to leave etc to continue operating in the city.

Uber was the first company to start operating in Chicago with a black car service. The black car was a luxury service, with rates higher than taxi rates. When Uber entered Chicago, in 2011, the rideshare industry was not heavily regulated. Prior to the company's official launch, over 1,000 users signed up to use Uber in Chicago. Kalanick, Uber's co-founder says, "there's much less regulation around black car industry, and drivers who own one or two cars are allowed to exist (as opposed to other cities where there are more restrictions on drivers). Because of this flexibility, the integration of Uber with drivers is much more seamless for both parties."

Uber faced little legal resistance for roughly one year after its entry. However, in October 2012, several taxi and vehicle-service companies filed a federal lawsuit containing allegations

[3] I exclude total crashes from the analysis since the parallel trends assumption is violated when employing a standard difference-in-differences methodology for most of the specifications

[4] https://www.theguardian.com/technology/2017/apr/12/why-everyone-hates-uber-seven-step-playbook

that Uber's business model violated city regulations as well as state and federal law. This move was an attempt make it costly for the company to operate in Chicago since the taxi companies wanted protection from the competition from Uber.

Later that month, the City of Chicago Business and Consumer Protection proposed regulations to prohibit Uber to operate in Chicago. The new regulations would prohibit "public passenger vehicles" from using any device that measures time or distance to determine fares. That would make Uber's black cars illegal since they measure time and distance using Uber's GPS-enabled app. [5]

Uber responded by garnering public support through tweets and petition signing and the bill was vetoed. Uber also went ahead and started operations in other cities of Illinois. For example, Uber entered Evanston in Sept, 2013 and Schaumburg and Naperville in August 2014. On December 2014, Illinois lawmakers approved a bill that was regulatory in nature and placed certain insurance and safety standards on ridesharing companies. This bill however, effectively allowed ridesharing companies to legally operate in Illinois. (Crespo, 2016) Post the passage of the bill, rideshare entered cities Rockford, Bloomington, Urbana, Champaign, Peoria, Aurora, Springfield and Kankakee. List of ridesharing cities of Illinois is in Table 1.

For a city without rideshare, people cannot use rideshare because the service will not be available on their device/mobile. In order to use rideshare one would have to travel to a city with rideshare to use it. This feature reduces compliance bias by ensuring the treatment cities take up the treatment (rideshare in this case) and control cities do not take up the treatment.

3 Theoretical Motivation

According to the theory of consumer behavior, consumers are assumed to be rational i.e. they want to get most value for their money, have clear preferences for various goods and services

[5] https://technori.com/2013/02/3289-startup-innovation-government-vs-uber/jacobhuebert/

and have limited incomes. Therefore consumers maximize their utility subject to a budget constraint, and hence must choose among alternative goods and services given their prices. People planning to drink or are drunk will choose to use rideshare if it maximizes their utility among the alternative means of transportation (e.g. hailing taxis, using public transport, driving). In general, people might prefer one mode of transport over the other because of time and effort costs (e.g. availability, convenience of use and safety) and monetary costs. These mechanisms are explained in detail in the following paragraphs.

Rideshare entry introduces an important alternative way of getting home. There are many more rideshare cars on the road than taxis. Chicago has about 7,000 cabs on its streets, a number artificially controlled by the government through its sale of medallions, which gives drivers permission to operate. As of 2015, Uber, one of the ride-sharing companies operating in Chicago, had more than 20,000 drivers in the city. [6] As of 2014, riders can get a Uber ride in less than 20 minutes with the typical wait being 4 minutes. The time and effort costs are higher for a drunk person because of the effects of alcohol on cognitive ability. For such passengers being able to just choose their home address from a drop down menu which is typically stored in the app and get dropped right at their doorstep is considerably more convenient than knowing when the last bus/train back home is and navigating to the bus/train stop and getting on the right bus/train. Rideshare also offers some advantages over traditional taxi services. One can track the car's progress toward the requested location, therefore offering more assurance of getting a ride as opposed to taxis where one may have to call the driver and waits for the taxi to arrive. After a ride has ended, the payment automatically gets deducted from the linked credit card. There is no hassle of carrying required amount of cash and change for taxis or a ride card/ticket for public transit which is harder for someone under the influence of alcohol.

Ridesharing may also be a safer way to get back home as compared to public transit and taxis. One typically drinks at night, a time when public transit is perceived to be unsafe. [7]

[6] http://nprillinois.org/post/illinois-issues-how-uber-and-lyft-are-catering-communities-color

[7] https://www.citylab.com/transportation/2014/03/will-women-ever-feel-completely-safe-mass-

Customers and drivers self-identify themselves in rideshare, which doesn't happen in taxis. In addition, Uber's and Lyft's screening of drivers is comparable if not better than screening of taxi drivers. [8] Safety of the ride back home might be especially important for alcohol-impaired persons because of lower awareness of their surroundings and reduced ability of defending themselves (implying higher effort costs for drunk people). In the absence of rideshare, people might have driven back home after drinking considering the disadvantages of public transit and taxis. But after the launch of rideshare these people might opt to use rideshare because of its lower effort and time costs.

Ridesharing started out as a service that was more expensive than taxis in 2011. The first ridesharing service, Uber, was more expensive than taxis by around 20-30%. Post spring 2013, options of rides cheaper than taxis by around 20-30% were introduced (Greenwood and Wattal 2015). Other companies joining the rideshare market in Chicago, followed pricing similar to Uber's with ridesharing options available at much lower prices as compared to taxis. Monetary costs of rides applies to all passengers, not just people planning to drink. Despite this, the price of a ride could be an important factor in determining if drunk drivers choose rideshare instead of the other modes of transit. Therefore, the discussion so far suggests that rideshare might not just replace the use of public transit/taxis but also replace drunk-driving, thereby translating into a decrease in number of alcohol-related crashes (ARCs).

While I expect a decrease in alcohol-related crashes it is possible that drunk driving crashes may not decrease and could also increase. If ride sharing simply replaces the use of public transport or other safe means of getting home there will not be a significant reduction in alcohol-related crashes. For example, people using public transport switch to ride sharing and people driving back after drinking continue to drive back home. It is also possible that rideshare could also increase the number of alcohol-related crashes relative to the total crashes. Rideshare could increase traffic in cities. In fact, (Clewlow 2017) report

transit/8728/ https://www.nbcchicago.com/investigations/Data-Shows-Which-CTA-Stations-Are-Most-Dangerous-242874801.html

[8] Feeney, Matthew, and Rideshare companies Uber. "Is ridesharing safe?." (2015)

findings of a residential and travel survey of seven major U.S. cities and provide evidence of rideshare induced increase in traffic. A drunk driver is less likely to make his way back home without colliding into another car with more cars on the road. Therefore, with increased traffic, alcohol-impaired drivers will be more likely to crash than they would have otherwise. Therefore while increased traffic due to rideshare will increase overall accident rate, it could increase alcohol-related crashes by more than the overall crash rate increase.

In addition to impacting ARCs, rideshare's introduction may also effect the overall fatal crash rate. This might occur because of the changes to traffic that rideshare usage brings with it. Further, rideshare drivers possibly enjoy driving, are experienced and more rule-following than the average driver. These competing forces might impact overall crash rate in rideshare cities in Illinois. This paper quantifies the net effect of rideshare on various measures of crash rates.

4 Literature

There is a large literature in health economics on the determinants of alcohol-related traffic accidents. Many prior studies focus on the effects of state laws aimed at reducing drunk driving such as Blood Alcohol Content (BAC) Laws, Administrative License Revocation Laws, Minimum Drinking Age Laws and taxes on alcohol (Dee, Thomas 2001, Wagenaar and Toomey 2002, Voas et al. 2000, Hingson et al. 1996, Wagenaar et al. 2007, Ruhm 1996, Anderson and Rees 2015). As a group, these papers generally support the idea that policies are effective in reducing alcohol-related accidents.

More recent papers consider the role of changes in modes of alcohol use (e.g. beer container size, bar hours) and changes in the community (e.g. casino expansion, minimum wages) on alcohol-related accidents (Hoke and Cotti 2015, Cotti and Walker 2010, Adams and Cotti 2008, Adams et al. 2012, Green et al. 2014). I begin by first summarizing two such papers, Hoke and Cotti 2015 and Cotti and Walker 2010. Although these papers are not directly relevant to the current study which is focussed on rideshare usage, they are instructive since they detail the appropriate empirical methodology for extracting the causal effect when the output is motor vehicle crashes. I also summarize Abouk and Adams 2013 which studies the impact of state texting bans on traffic accidents for the same reason. This is followed by a summary of all the papers estimating the relationship between rideshare and motor vehicle crashes. (I have excluded 2 papers which are written by graduate students).

Hoke and Cotti 2015 examine the relationship between beer container size and alcohol-related fatal accidents. Owing to the fact that beer consumption is optimal within a few hours after opening the container, they are typically sold in serving size containers unlike wine and liquor, which have a greater shelf life and which are typically consumed by the glass. In recent years beer manufactures have begun to market beer in larger than standard (12 oz.) containers at a cheaper price per unit. The combination of the lower per unit price, larger container size, and a short consumption window after opening, may cause people to consume alcohol more quickly, or in greater quantities, or both. Hence, consumption of beer in larger container sizes may lead to greater average levels of intoxication and, subsequently, an increase in alcohol-related fatal vehicle accidents. They use fatal accidents data from FARS and data on alcohol purchases for designated market areas (DMAs) from retail outlets from Nielsen scanner panel data. The dependent variable is the number of fatal accidents in a DMA-time period in which at least one driver has a blood alcohol concentration (BAC) is greater than 0. The variable of interest is the log of Container12, total beer purchases of containers greater than 12 oz in each of the 12 DMAs for every week of the time period 2008-2011. They controls for area and time fixed effects, changes in population. Changes in factors that may influence overall driving risk separate from drinking behavior (e.g., construction, weather, etc.) are controlled for by including number of non alcohol related fatal accidents (BAC = 0). They also control for total beer purchases and overall alcohol consumption from all alcohol types and sources (not just retail purchases). These measures will account for changes in overall alcohol consumption habits in a DMA, and will also capture the impact of related public policies that may impact alcohol purchases habits (both in retail stores or at bars and restaurants) and might change during the time period under investigation, such as beer taxes. They employ a weighted least squares (WLS) specification. They find that a 10% increase in beer purchases in containers that are greater than 12 oz in size increases the number of alcohol-related fatal accidents by 1.95%

Cotti and Walker 2010 find a link between casino expansion and alcohol related fatal traffic accidents. Casinos often serve alcohol to their customers and if tourists drive far distances to go to the casinos this could impact driving distance after drinking. For example, in the case of rurally located casinos, a large proportion of the casino's customers are likely to have driven longer distances relative to customers at urban casinos. Therefore miles driven and the number of alcohol related crashes following introduction of alcohol related crashes to be greater in rural than ini urban areas. They use a FARS data and a time period of 1990-2000. They use data on 1568 counties. 131 of these counties opened casinos in that time period and therefore form the treatment group. The dependent variable is the annual number of fatal accidents in a county and year for which a driver's imputed blood alcohol content (BAC) exceeds 0.08. The independent variable is the interaction of the casino dummy and the demeaned log of the county population. i.e. it is casino dummy x [ln(population) - ln(mean population)]. They find that opening of a casino increases alcohol-related fatal accidents by a statistically significant 9.2%. The casino-population interaction is -0.058. This shows that ARFAs declines as population size increases (decreases) from mean population and decreases (increases). The result is in agreement with the hypothesis that casinos in rural tend to increase miles driven by intoxicated drivers therefore increases ARFAs. Where as in urban areas this effect is offset by a substitution of casinos for other drinking venues and presence of public transport etc.

Abouk and Adams 2013 study the effect of state texting bans on fatal accidents. Since data on wether the driver was texting during a crash is not available, the authors use crashes that most likely resulted by a driver sending text messages. i.e. single vehicle accident with a single occupant. They use FARS crash data from 2007-2010 for 49 states. The dependent variable is the log(number of fatal accidents + 1) for state i month m. The independent variable is B, an indicator of whether a state i has a texting ban in place in month m. Further, the paper defines strong bans as bans that consider texting while driving as a primary offense. When texting and driving is considered as a secondary offense or is a primary offense for young drivers, these bans are weak bans. There were four states (Nebraska, New York, Virginia, and Washington) for which texting is enforced as a secondary offense during the sample period. Bans in two states (Indiana and Missouri) cover only younger drivers. Strong bans should have a larger effect on accidents than weak bans. Therefore they look at another model with the independent variables being an indicator for strong bans SB and weak bans WB in state i month m. To test texting ban effect over time, they include 5 lags and 5 leads of SB and WB. They weight estimations by state population because of the greater variation in accidents in smaller states. They find that strong bans reduce single vehicle, single occupant accidents. Weak bans have no effect on accidents. Any reduction is short lived and accidents return to former levels within a few months.

Only a few very recent papers focus specifically on availability of ride-sharing and its effects on alcohol-related accidents. There are four of them and three of which (Brazil and Kirk 2016, Greenwood and Wattal 2015, Dills and Mulholland 2018) use an OLS Difference-in-Differences approach, have fatal crashes as their output variable and use a 1-0 indicator variable for rideshare introduction. One of them (Morrison et al. 2017) uses a time series ARIMA model and examines all alcohol involved injury crashes. With the exception of Brazil and Kirk 2016, which finds no effect of rideshare, all the other three papers find a decrease in some measure of crash (fatal or non fatal). This might partly be because papers focus on different geographic areas, and areas differ in their road network, public transit system and road usage patterns leading to the dissimilar results. I summarize the papers here.

Brazil and Kirk 2016 examine the relationship between the Uber and traffic fatalities within the most populated county in each of the 100 most populated metropolitan areas (as defined by the 2010 US Census population counts) across the United States from 2005 to 2014. They examined 3 categories of traffic fatalities: total, drunk driving?related, and weekend- and holiday-specific.They use monthly county-level data on traffic fatalities from the Fatality Analysis Reporting System and a standard Difference-in-Differences methodology. Since many of the observations have few or no fatalities, they use a negative binomial specification to account for the extreme skewness of the data and the measure of exposure used is the number of vehicle miles traveled (VMT) in a county-month. They estimate county- month VMT by multiplying the state's monthly VMT by the county's proportion of its state's total roadway mileage and obtained VMT and roadway length data from the Federal Highway Administration. For drunk driving?related fatalities Negative binomial models did not converge; they instead report results from Poisson models which have the same distributional assumptions but do not correct for overdispersion. Uber had no statistically significant association with for any of the 3 categories for all modeling specifications. They supply several possible explanations for this lack of reduction in traffic fatalities: if there are few Uber drivers in comparison with the number of adults who drive drunk, Uber may not be a substitute for drunk driving. Also drunk drivers may rationally conclude that Uber rides are expensive given the low likelihood of getting caught for drinking and driving.

Greenwood and Wattal 2015 studies the impact of introduction of Uber in cities of California between 2009 and 2014 on alcohol related fatal crashes. They create a dataset using the California Highway Patrol?s Statewide Integrated Traffic Report System (SWITRS). They use the ln(NumDeaths), the natural log of one plus the number of people who were killed in a motor vehicle accident in a town during a quarter where at least one of the involved parties was under the influence of alcohol as the dependent variable and use a difference in difference approach to estimate the effect. In addition to finding the reduction of DUI deaths due to Uber, This paper also analyses the mechanism through which Uber's introduction reduces DUI deaths. In other words, they test whether availability of ride sharing as an alternative to taxis reduces the DUI deaths or the availability of ride-sharing in addition to a lower price as compared to taxis leads to reduces DUI deaths. To do so they use two specifications. In one, the independent variable of interest is an indicator of entry of Uber Black into the county. Uber Black, offers transportation with the price being 20-30% higher than taxis. In the second specification the Uber X which entered the market later, is 20-30% cheaper than taxis. They also control for factors that might influence uber entry in counties: population, median income and number of college graduates etc. They find that while Uber X reduces DUI driving deaths, Uber Black does not. This shows that the cost and availability of rides together (not just availability of rides) determines the reduction in DUI deaths. They find on an average alcohol related homicides decrease 3.6% in locations treated by Uber X in the state of California.

Dills and Mulholland 2018 use US county level monthly data from 2007 to 2015 and the FARS data set to study the introduction of ridesharing service Uber's association on fatal vehicle crashes. They also study several related outputs: alcohol-related fatal crashes, night-time fatal crashes and the number of vehicular fatalities per 100,000. They use a standard DD method. They control variables they use are factors that influence alcohol consumption, driver safety or both. To alleviate the bias caused by the possibility of endogenous entry, in an alternative specification they estimate the effect using only counties in which Uber enters at some point. Here the 'control' group is likely to share more characteristics with the 'treatment' group. Overall, their findings suggest that Uber does not increase overall fatal crash rates and, for some specifications, is associated with a decline in fatal crash rates.

