Poznań University of Economics and Business

Faculty of Informatics and Electronic Economy

Piotr Opiela

Estimation of the impact of automatic traffic supervision on vehicle speed using the difference-in-differences approach

Estymacja wpływu automatycznego nadzoru nad ruchem drogowym na prędkość pojazdów z wykorzystaniem podejścia difference-and-differences

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Thesis Supervisor: dr Maciej Beręsewicz

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Contents

Introduction

Road traffic deaths are the number eight cause of death for people of all ages worldwide according to the World Health Organization (World Health Organization, 2018). In Poland the number of fatalities from road accidents has been decreasing since the year 2000, although for 2017 this country's position in the European Union is still one of the highest. Factors such as age, weather, month, excessive speeding, driving under the influence of alcohol and time of day have been associated to road traffic deaths.

The primary cause of death on Polish roads accident according to Polish Police (2019) is not adapting the speed of the vehicle to traffic conditions. Due to this reason speed humps, automatic traffic supervision and roundabouts, have been implemented attempting to decrease average velocity.

In this thesis our main focus is evaluating the effectiveness of speed cameras and average speed measuring devices in Poland. We attempt to estimate the effect of these appliances on different vehicle types, as well.

In order to complete our evaluation we obtained data for the treatment group from The Centre for Automatic Traffic Supervision. This data source contained information from the „Construction of a central system of automatic traffic supervision" project where vehicle speeds were measured before and after implementing speed cameras or average speed measuring devices. For the control group we acquired data from The General Director for National Roads and Motorways, that collects data continuously from different monitoring stations in Poland.

Our main goal was to check whether automatic speed supervision is helpful in reducing the average speed on Polish roads. Our hypothesis was that both speed cameras and average speed measuring devices decrease the velocity of different vehicles.

The set up of our experiment does not fulfill the requirements of a randomized (controlled) trial, because participants where not randomly assigned to each group. For this reason we implemented the difference-in-differences method, a popular approach in measuring the effect of an intervention in observational studies.

From chapter one we learn that there many definitions associated with road safety. Road safety is usually associated with the amount of accidents or deaths on roads. In this chapter we also find out that there is a substantial amount of factors influencing road safety. We can also learn about different data sources and descriptive statistics on road safety in Poland.

In chapter two we look into causality in econometrics. We learn about different approaches in measuring treatment effects, like propensity score matching, regression discontinuity and difference in difference estimators. Additionally we look into the case where constant variance of standard errors is not present, that is why we introduce theory on robust standard errors.

In chapter three first we present descriptive statistics on the control and treatment group, and then we measure the effect of automatic traffic supervision. After visually inspecting the influence of speed cameras and average speed measuring devices we implement the difference in difference method. We also calculate robust stand errors, so that the variance of standard errors would be constant. Marginal effects were calculated as well in order to measure the effect of automatic traffic supervision on different vehicle types.

The thesis ends with conclusions and further steps.

Chapter 1

Quantifying road safety

1.1 Road safety – definitions and measurement

1.1.1 Road safety – Basic definitions

Road safety is usually defined and evaluated in terms of the recorded number of accidents or the number of killed or injured road users. While an accident rate is the the number of accidents per unit of exposure; the number of accidents per million vehicle kilometers of travel (Elvik, Vaa, Hoye, & Sorensen, 2009). Improving road safety refers to a reduction in the expected number of accidents, a reduction in accident or injury severity or a reduction in the rate of accidents or injuries per kilometre of travel (Elvik et al., 2009).

Our main country of focus is Poland, thus we start with definitions of main indicators that describe road safety based on regulations from the Polish Police (Bieńkowski, 2006; Gajewski, 2012)

Definition 1.1 *Road accident – a road incident which resulted in victims, including the perpetrator, regardless of how the event ended.*

Definition 1.2 *Road collision – a traffic incident that only lead to material damage.*

Definition 1.3 *Fatal victim of an accident – a person who died at the scene of an accident or within 30 days of an accident due to injuries.*

Definition 1.4 *Seriously injured person – a person who has suffered severe disability, incurable long-term or life threatening disease, permanent mental illness, total or significant inability to work in a profession, permanent or significant disfigurement or distortion to the body; this* *term also includes a person who has suffered other injuries that result in impairment to the body or other health disorders for a period lasting longer than 7 days.*

Definition 1.5 *Minorly injured person – a person who suffered a disability other than specified in definition 1.4, fracturing the body's organism functions or a health disorder, determined by a doctor, that lasted no longer than 7 days.*

The OECD also provides a definition on road accidents and its elements. For example, from OECD (2019b) we read that *road accidents are measured in terms of the number of persons injured and deaths due to road accidents, whether immediate or within 30 days of the accident, and excluding suicides involving the use of road motor vehicles. A road motor vehicle is a road vehicle fitted with an engine as the sole means of propulsion and one that is normally used to carry people or goods, or for towing, on the road. This includes buses, coaches, trolleys, tramways (streetcars) and road vehicles used to transport goods and to transport passengers. Road motor vehicles are attributed to the countries where they are registered, while deaths are attributed to the countries in which they occur. This indicator is measured in number of accidents, number of persons, per million inhabitants and million vehicles*.