Morrison et al. 2017 using time-series analysis examined the relationship between motor vehicle crashes and rideshare in 4 cities where Uber launched, abruptly ceased operations and then abruptly resumed again. These cities are Reno and Las Vegas in Nevada, San Antonio, Texas and Portland, Oregon. They take this approach since the driver and rider base builds slowly over time after Uber launch and an abrupt cessation and resumption might produce a more severe disruption than the initial launch. The interruption of interest was when Uber operations resumed. To construct time-series for each of the 4 cities, they count all injury crashes, all alcohol-involved injury crashes and all serious injury crashes per week with a week defined as 12:00 AM Wednesday to 11:59 PM Tuesday. They denominate counts of alcohol involved and serious-crashes by the count of the all injury crashes to calculate a proportion. They then conduct an interrupted time-series analysis using Autoregressive Integrated Moving Average (ARIMA) models. They find an absolute decrease of 3.1% (95% CI: 1.7, 4.4) alcohol-related crashes per week in Portland.

My paper expands the rideshare and crash literature, by examining rideshare and crash rate in Illinois. Illinois was the second state to get rideshare, the first being California, and has not been studied before. Secondly, I use city-level data of Illinois as opposed to county-level data since rideshare starts on a city level. Most papers in the field use county level data. Lastly, papers in the crash literature typically examine traffic fatalities. I also examine total alcohol related crashes.

5 Data and Data Sources

I use crash data provided by the Illinois Department of Transportation (IDOT) from 2006-2016. Each row of the data represents a crash that occurred in Illinois. The data set has detailed information on the crash including the date and time, the coordinates/location, the two main reasons for the crash, and if the crash resulted in a property damage, injury or was fatal. Reasons for a crash include "Failing to Reduce Speed to Avoid Crash" and "Distraction from Inside Vehicle". Full list of possible reasons of crash is given in Appendix, Table 7. I consider a crash to be an alcohol-related crash if any of the two reasons involve drinking or alcohol. i.e. "Had Been Drinking" or "Under Influence of Alcohol/Drugs". I refer to these as alcohol-related crashes. The alcohol-related crashes for each city-month per 100,000 population is a dependent variable in the analysis. Non-fatal ARCs are based on the officer's perception on whether alcohol was involved in the crash and is often not updated when the Blood Alcohol Content (BAC) results are received 3, 6 or 12 months down the road. The fatal crashes, on the other hand, are more reliable since they are updated when the BAC results are received. I consider a fatal crash to be an alcohol-related fatal crash (ARFC) if the BAC of the driver is greater than 0 (BAC > 0). Therefore another variable in the analysis is the fatal crash rate in a city-month in which at least one driver has a BAC greater than 0. As mentioned previously another dependent variable in the analysis is the fatal crash rate.

Plots for all the measures of crash rates for each of the 17 cities with rideshare is in Figure 1.1 to 1.17 (Figure 1.5 to 1.17 is in the Appendix). These crash-rates are normalized so that all the plots can fit in one frame. Each crash-rate was transformed by subtracting the mean (of the crash rate) from each observation and dividing it by the range (of the crash rate). The vertical red line indicates the entry of rideshare in the city. There is no noticeable shift in trends for the crash rates after the entry of rideshare for any of the cities. Therefore visually it is appears that the rideshare did not significantly effect crash rate in the rideshare cities of Illinois.

In addition to using data provided by IDOT I use data on population from US Census Bureau and unemployment rate data from Illinois Department of Employment Security.

6 Empirical Methodology

My analysis covers the years 2006-2016. I begin by estimating the following equation to establish the association of rideshare's entry with traffic accidents:

$$\text{number per } 100,000 \text{ population}_{\text{jmy}} = \alpha + \beta \text{RideShareEntry}_{\text{jmy}} + \text{X}'_{\text{iy}}\nu + \delta_{\text{j}} + \theta_{\text{y}} + \gamma_{\text{m}} + \phi_{\text{j}} * \text{trend}_{\text{my}} + \text{e}_{\text{jmy}} \tag{1}$$

where subscript j denotes the city, m denotes month and y denotes year.

The dependent variable is the monthly count of crashes per 100,000 residents. This includes the following three measures of crashes: alcohol-related, alcohol-related fatal and total fatal crash rate. Cities with larger population have more crashes, to make the cities comparable, I normalize crash counts with the resident population. The variable of interest, RideShareEntry, indicates if rideshare was available to people in the city in that month and year. I estimate the equation using Ordinary Least Squares (OLS).

The term δ_j denotes the city fixed effects. The inclusion of δ_j helps to capture the differences in crashes across cities that are time-invariant. θ_y and γ_m are year and month fixed effects respectively and help capture differences in accidents that are common for all the cities.

The vector X is set of time-varying factors that influence crash rate. This includes the unemployment rate of the city and the population density. I use unemployment rate as a measure of the economic conditions, which can effect alcohol related crash risk through its impact on alcohol consumption. I control for population density to allow for cities with more people per square mile to differ in crash rates. The specification also includes city-specific linear, monthly time trends, $\phi_j * trend$. The city-specific linear time trends capture differing trends specific to the city. In order to account for correlation in errors within each city due to unobservables the standard errors are clustered at city level.

I estimate another specification using leads and lags of rideshare's entry in a city. This specification allows to estimate any pre-existing difference in the cities' trends prior to rideshare's entry. In addition, the inclusion of lags and leads allows the effect of rideshare to vary over time. More specifically, I estimate the following for city j, month m and year y.

$$\text{number per } 100,000 \text{ population}_{\mathrm{jmy}} = \alpha + \sum_{g=1}^{g=14} \beta_g \mathrm{Rideshare}_{\mathrm{jmyg}} + \mathrm{X}'_{\mathrm{iy}}\nu + \delta_{\mathrm{j}} + \theta_{\mathrm{y}} + \gamma_{\mathrm{m}} + \phi_{\mathrm{j}} * \mathrm{trend}_{\mathrm{my}} + \mathrm{e}_{\mathrm{jmy}} \tag{2}$$

$\mathrm{Rideshare}_{\mathrm{jmyg}}$ are a set of dummy variables which equal one or if ridesharing service is present in city j and whose duration of operation in the city is assumed to be in group g. I use seven groups before rideshare and seven after rideshare, with each group comprising a three month interval. The omitted variable category is rideshare entering in 21 or more months. If any of the first seven coefficients of β_g are significant, it is an indication of pre-existing trend differences which could imply endogenous entry.

Entry of rideshare in cities could be non-random and influenced by the characteristics of the population in the city. Rideshare entry in cities with little regulation on rideshare companies are possibly more endogenous than in cities with more regulations and checks. This is because with fewer rules and regulations the rideshare entry decision and timing depends heavily on the unobservable characteristics of the people of the city. Rideshare was allowed to legally operate in Illinois after Dec 2014. The bill that made this possible was regulatory in nature and placed certain insurance and safety standards on ridesharing companies. However, rideshare entered Chicago and a few cities near Chicago (suburbs of Chicago) prior to the passage of this law. Therefore, to reduce bias caused by endogenous entry I estimate another specification where I eliminate cities which had very little regulation or restriction to rideshare entry when rideshare entered those cities. The cities are Chicago, Evanston, Oak Brook, Lombard, Schaumburg, Naperville, Northbrook, Glenview, Arlington Heights, Palatine, Wheaton, Glen Ellyn (Here all the cities except Chicago are suburbs of Chicago).

In the next specification, I consider Chicago and its suburbs as one unit. The reason I do this is because of non-independence of observations of Chicago and its suburbs. For example, people are more likely to visit Chicago once rideshare is available in the suburbs. This in turn could increase traffic and drinking in Chicago. Availability of rideshare in Chicago could also impact crash rate in it's suburbs. For example, people will be more eager to go to Chicago to consume alcohol rather than drink in their city since they can get a ride back. This in turn might reduce crash rate in the suburbs of Chicago. I test for the hypothesis that availability of rideshare in Chicago is associated with crash rate in its suburbs in the next specification.

$$\text{number per } 100,000 \text{ population}_{\text{jmy}} = \alpha + \beta \text{RideShareEntry}_{\text{cjmy}} + \text{X}'_{\text{iy}}\nu + \delta_{\text{j}} + \theta_{\text{y}} + \gamma_{\text{m}} + \phi_{\text{j}} * \text{trend}_{\text{my}} + \text{e}_{\text{jmy}} \tag{3}$$

$\text{RideshareEntry}_{\text{cjmy}}$ for Chicago or any of its suburbs (c=1) takes the value 1 when rideshare enters the Chicago. For other cities (c=0) $\text{RideshareEntry}_{\text{cjmy}}$ is 1 when rideshare enters the city.

I present both population weighted and unweighted estimates. Figure 2.1 through 2.3 shows standard deviation of the various measures of crash rates ordered by increasing city population. The standard deviation of the crash rate is strongly associated with the city population and decreases with increasing city population. For these crash rates, the population weighted estimates might be more efficient.

7 Heterogeneity effect across age groups

I examine the impact of rideshare on various measures of crash rates across different age groups. These age groups are 0-18 years, 19-25 years, 26-44 years and 45 plus. The reduction in crash rate must be higher for age groups that use rideshare technology more than other age groups. The effects must be most pronounced for age groups 19-25 since they are likely to use new technology. In addition, population under 25 is least likely to own a car. [9] Age group 0-18 includes people too young to use rideshare, age group 26-44 being most likely to own a car and age group 45 plus might be reluctant to use rideshare technology.

8 Synthetic control analysis

From Table 4 and Table 5, it can be seen that with the standard difference-in-difference method the pre-trend assumption is being violated. For this reason I check if the method

[9] https://www.bls.gov/cex/anthology/csxanth8.pdf

of synthetic control is a suitable method for finding the effect of rideshare on motor vehicle crash rate.

I start by plotting for Chicago and its synthetic control with the outcome variable being various measures of crashes (alcohol-related crash rate, alcohol-related fatal crash rate and fatal crash rate). These plots are at the monthly level. Visual inspection of Figure 3.1 - Figure 3.3 shows a lack of affinity of the treatment and control group. As the figures suggest, the synthetic control does not provide a suitable comparison group to study the effects of rideshare on crash rates. Even before the introduction of rideshare the time series of crash rates in Chicago and the synthetic control differ notably. Therefore, I conduct the synthetic control analysis at the quarterly level for the same outcome variables. Figure 3.4 - Figure 3.6 also show that the plots for Chicago and the synthetic control cross each other multiple times before the policy goes into effect.

I try the method of synthetic control for other treatment cities that had rideshare introduced before 2015. Figure 3.7 - Figure 3.12 has plots for the city of Naperville. Plots for other rideshare cities listed in Table 1 are not shown since they are very similar in nature to the plots of Naperville. Visual inspection for all the other cities also suggest that the method of synthetic control is not suitable for studying the effect of rideshare.

The reason behind the lack of a good synthetic control might be the disparity in outcome variables for the treatment groups and the remaining cities. Synthetic control tries to ensure the pre-period trends equal between treatment and synthetic control. On the other hand, valid control group for DD requires parallel trends of the outcome variable in the pre-period. It might be possible to obtain parallel pre-trends for some outcomes if not all. For this reason, DD might be a better method to use in this study.

9 Results

Table 3 presents estimates for the association between entry of rideshare in cities of Illinois and crash rate. I use three measures of crash rate per 100,000: fatal, alcohol and alcohol-related fatal. Panel A presents the difference-in-differences estimates with control variables and month-year dummies. Panel B presents the difference-in-differences estimates with city-specific linear time trends. Panel C presents the population weighted difference-in-differences estimates with city-specific linear time trends. All these estimates are statistically insignificant.

Table 4 investigates effects using "lags" and "leads" of rideshare's entry. In column (2) and column (3), certain coefficients on the leads of total and fatal crashes are significant and large. This suggests estimates for the DD for fatal and alcohol-related fatal crashes must be interpreted with caution. The coefficient of the leading variables for alcohol-related crashes (column (3)) are statistically insignificant. Alcohol-related crashes increases 3 months after rideshare's operation but this effect decreases with time.

Table 5 presents population weighted estimates for rideshare entry and crash rate estimates. In all columns there are many coefficients with significant lead variables showing that difference-in-difference estimates using this specification are not reliable.

Table 6 has results for effect of rideshare in the restricted sample that excludes cities that had rideshare prior to Dec 2014. In every panel all the coefficients are statistically insignificant.

Table 7 and 8 (population weighted) has effects of rideshare using the leads and lags model. Quite a few coefficients on leading variables on the remaining columns are significant, therefore coefficients on lagged variables must be interpreted with caution, many of which are negative and significant.

Table 9 has the effect of rideshare in Chicago on its suburbs. From Panel C it can be seen that none of the measures of crashes are significant. From Table 10 and Table 11, we can see that the alcohol-related fatal crashes might have reduced in the long term in Chicago and its suburbs as a results of rideshare in Chicago. The result for fatal and alcohol related crashes is unreliable since there are significant estimates in the pre-period in the specification with population weights. I suspect this might be because the observations belonging to different cities are assumed to be independent but may not be independent.

Table 12 has the effect of rideshare when Chicago and its suburbs are considered one single unit. From Panel C it appears that rideshare did not effect overall fatal, alcohol-related or alcohol-related fatal crashes. Table 13 has effects of rideshare in when Chicago and its suburbs are considered one unit using the leads and lags model. Table 14 has regression results same as those of Table 13, population weighted. From Table 13 and 14, none of the coefficients in the pre-rideshare entry period are significant. This is an indication that this specification is a valid specification. From Table 13, it appears that the fatal crashes and ARFCs do not change significantly while the ARCs increase as a result of the rideshare entry. However, once the estimates are weighted by population, the estimates for ARCs are no longer significant. Therefore from Table 13 and 14 one can conclude that rideshare did not impact the any of the measures of crashes significantly.

Table 15 has heterogeneity effects across age groups 0-18, 19-25, 26-44 and 45 plus years. None of the estimates for 0-18 years are significant (Panel A). This is expected since this group has people for whom it is illegal to drink and part of the age group is too young to use rideshare. Similarly, none of the estimates for 45 plus years are significant (Panel D). This might be because this group is reluctant to use rideshare. From Panel B we can see that for age group 19-25 rideshare entry is associated with a decrease of 0.106 in fatal crash rate. The result is expected since this age group is very likely to use rideshare for two reasons. This group consists of young people who are generally willing to accept new technology and is also the group least likely to own a car. For age group 26-44, the estimate for alcohol related fatal crashes are positive and significant. This age is the most likely to own a car and hence is less likely to use rideshare. In addition people of this age group drive more. This might result in more crashes because of increased traffic, especially alcohol related when judgement is compromised.

Table 1: List of ride sharing treated cities, counties

City	County	Rideshare
Chicago	Mainly Cook, also DuPage	9/2011
Evanston	Cook County	9/2013
Oak Brook & Lombard	Cook	06/2014
Shcaumburg, Naperville	Cook	07/2014
Northbrook & Glenview	Cook	08/2014
Arlington Heights & Palatine		
Wheaton, Glen Ellyn	Cook	09/2014
Rockford	Winnebago	2/2015
Bloomington	McLean	2/2015
Urbana, Champaign	Champaign	2/2015
Aurora	Mainly Kane, DuPage; also Kendall, Will	2/2015
Springfield	Sangamon	2/2015
Kankakee	Kankakee	06/2015
Peoria	Peoria	11/2015

Post Dec, 2014 rideshare was allowed to legally operate in Illinois.

Table 2: Descriptive Statistics: Mean of key outcome variables

	Rideshare = 0	Rideshare = 1	All	Minimum	Maximum
Fatal	0.52	0.50	0.53	0.00	26.03
Alcohol	8.09	7.05	8.06	0.00	64.30
Alcohol Fatal	0.11	0.13	0.11	0.00	10.66

All crashes are per 100,000 population. There are 13,666 observations. Cities with rideshare are Aurora, Bloomington, Champaign, Chicago, Evanston, Naperville, Rockford, Springfield, Urbana, Peoria.

Table 3: Rideshare entry and crashes per 100,000

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
Panel A: Time-month dummy			
RideshareEntry	0.013	0.286	0.008
	(0.045)	(0.221)	(0.022)
Panel B: City-specific linear time trend			
RideshareEntry	−0.048	0.477	0.013
	(0.049)	(0.298)	(0.024)
Panel C: City-specific trend			
RideshareEntry	−0.003	0.095	0.023
	(0.034)	(0.137)	(0.016)

There are 13,666 observations. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 4: Rideshare entry and crashes per 100,000, lead and lag

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
18-21 months before	−0.103	−0.530	−0.077***
	(0.089)	(0.356)	(0.028)
15-18 months before	0.374**	−0.005	−0.050
	(0.184)	(0.322)	(0.065)
12-15 months before	−0.166**	−0.024	−0.061
	(0.079)	(0.449)	(0.049)
9-12 months before	0.005	0.341	−0.066
	(0.101)	(0.394)	(0.050)
6-9 months before	−0.071	0.173	−0.035
	(0.078)	(0.454)	(0.069)
3-6 months before	−0.012	−0.091	−0.009
	(0.114)	(0.432)	(0.083)
0-3 months before	−0.211**	−0.005	−0.157***
	(0.101)	(0.389)	(0.038)
Rideshare entry			
0-3 months after	−0.059	1.093	−0.037
	(0.106)	(0.678)	(0.067)
3-6 months after	−0.136	1.063**	−0.110***
	(0.094)	(0.525)	(0.041)
6-9 months after	−0.058	0.652	−0.046
	(0.094)	(0.493)	(0.062)
9-12 months after	0.229	0.246	0.090
	(0.275)	(0.506)	(0.153)
12-15 months after	−0.028	0.314	0.030
	(0.120)	(0.557)	(0.100)
15-18 months after	−0.135	−0.169	0.019
	(0.138)	(0.501)	(0.094)
18 months +	−0.195**	−0.006	−0.080
	(0.090)	(0.463)	(0.052)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 5: Rideshare entry and crashes per 100,000, lead and lag, Population weighted

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
18-21 months before	−0.004	−0.125	−0.010
	(0.043)	(0.159)	(0.018)
15-18 months before	0.146	0.547**	−0.005
	(0.091)	(0.219)	(0.030)
12-15 months before	−0.035	−0.061	0.012
	(0.044)	(0.165)	(0.021)
9-12 months before	−0.019	−0.103	−0.024
	(0.041)	(0.198)	(0.028)
6-9 months before	−0.131***	−0.186	−0.038**
	(0.034)	(0.189)	(0.015)
3-6 months before	−0.085	−0.377**	−0.015
	(0.056)	(0.187)	(0.022)
0-3 months before	−0.162**	−0.472**	−0.041
	(0.069)	(0.206)	(0.042)
Rideshare entry			
0-3 months after	−0.051	0.036	−0.0002
	(0.049)	(0.240)	(0.024)
3-6 months after	−0.113***	−0.112	−0.011
	(0.034)	(0.236)	(0.025)
6-9 months after	−0.031	0.338	0.006
	(0.053)	(0.215)	(0.035)
9-12 months after	0.032	−0.364	−0.004
	(0.065)	(0.233)	(0.042)
12-15 months after	−0.061	0.081	0.010
	(0.056)	(0.298)	(0.035)
15-18 months after	−0.080	−0.102	0.028
	(0.081)	(0.283)	(0.031)
18 months plus	−0.139**	−0.165	−0.050
	(0.066)	(0.261)	(0.034)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 6: Rideshare entry and crashes per 100,000 for rideshare cities, exclude cities with rideshare prior to Dec 2014

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
Panel A: Time-month dummy			
	0.083	0.092	0.019
	(0.087)	(0.369)	(0.050)
Panel B: City-specific linear time trend			
	−0.021	0.874	0.031
	(0.080)	(0.552)	(0.037)
Panel C: City-specific linear time trend population weighted			
	−0.092	0.346	−0.002
	(0.068)	(0.405)	(0.034)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 7: Rideshare entry and crashes per 100,000 for rideshare cities, lead and lag, exclude cities with rideshare prior to Dec 2014

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
18-21 months before	−0.144	−1.077**	−0.084*
	(0.152)	(0.460)	(0.046)
15-18 months before	0.532	−0.357	−0.007
	(0.338)	(0.335)	(0.129)
12-15 months before	−0.030	−0.932*	−0.001
	(0.138)	(0.537)	(0.087)
9-12 months before	0.015	0.114	−0.009
	(0.126)	(0.706)	(0.090)
6-9 months before	0.076	−0.085	0.027
	(0.111)	(0.481)	(0.132)
3-6 months before	0.151	−0.290	0.110
	(0.196)	(0.776)	(0.154)
0-3 months before	−0.195	0.282	−0.171***
	(0.157)	(0.640)	(0.054)
Rideshare entry			
0-3 months after	0.040	1.320	−0.037
	(0.165)	(1.160)	(0.108)
3-6 months after	−0.156	0.837	−0.119*
	(0.135)	(0.591)	(0.062)
6-9 months after	0.046	0.859	−0.038
	(0.123)	(0.766)	(0.103)
9-12 months after	0.691	0.490	0.356
	(0.507)	(0.896)	(0.283)
12-15 months after	0.078	−0.011	0.095
	(0.202)	(0.797)	(0.161)
15-18 months after	−0.326	0.160	−0.098
	(0.199)	(0.725)	(0.109)
18 months plus	−0.048	−0.813	−0.017
	(0.141)	(0.770)	(0.059)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 8: Rideshare entry and crashes per 100,000 for rideshare cities, lead and lag, exclude cities with rideshare prior to Dec 2014, population weighted

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
18-21 months before	−0.075	−0.818**	−0.111*
	(0.187)	(0.374)	(0.061)
15-18 months before	0.497	−0.558	0.057
	(0.412)	(0.367)	(0.160)
12-15 months before	0.109	−0.953**	0.017
	(0.154)	(0.442)	(0.067)
9-12 months before	0.120	−0.663	0.068
	(0.096)	(0.685)	(0.110)
6-9 months before	−0.051	−0.490	−0.055
	(0.093)	(0.550)	(0.071)
3-6 months before	0.035	−1.142	−0.049
	(0.226)	(0.797)	(0.076)
0-3 months before	−0.349**	−0.340	−0.195***
	(0.163)	(0.848)	(0.044)
Rideshare entry			
0-3 months after	−0.119	0.283	−0.089
	(0.125)	(0.897)	(0.068)
3-6 months after	−0.140	0.211	−0.108*
	(0.114)	(0.512)	(0.061)
6-9 months after	−0.110	0.433	−0.157**
	(0.093)	(0.846)	(0.073)
9-12 months after	0.349	−0.835	0.230
	(0.269)	(0.907)	(0.180)
12-15 months after	0.017	0.092	0.062
	(0.312)	(1.149)	(0.179)
15-18 months after	−0.447**	−0.485	−0.110
	(0.188)	(0.682)	(0.124)
18 months plus	−0.135	−0.831	−0.044
	(0.210)	(0.936)	(0.114)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 9: Rideshare in Chicago and its impact on crashes in Chicago, suburbs

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
Panel A: Time-month dummy			
	−0.017	0.513**	0.001
	(0.037)	(0.258)	(0.019)
Panel B: City-specific linear time trend			
	0.005	0.395	−0.043
	(0.067)	(0.356)	(0.037)
Panel C: City-specific linear time trend population weighted			
	0.034	0.236	−0.028
	(0.058)	(0.296)	(0.035)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 10: Rideshare in Chicago and its impact on crashes in Chicago, suburbs, lead and lag

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
18-21 months before	0.062	0.132	0.020
	(0.075)	(0.392)	(0.045)
15-18 months before	0.061	−0.075	−0.027
	(0.082)	(0.387)	(0.048)
12-15 months before	0.080	0.337	−0.033
	(0.083)	(0.439)	(0.036)
9-12 months before	0.056	0.362	−0.027
	(0.074)	(0.407)	(0.035)
6-9 months before	0.121	0.637	−0.048
	(0.098)	(0.462)	(0.043)
3-6 months before	0.054	0.510	−0.015
	(0.113)	(0.526)	(0.057)
0-3 months before	−0.005	0.746	0.004
	(0.107)	(0.521)	(0.052)
Rideshare entry			
0-3 months after	−0.003	0.349	−0.031
	(0.107)	(0.495)	(0.053)
3-6 months after	0.083	1.040**	−0.036
	(0.118)	(0.495)	(0.053)
6-9 months after	−0.089	0.183	−0.050
	(0.113)	(0.531)	(0.059)
9-12 months after	−0.083	0.858	−0.092*
	(0.117)	(0.557)	(0.050)
12-15 months after	0.098	1.234**	−0.072
	(0.123)	(0.561)	(0.053)
15-18 months after	0.240**	0.761	−0.008
	(0.121)	(0.581)	(0.080)
18 months plus	0.123	1.091*	−0.086
	(0.124)	(0.610)	(0.068)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 11: Rideshare in Chicago and its impact on crashes in Chicago, suburbs, lead and lag, population weighted

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
18-21 months before	0.115**	0.503**	0.005
	(0.049)	(0.237)	(0.030)
15-18 months before	0.025	0.142	−0.007
	(0.046)	(0.243)	(0.025)
12-15 months before	0.074	0.162	−0.034
	(0.047)	(0.247)	(0.024)
9-12 months before	0.027	0.052	−0.007
	(0.058)	(0.266)	(0.023)
6-9 months before	0.033	0.175	−0.034
	(0.089)	(0.370)	(0.029)
3-6 months before	0.065	0.346	0.020
	(0.069)	(0.394)	(0.033)
0-3 months before	0.017	0.249	−0.006
	(0.066)	(0.411)	(0.031)
Rideshare entry			
0-3 months after	−0.019	0.279	−0.053
	(0.081)	(0.361)	(0.034)
3-6 months after	0.088	0.596	0.029
	(0.078)	(0.365)	(0.047)
6-9 months after	0.016	0.260	−0.014
	(0.085)	(0.386)	(0.039)
9-12 months after	0.035	0.608	−0.052
	(0.097)	(0.404)	(0.035)
12-15 months after	0.087	0.609	−0.050
	(0.082)	(0.400)	(0.036)
15-18 months after	0.143	0.960**	−0.004
	(0.094)	(0.434)	(0.054)
18 months plus	0.071	0.628	−0.083*
	(0.098)	(0.485)	(0.048)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 12: Rideshare and crashes - Chicago and suburbs as one unit

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
Panel A: Time-month dummy			
	−0.020	0.560**	0.007
	(0.033)	(0.230)	(0.017)
Panel B: City-specific linear time trend			
	−0.005	0.537**	−0.008
	(0.051)	(0.244)	(0.026)
Panel C: City-specific linear time trend population weighted			
	−0.022	0.248	0.002
	(0.043)	(0.205)	(0.022)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 13: Rideshare and crashes - Chicago and suburbs as one unit, lead and lag

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
18-21 months before	−0.046	−0.128	−0.019
	(0.057)	(0.280)	(0.022)
15 -18 months	0.138	0.264	−0.005
	(0.087)	(0.360)	(0.038)
12-15 months	0.038	0.038	−0.030
	(0.080)	(0.314)	(0.040)
9-12 months before	0.044	0.406	−0.024
	(0.066)	(0.374)	(0.034)
6-9 months before	0.056	0.318	−0.006
	(0.065)	(0.317)	(0.034)
3-6 months before	0.094	0.621	−0.009
	(0.089)	(0.415)	(0.042)
0-3 months before	0.039	0.561	0.027
	(0.085)	(0.377)	(0.049)
Rideshare entry			
0-3 months after	−0.083	0.462	−0.056
	(0.077)	(0.418)	(0.036)
3-6 months after	0.051	0.586	−0.001
	(0.078)	(0.423)	(0.041)
6-9 months after	0.083	1.071***	−0.015
	(0.095)	(0.414)	(0.055)
9-12 months after	−0.034	0.345	0.018
	(0.127)	(0.415)	(0.067)
12-15 months after	0.028	0.732*	−0.040
	(0.103)	(0.417)	(0.051)
15-18 months after	0.039	1.159**	−0.039
	(0.100)	(0.481)	(0.045)
18 months plus	0.087	1.000**	−0.049
	(0.104)	(0.498)	(0.058)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 14: Rideshare and crashes - Chicago and suburbs as one unit, lead and lag, population weighted

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
18-21 months before	−0.006	−0.196	−0.016
	(0.040)	(0.184)	(0.018)
15-18 months before	0.114	0.303	−0.013
	(0.071)	(0.253)	(0.029)
12-15 months before	0.024	−0.161	−0.006
	(0.050)	(0.230)	(0.021)
9-12 months before	0.035	−0.190	−0.024
	(0.050)	(0.228)	(0.032)
6-9 months before	−0.043	−0.046	−0.023
	(0.059)	(0.233)	(0.025)
3-6 months before	0.004	−0.037	−0.014
	(0.074)	(0.298)	(0.025)
0-3 months before	−0.042	0.084	0.015
	(0.063)	(0.352)	(0.031)
Rideshare entry			
0-3 months after	−0.052	0.085	−0.021
	(0.060)	(0.273)	(0.026)
3-6 months after	−0.016	0.160	−0.002
	(0.059)	(0.289)	(0.022)
6-9 months after	0.028	0.461	−0.006
	(0.055)	(0.311)	(0.031)
9-12 months after	0.008	−0.090	0.005
	(0.065)	(0.320)	(0.043)
12-15 months after	−0.002	0.218	−0.014
	(0.053)	(0.318)	(0.034)
15-18 months after	−0.047	0.568	−0.034
	(0.088)	(0.349)	(0.040)
18 months plus	−0.057	0.433	−0.070
	(0.086)	(0.377)	(0.047)

There are 13,666 observations. The omitted variable category is 21 months before rideshare. All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

Table 15: Heterogeneity Effects across Age Groups

	(1) Fatal crashes	(2) Alcohol related	(3) Alcohol related fatal
Panel A: **0-18 years**			
RideshareEntry	0.039	−0.051	0.0004
	(0.056)	(0.153)	(0.003)
Panel B: **19-25 years**			
RideshareEntry	−0.106*	0.380	−0.0001
	(0.060)	(0.233)	(0.016)
Panel C: **26-44 years**			
RideshareEntry	0.089	0.516	0.041*
	(0.118)	(0.425)	(0.023)
Panel D: **45 plus years**			
RideshareEntry	−0.116	0.224	0.003
	(0.071)	(0.221)	(0.017)

All specifications include city fixed effects, month and year fixed effects and city-specific linear trends. I also include population density and unemployment rate. Standard errors are clustered by city. *p<0.1; **p<0.05; ***p<0.01

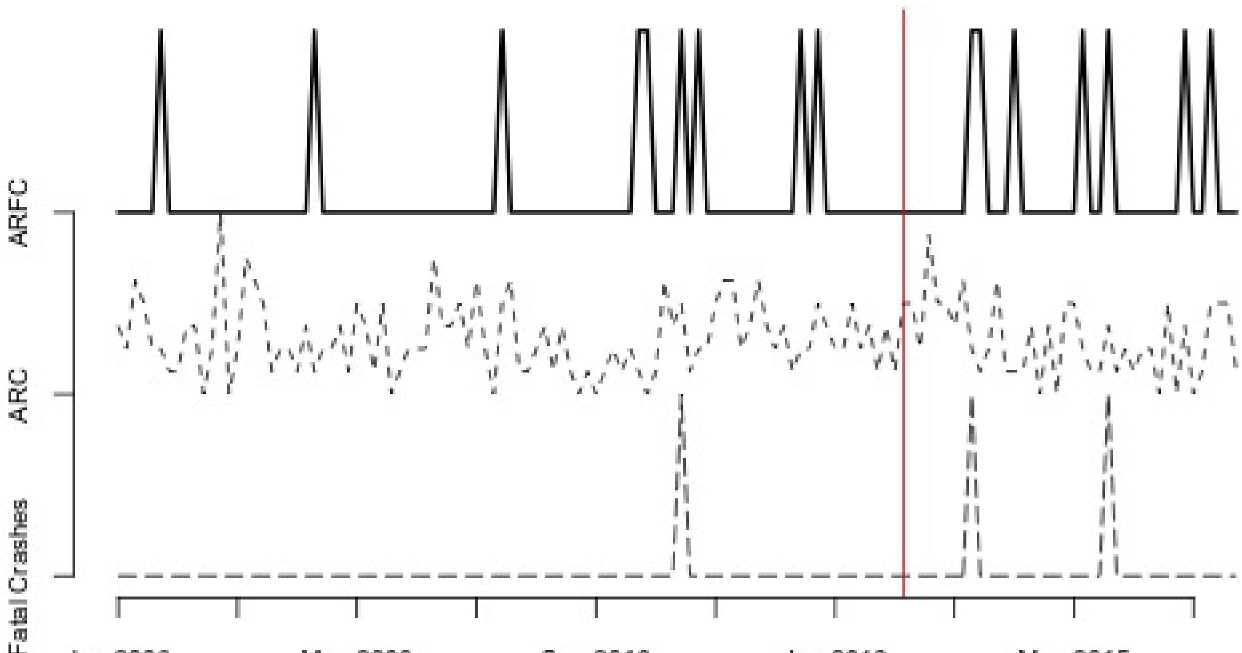


Figure 1.1: Crash rate for Evanston

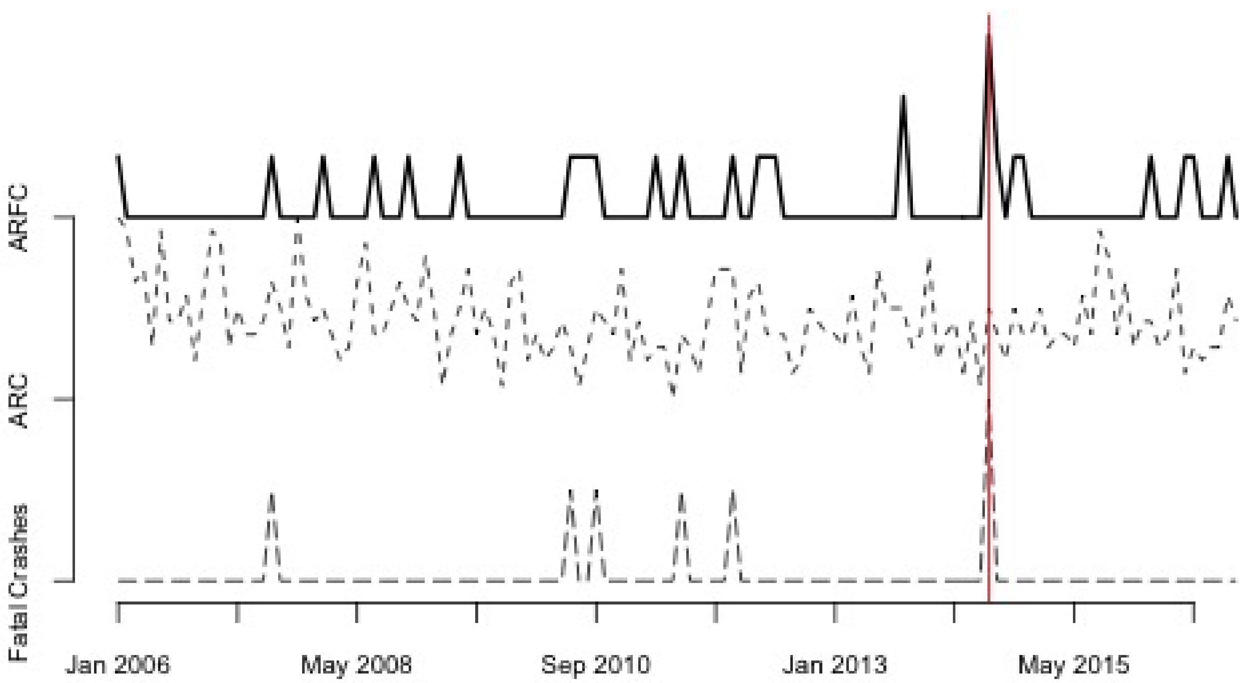


Figure 1.2: Crash rate for Naperville

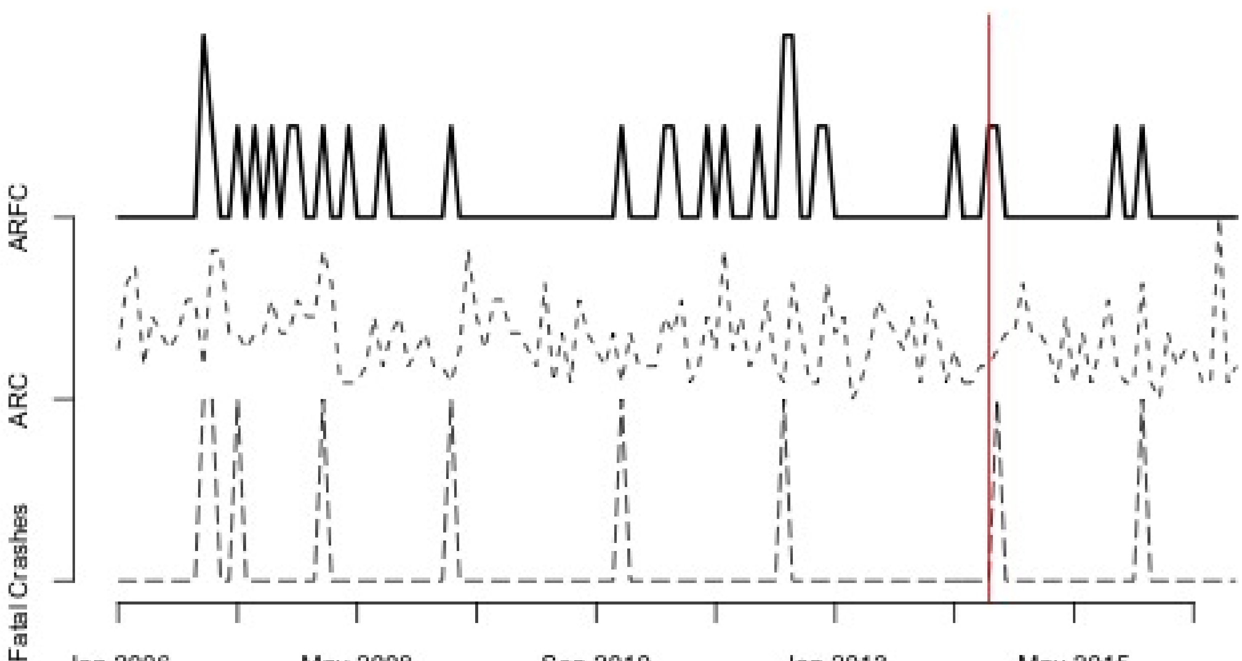


Figure 1.3: Crash rate for Schaumburg

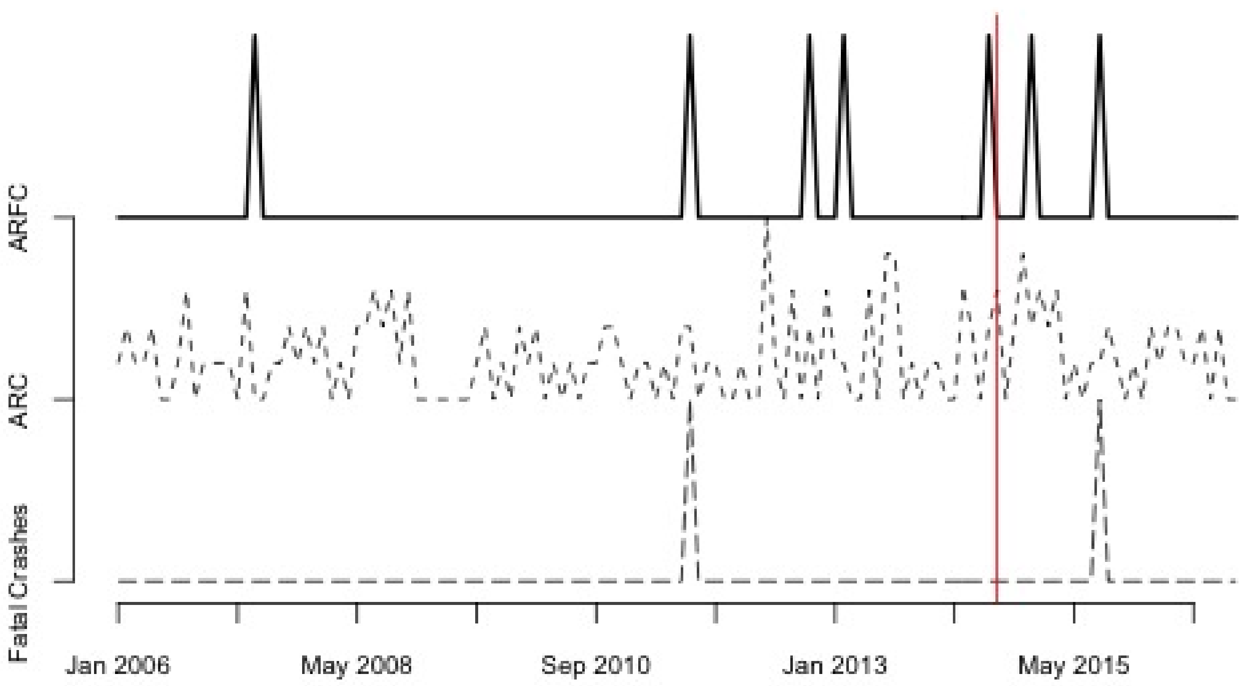


Figure 1.4: Crash rate for Northbrook

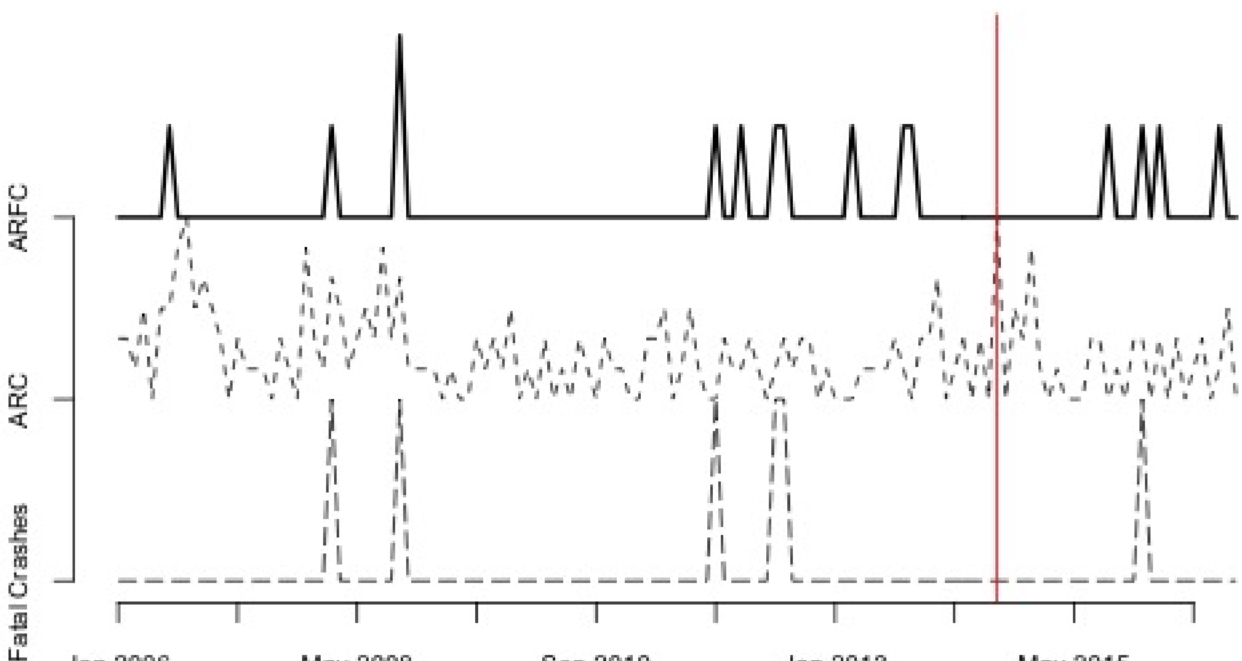


Figure 1.5: Crash rate for Glenview

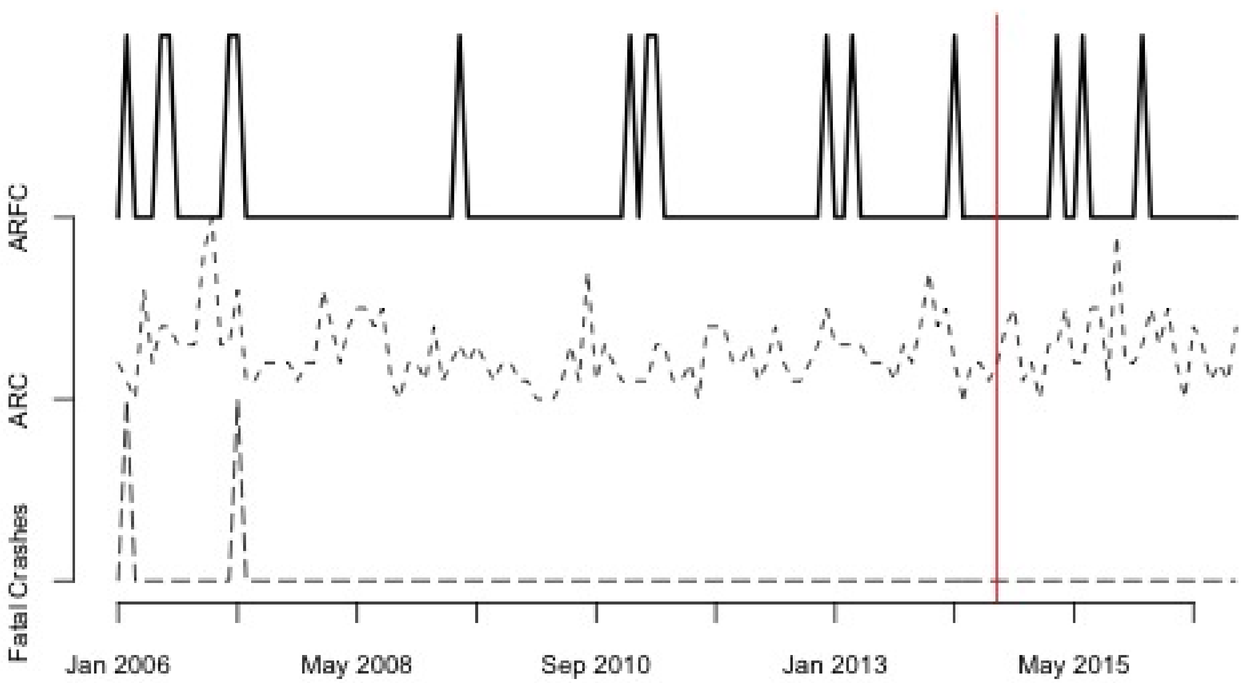


Figure 1.6: Crash rate for Arlington heights

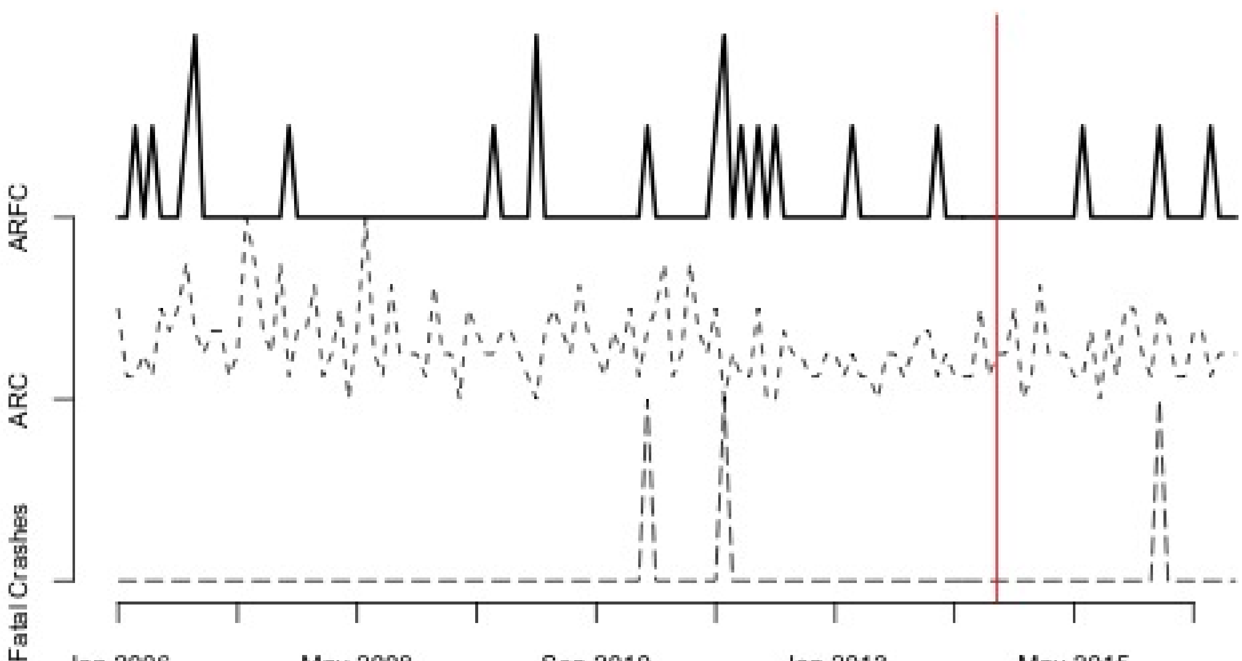


Figure 1.7: Crash rate for Palatine

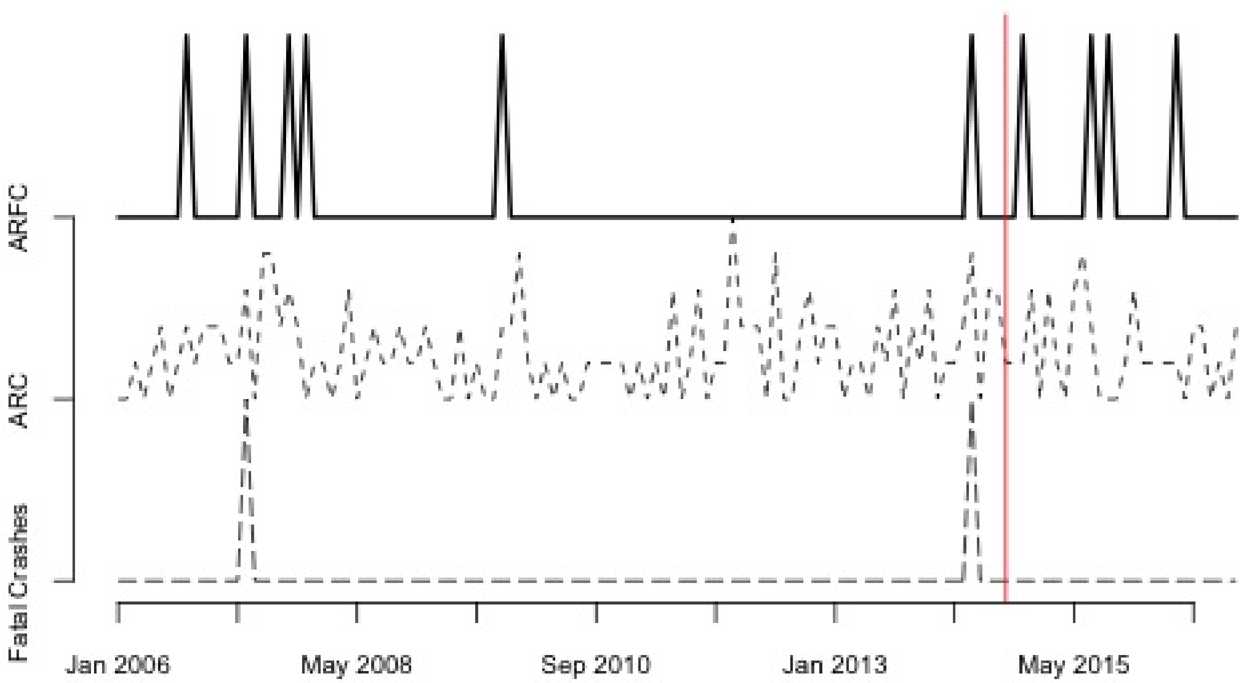


Figure 1.8: Crash rate for Wheaton

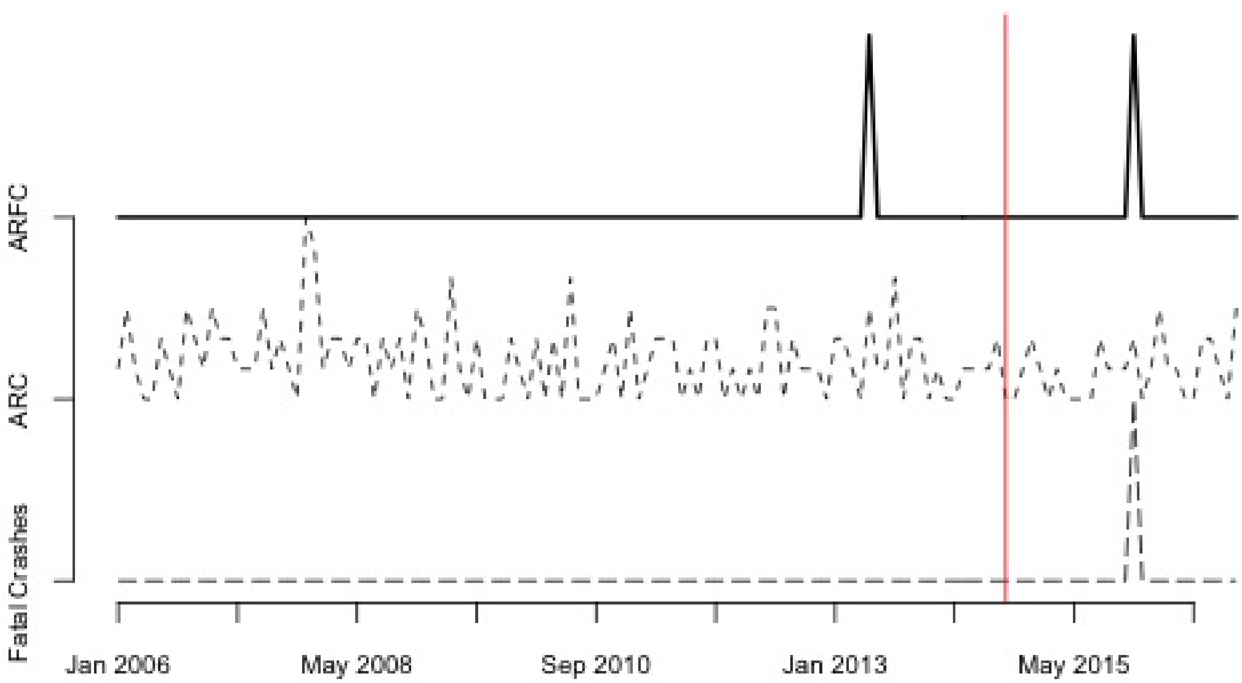


Figure 1.9: Crash rate for Glen ellyn

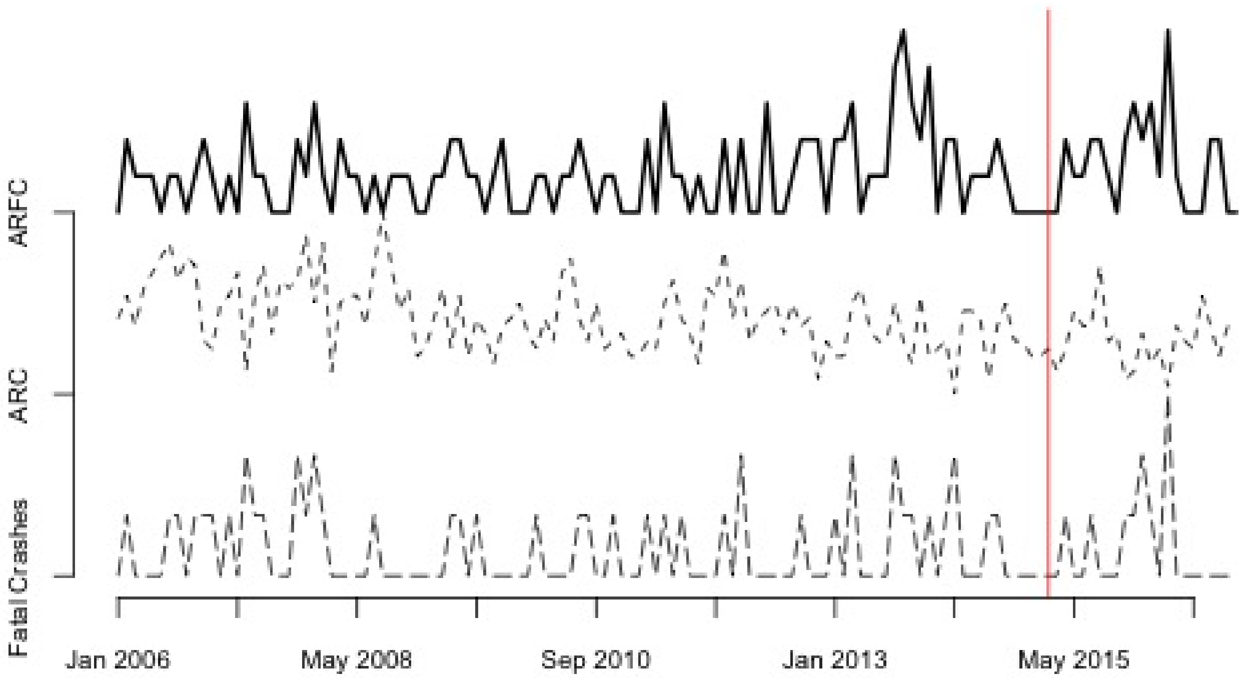


Figure 1.10: Crash rate for Rockford

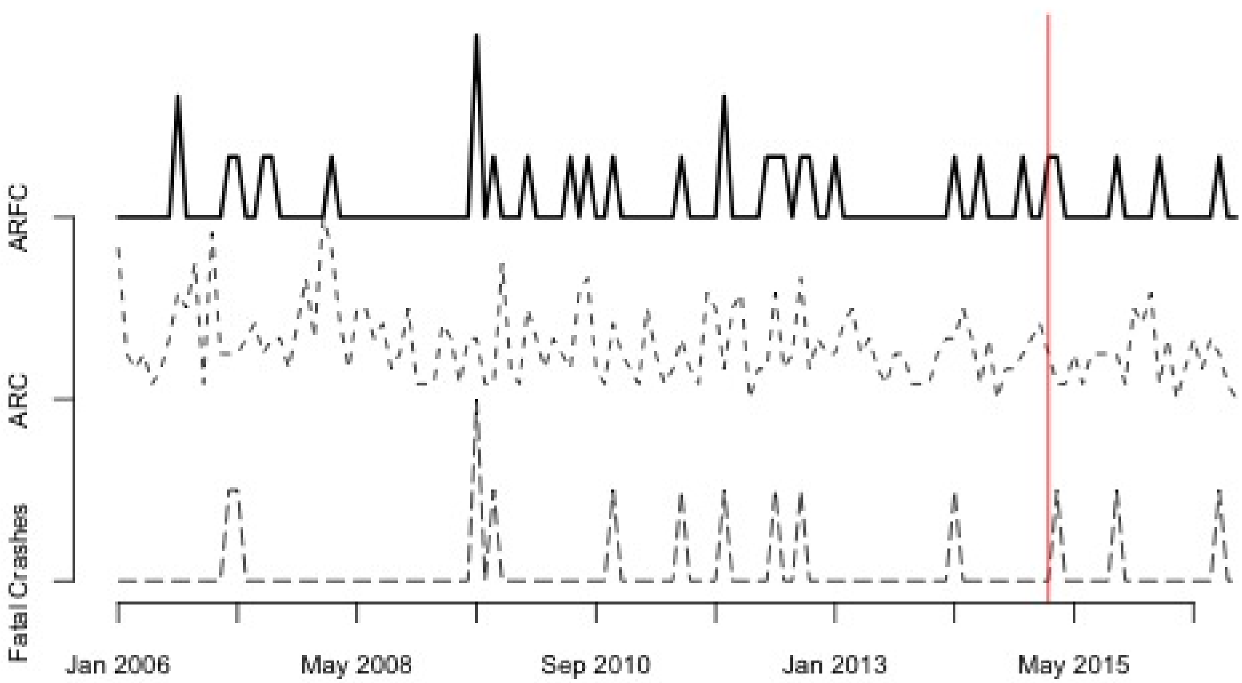


Figure 1.11: Crash rate for Bloomington

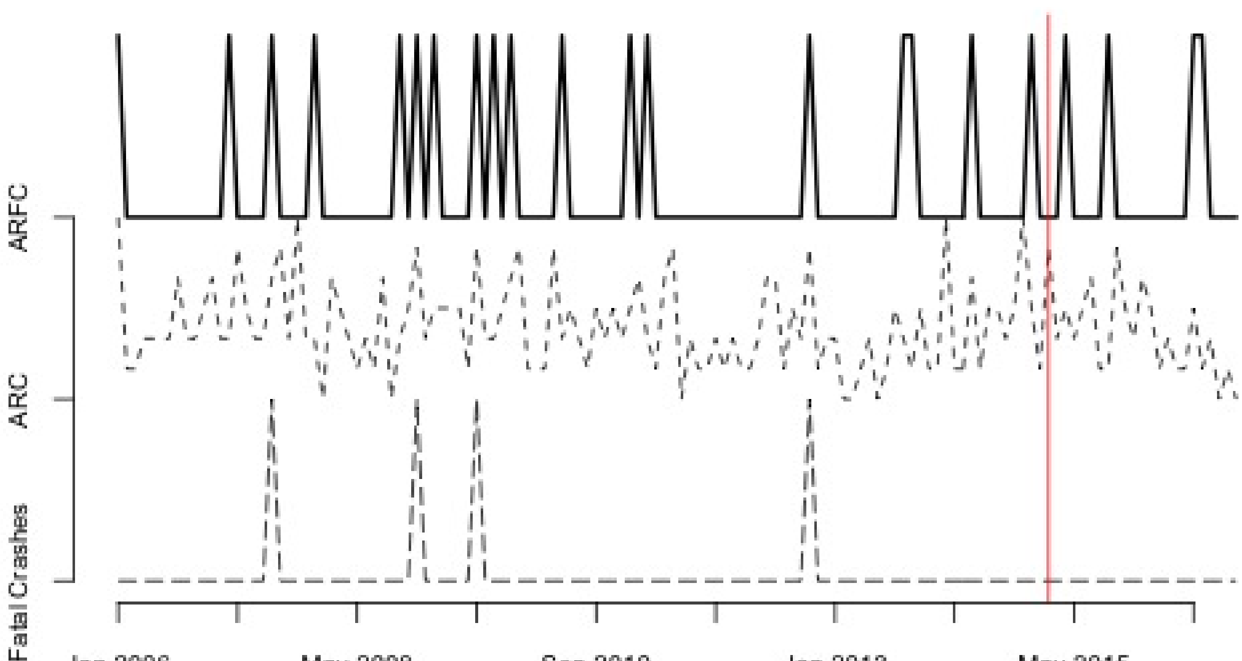


Figure 1.12: Crash rate for Urbana

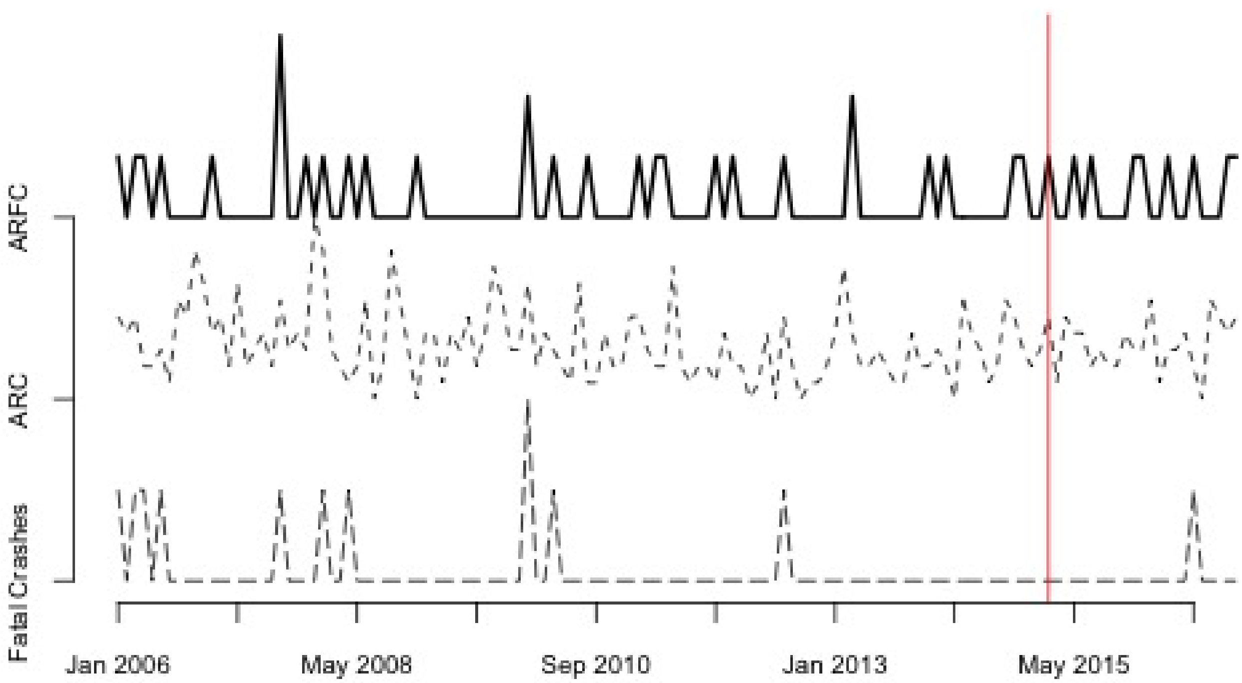


Figure 1.13: Crash rate for Champaign

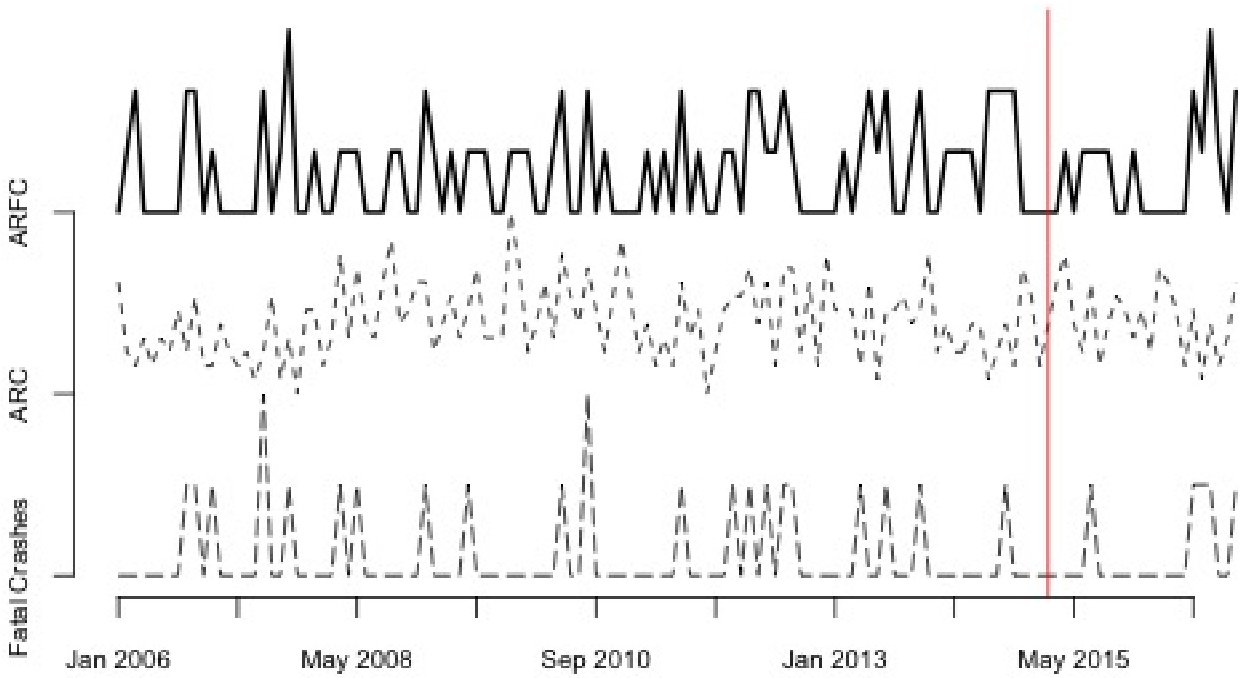


Figure 1.14: Crash rate for Springfield

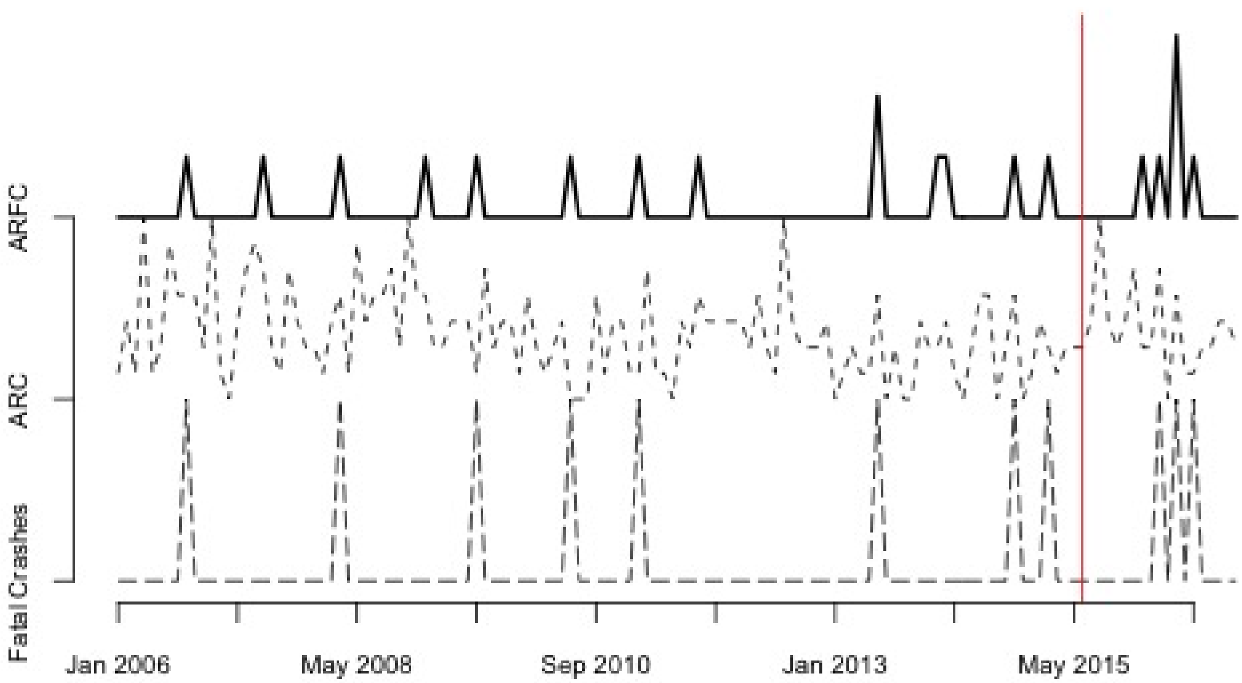


Figure 1.15: Crash rate for Kankakee

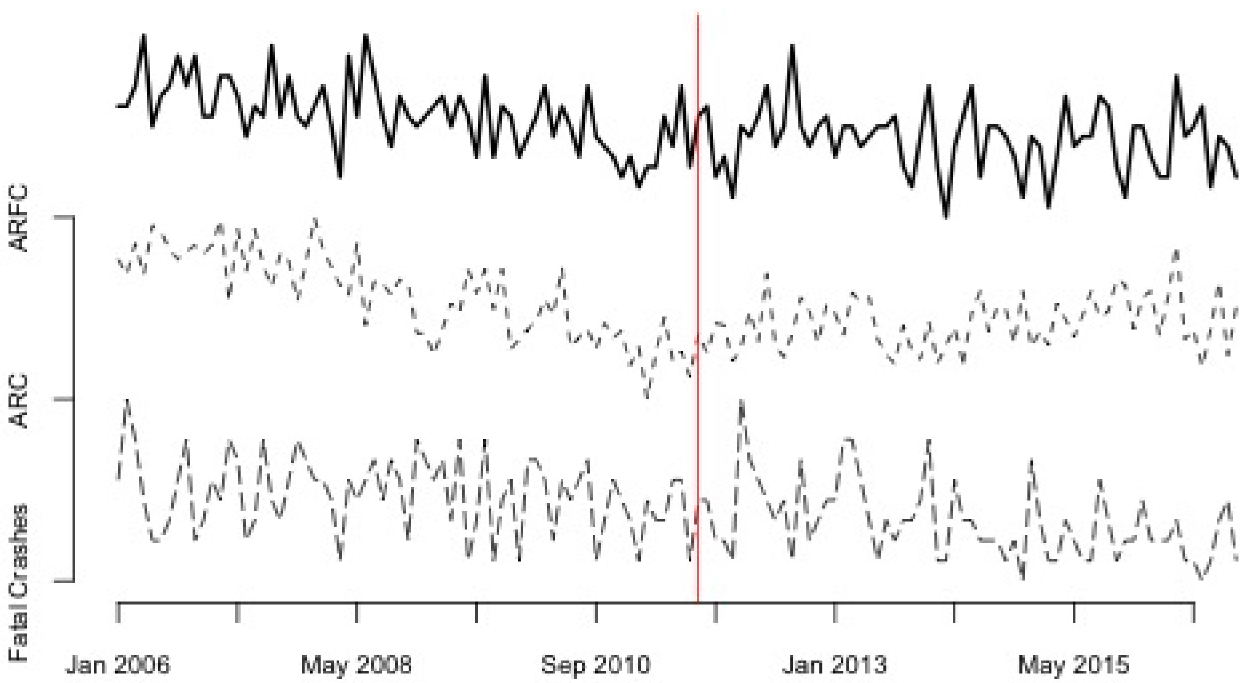


Figure 1.16: Crash rate for Chicago

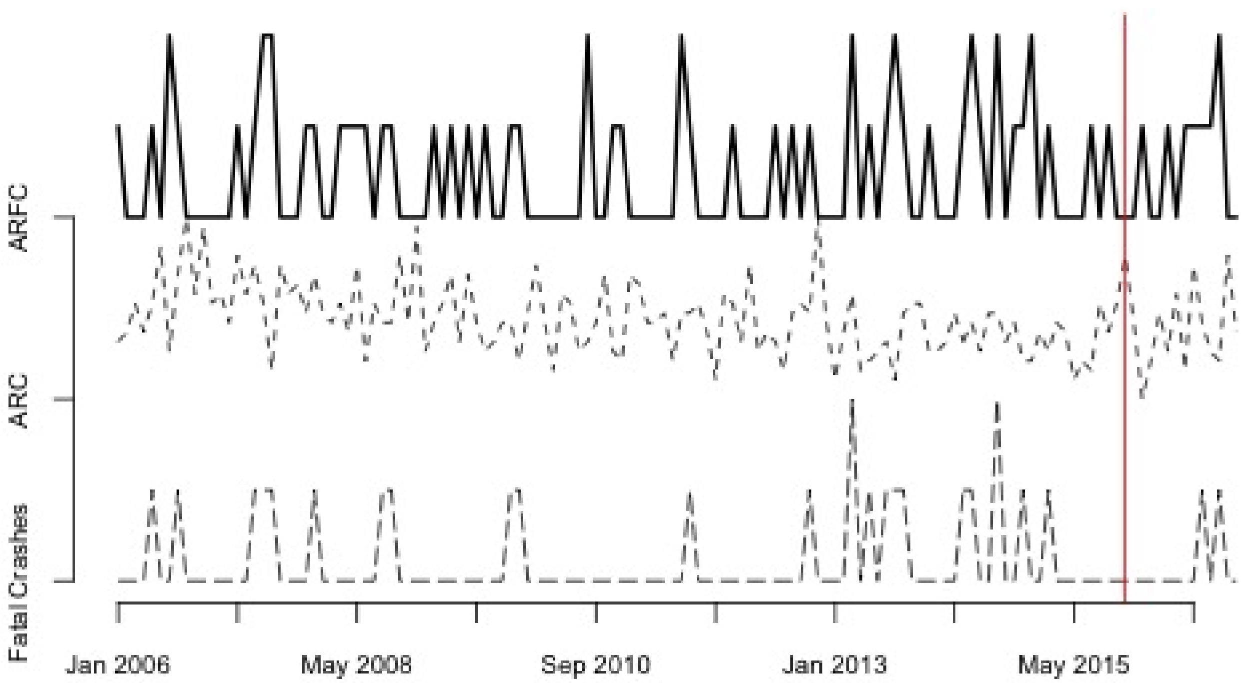


Figure 1.17: Crash rate for Peoria

Fig 2.2. Fatal crash rate

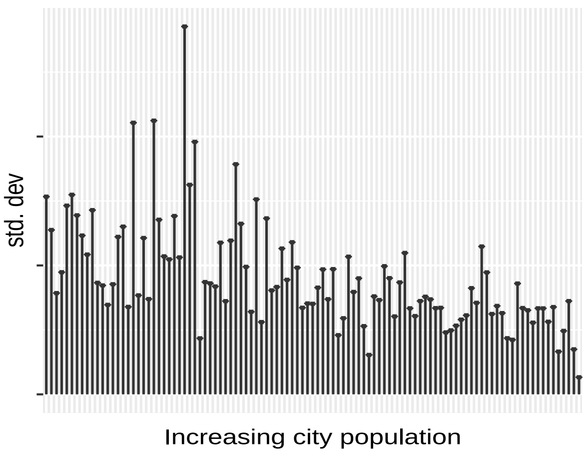


Fig 2.3. Alcohol−related crash rate

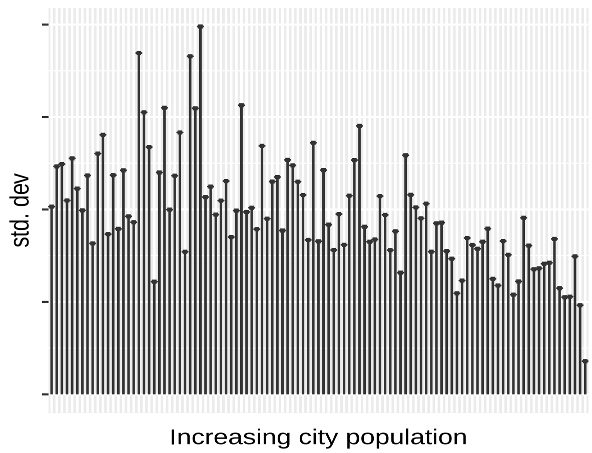


Fig 2.6. Alcohol−related fatal crash rate

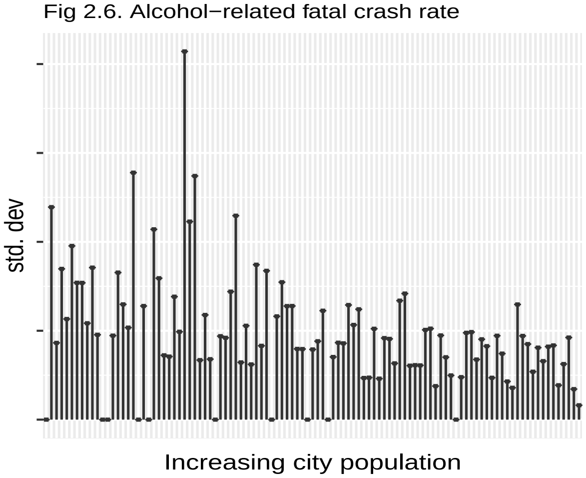


Fig 3.1 Alcohol−related crash rate: Synthetic control, Chicago

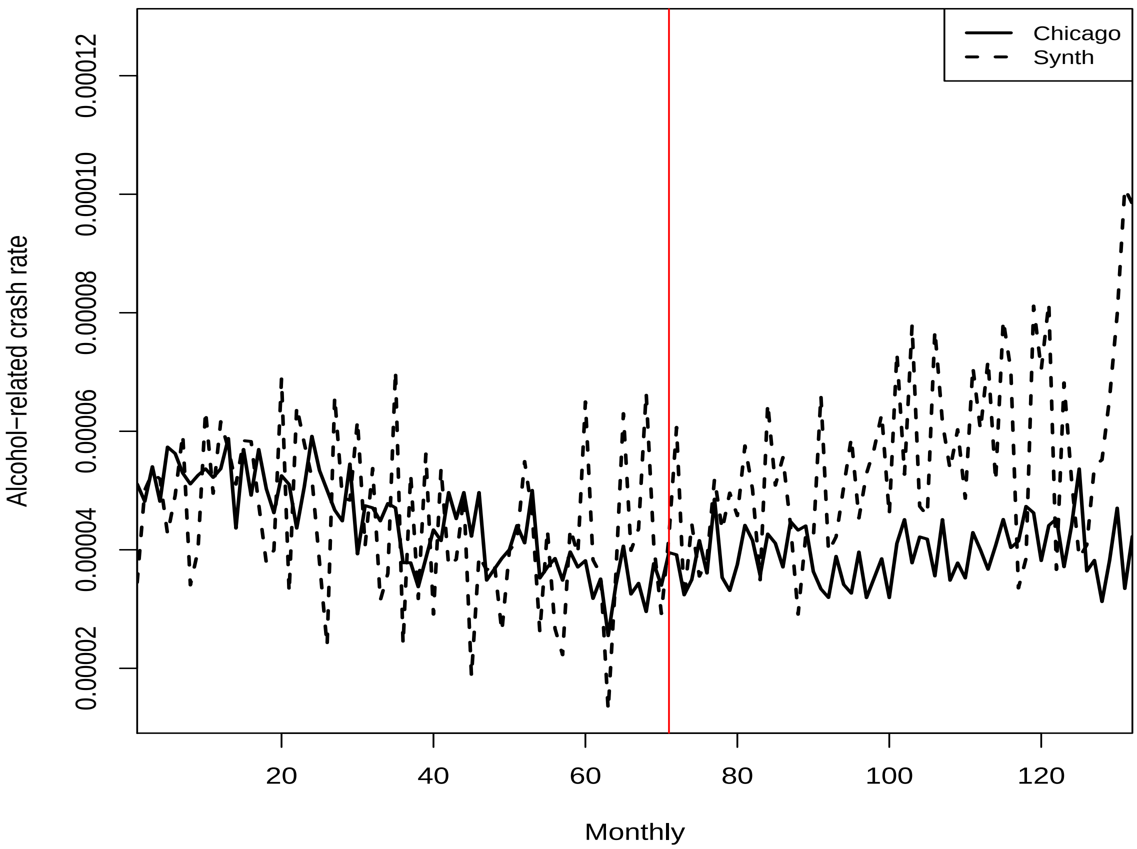


Fig 3.2 Alcohol−related fatal crash rate: Synthetic control, Chicago

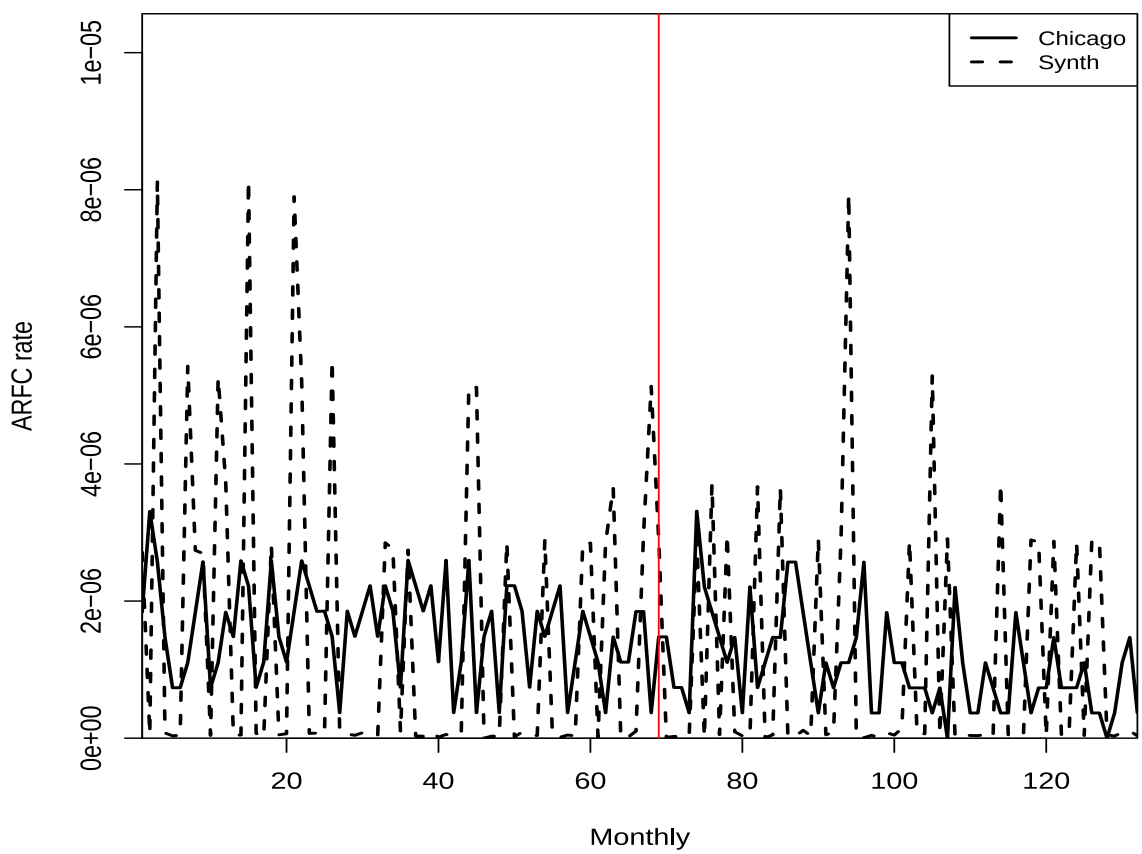
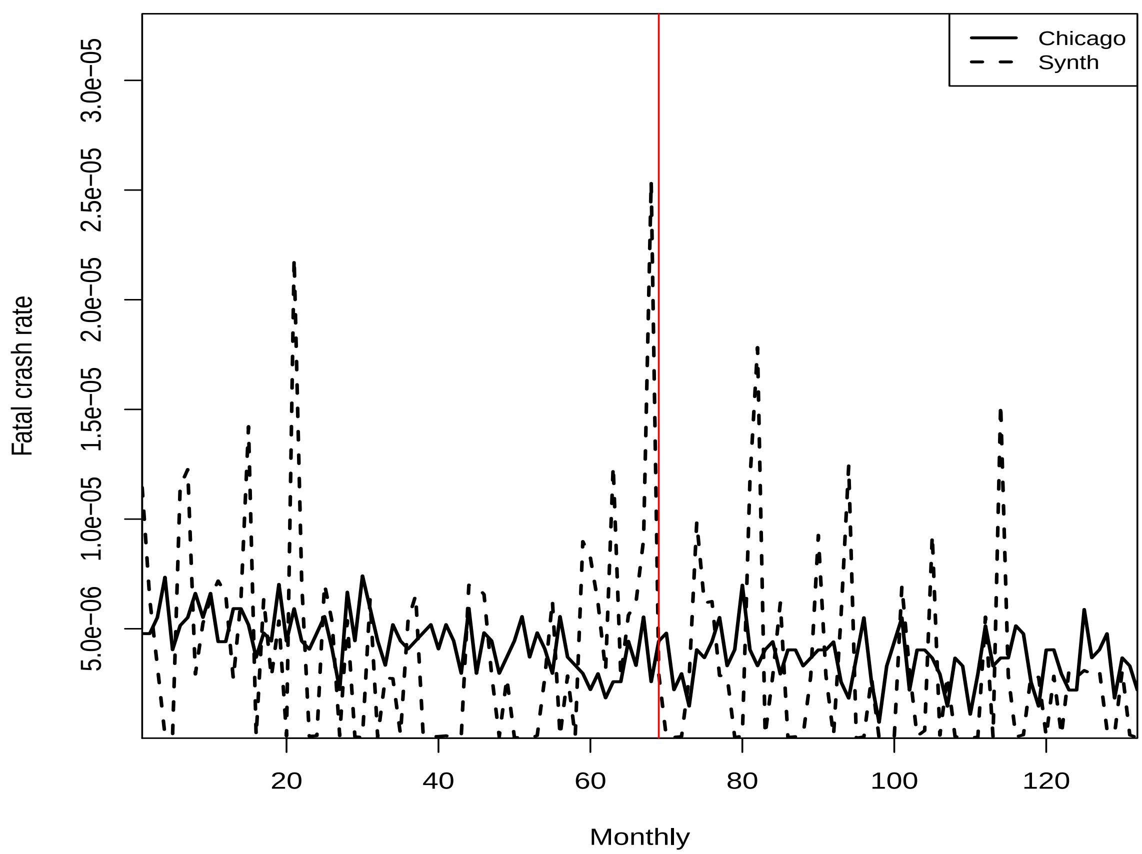


Fig 3.3. Fatal crash rate: Synthetic control for Chicago



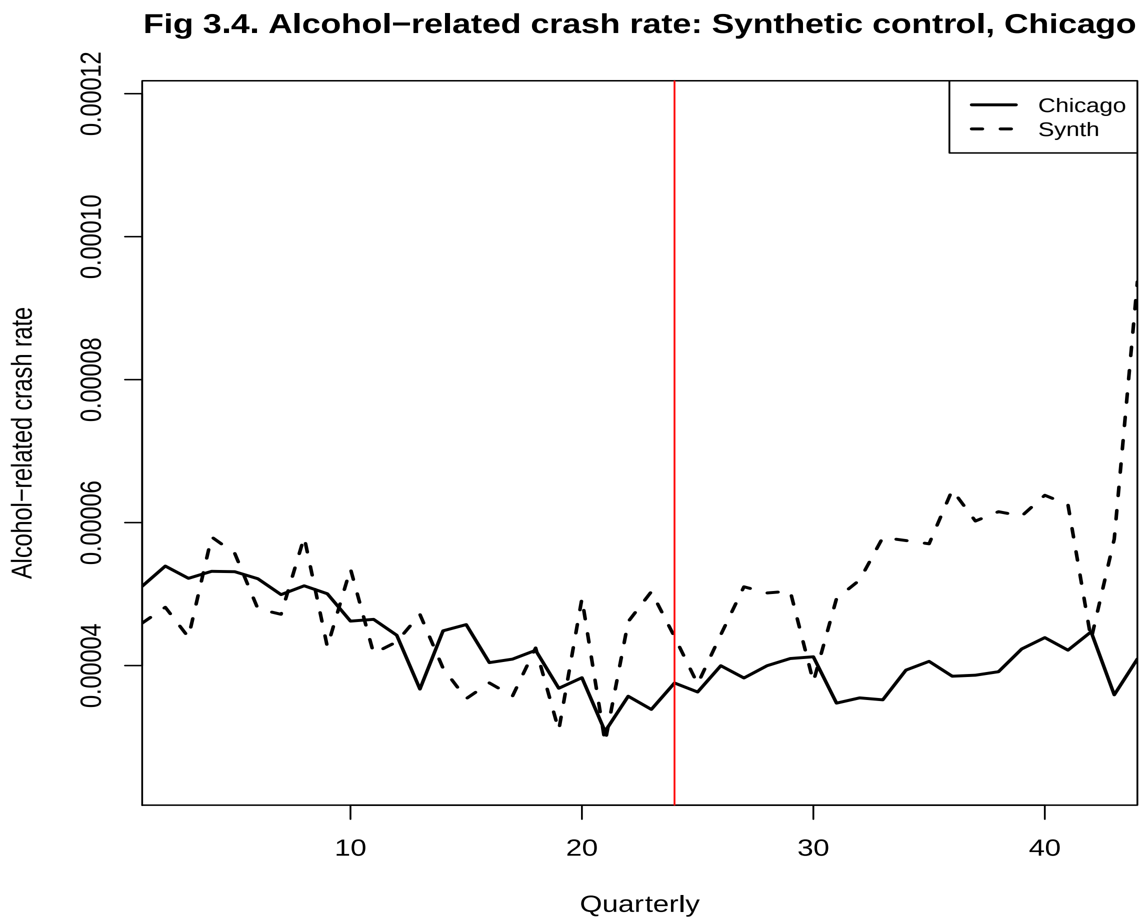


Fig 3.4. Alcohol−related crash rate: Synthetic control, Chicago
Chicago
Synth
Alcohol−related crash rate
0.00004
0.00006
0.00008
0.00010
0.00012
10
20
30
40
Quarterly

Fig 3.5. ARFC rate: Synthetic control for Chicago

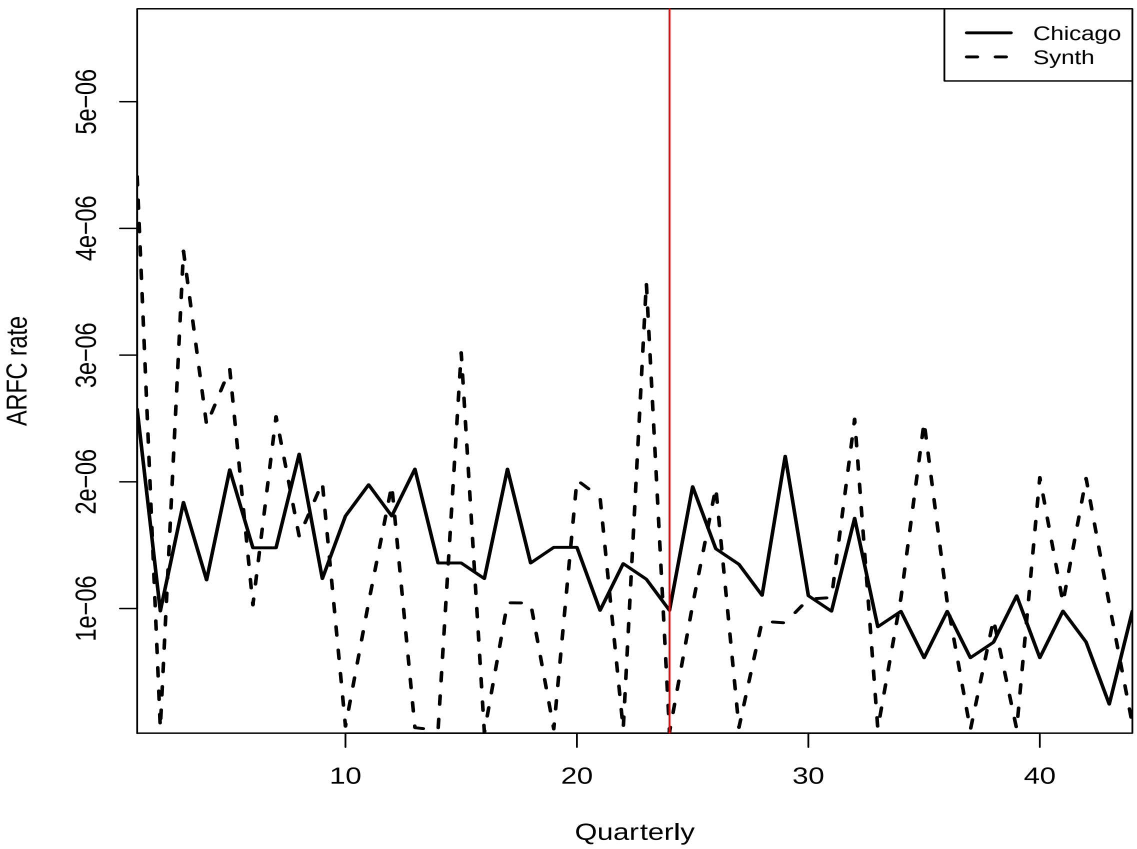


Fig 3.6. Fatal crash rate: Synthetic control for Chicago

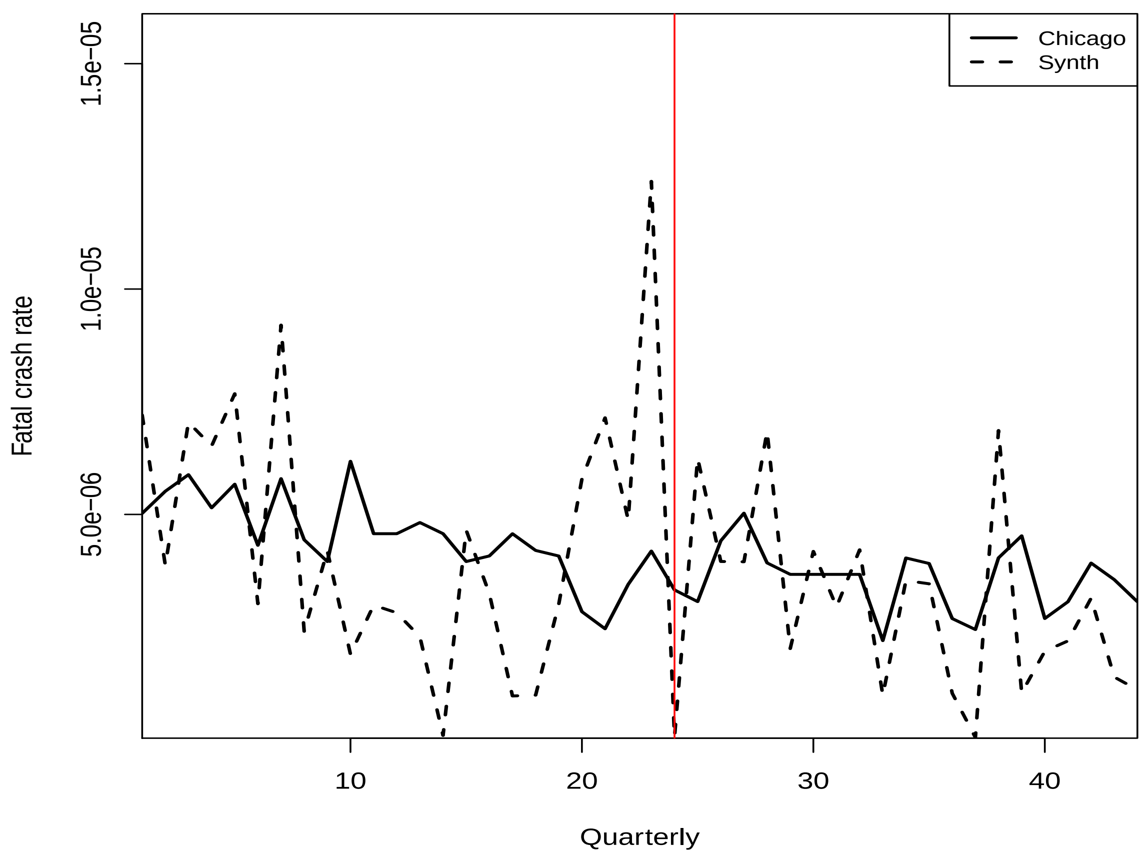


Fig 3.9. Alcohol−related crash rate: Synthetic control, Naperville

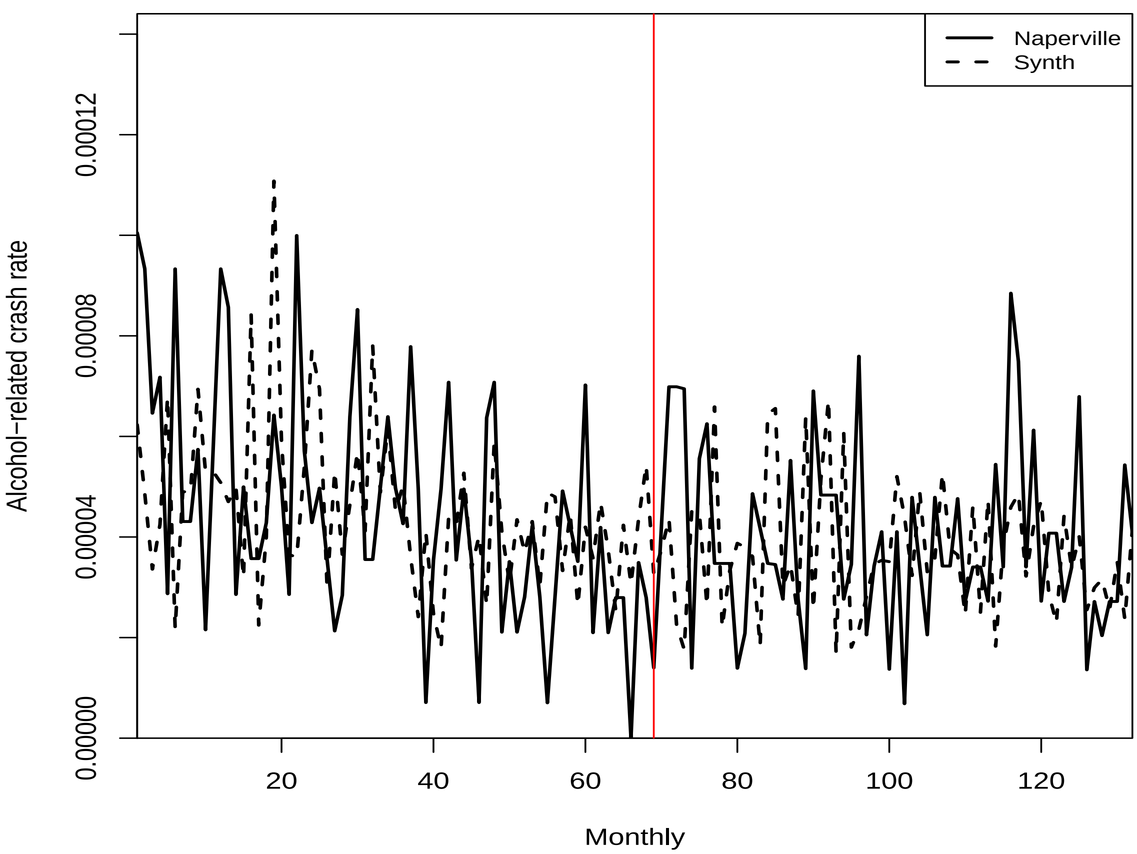
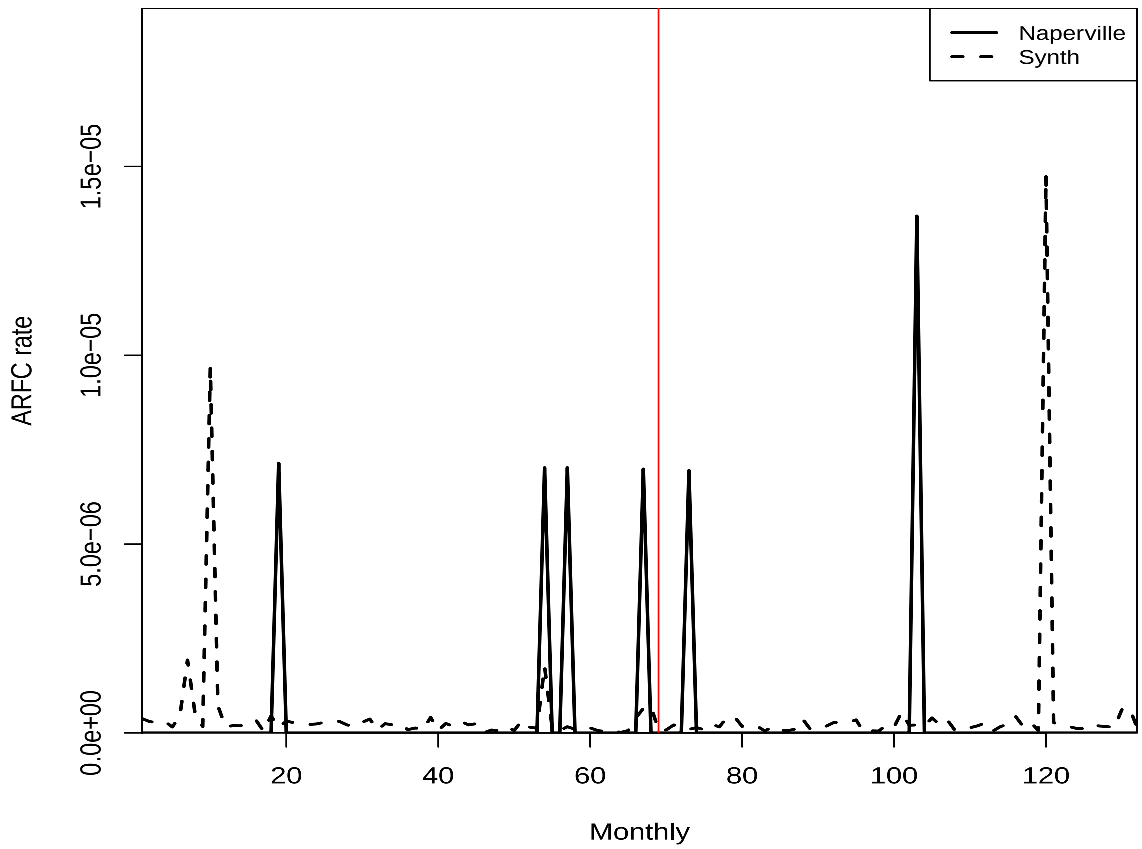


Fig 3.8. Alcohol−related fatal crash rate: Synthetic control, Naperville



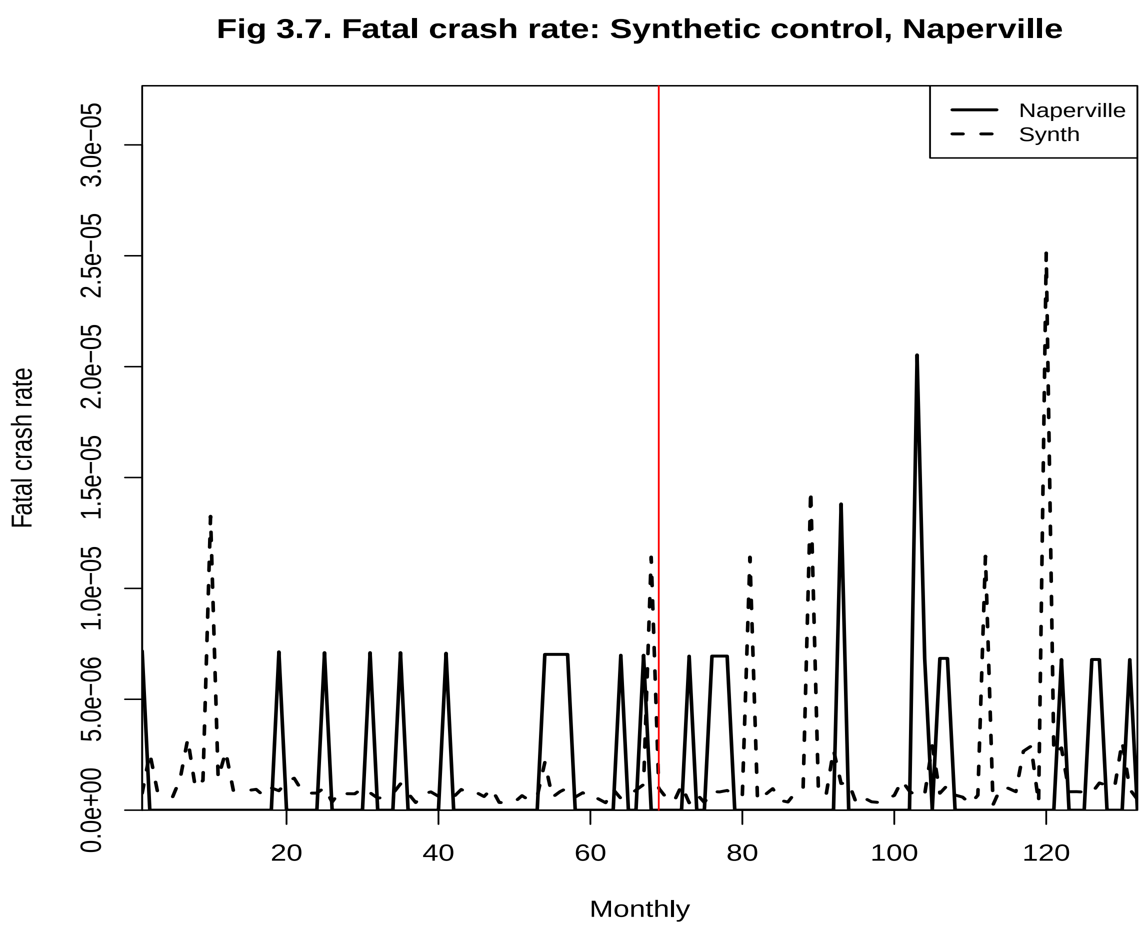


Fig 3.7. Fatal crash rate: Synthetic control, Naperville
Naperville
Synth
Fatal crash rate
0.0e+00
5.0e−06
1.0e−05
1.5e−05
2.0e−05
2.5e−05
3.0e−05
20
40
60
80
100
120
Monthly

Fig 3.10. Alcohol related crash rate: Synthetic control, Naperville

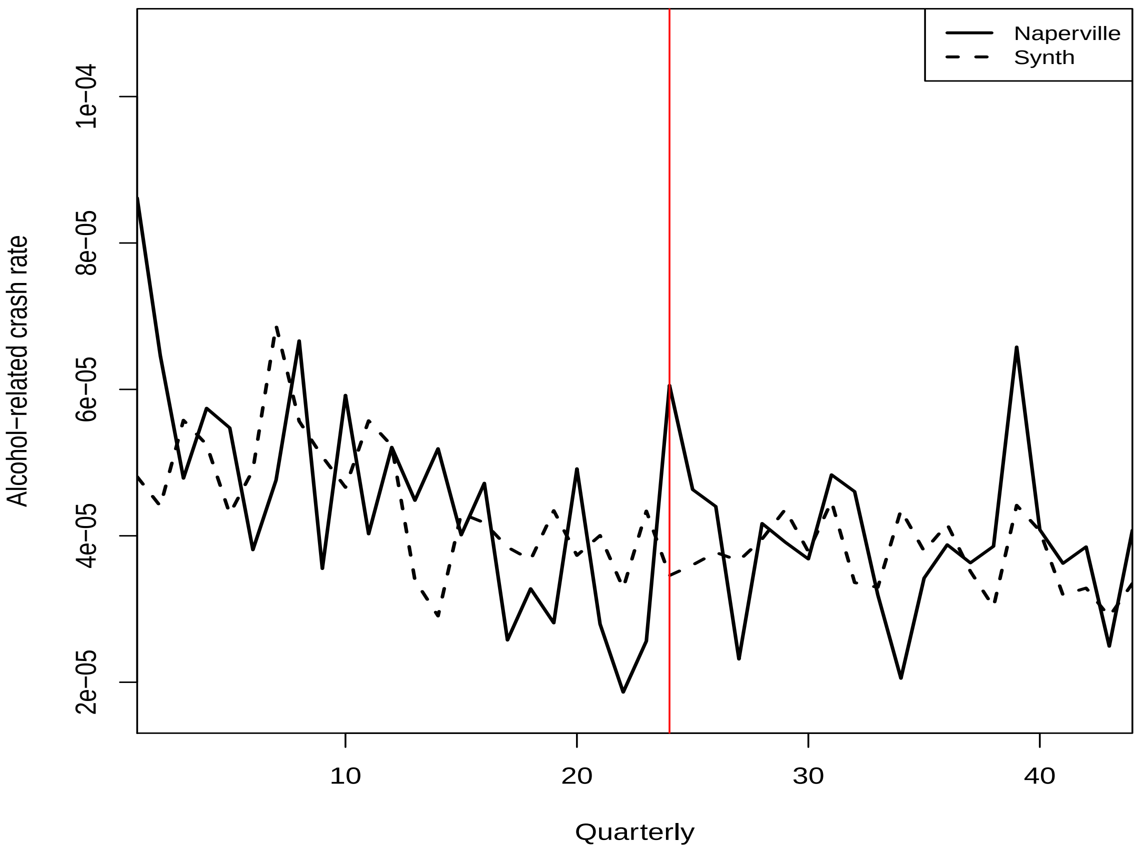


Fig 3.11. ARFC rate: Synthetic control, Naperville

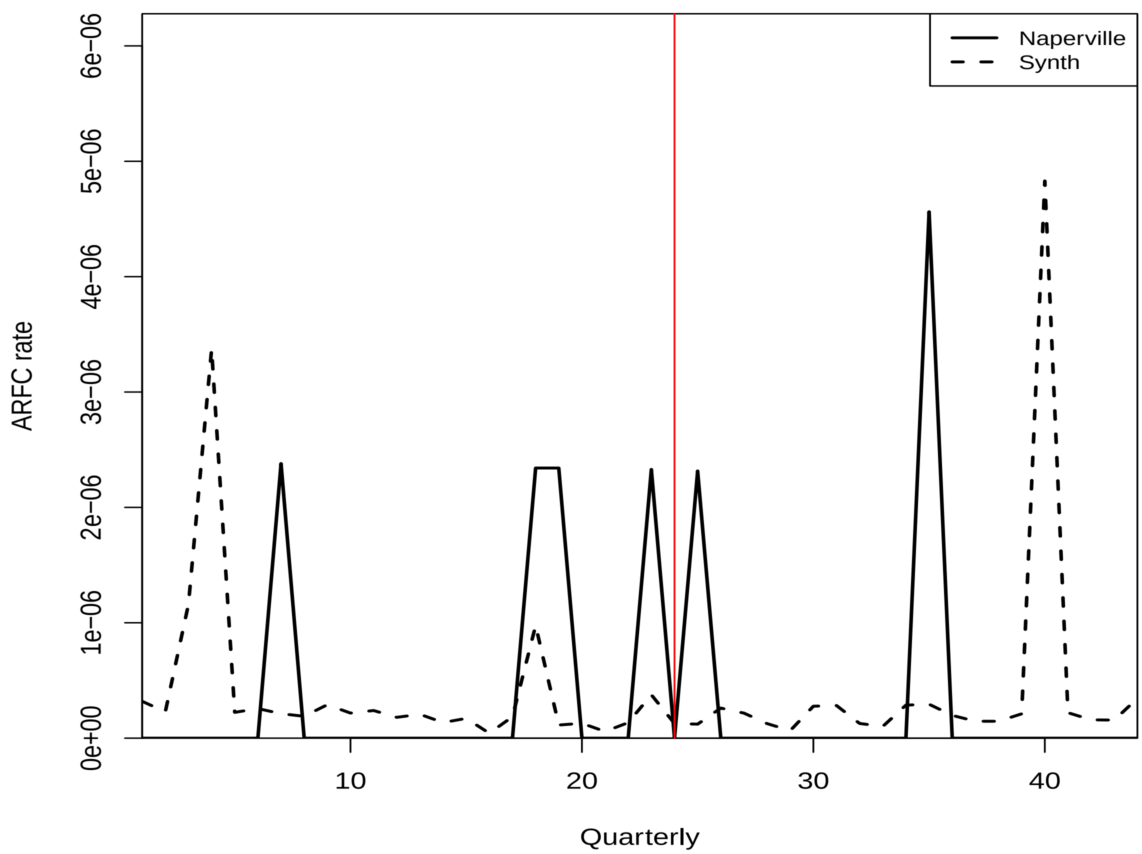


Fig 3.12. Fatal crash rate: Synthetic control, Naperville