1.1.2 Factors influencing road safety

According to the Polish Police (2019), the amount of accidents, deaths and injuries fluctuate between months, the day of the week, time, atmospheric conditions, part and type of road. As we can see there are many factors contributing to road safety some of them more vital some of them less. Polish Police (2019) report that 76.1 % of all road accident deaths were caused by the driver, with the main factor being not adapting the speed to traffic conditions, 35.7 % of all deaths caused by the driver.

Based on the European Commission (2018) we learn that across the EU July and August have the highest number of traffic fatalities, while February having the least. Authors state that the probability of an accident is linked with changing weather conditions and the amount of daylight. We read that highest total amount of pedestrian deaths is in winter, but the biggest sum of motorcyclist fatalities is in June. This report also notes that there is more seasonal variation on highways and rural roads than on urban roads. We can learn that day of the week and time of the day influence road safety. For example, Sunday has the greatest variation in road fatalities and there is a peak in deaths on Saturday and Sunday mornings which can be attributed to the social tendencies of younger drivers.

According to this report people aged 18 to 24 accounted for 14% of fatalities although 8 % of the population being in this age group. In this paper we can also learn that the likelihood of being killed in a car accident for a young person is twice as likely compared to an average person, and that the share of young men deaths is 80 %, which can be linked to the fact that thy usually drive longer and they have riskier behavior. From this report we can learn that are many ways of trying to make the roads in the EU safer including imposing speed limits depending on the type of weather, expanding the perception of hazards when driving in harsh conditions during driver training, popularizing the use of winter tires and making daytime running lights mandatory.

Elvik et al. (2009) provides summary of risk factors related to accident rates, but only some were commented. The first one being the type of road or traffic environment. We can learn that highways have the lowest risk of injury accidents of all roads and that all public roads have a higher mean accident rate than major roads in rural areas. The elements of the design of roads are listed as a factor influencing road safety in particular junctions, horizontal and vertical alignment, lane width, number of lanes and numerous other elements. From this book we can learn that in urban areas the accident rate rises as road width rises. This most likely can be attributed to the fact that as road width increases the amount of traffic increases making it more probable for an accident. On the other hand in rural areas accident rate decline as road width rises.

This most likely can be attributed to the fact that vehicle velocity is greater in rural areas than in urban areas, so a wider road may contribute to an added margin of safety. Environmental risk factors are also listed as a factor influencing road safety. For example challenging road surface conditions, reduced amount of sunlight, and precipitation, increase the risk of accidents.

Another element influencing road safety is the age and gender of road user. From this book we read that men at the age of 45-55 and 55-64 are the group with the lowest accident rate, but young men drivers have greater mean accident rates than young women. Overall the average accident involvement rate is higher for women than for men.

The reason for this might be first that women drive less than men in terms of kilometers, but accident involvement rates per kilometer of driving decrease as driving distance increases.

Second, females drive more in municipalities, where the risk of accidents is higher, than in provincial regions. Third, females drive smaller vehicles than males, petite cars do not give as reliable security against injury in an accident as sizable cars.

Another factor influencing road safety is the medical condition of road user. We learn that the enlargement of the accident rate is associated with the number of health complications and sicknesses, however not by a great amount. The reason for this is probably because of the fact that ill drivers are more careful when driving, they avoid driving at night, in harsh conditions, and in high traffic.

Drinking alcohol and driving has been identified as an essential safety obstacle for a long period, that is why it is a factor influencing road safety. We can learn that as blood alcohol levels increase, accident rates rise substantially.

The speed of travel is also a component influencing road safety. The effects of changes in traffic velocity on the amount and harshness of accidents have been assessed by a considerable number of studies. From this book we can learn that it is impossible to avoid severe injury when impact velocity of an accident is greater than 100 km/h, even when seat belts are worn. When a pedestrian is involved in a road accident impact speeds above 30 km/h increase the probability of being killed substantially.We can also read about estimating simple first-order attributable risks, which do not take into account correlations in exposure to varied risk factors or overlaps between types of accidents influenced by diversified risk components.

Elvik et al. (2009) divide risk factors to five groups, provision of medical services, environmental risks, bad system design, vulnerability of road users and unsafe road user behavior. From all the 20 factors that were included in the 5 groups the violation of speed limits was the most substantial risk factor.

All of the information from the paragraph below comes from World Health Organization (2017). According to this report 40-50 % of drivers from OECD countries were exceeding the speed limit. Also, about 33 % of deaths on roads in high income countries, are associated to vehicle velocity. The risk of major injury and death is greater at higher speeds, for example a rise of 1 km/h in average vehicle velocity contributes to an increase of 4-5 % of mortal accidents. Also, the amount of casualties can be decreased by 30 % by lowering the mean velocity by 5 %. We can also read from this report that for higher vehicle velocities the stopping distance required is longer, which increases the probability of a road accident.The reaction time of a driver is approximately one second.When a vehicle is moving at the speed of 80 km/h, it travels a distance of around 22 meters when the driver reacts to an event and needs 57 meters to come to a complete stop. However when driving at the speed of 50 km/h, the vehicle passes 17 metres when the driver reacts to an event and needs 27 metres to come to a complete stop.

1.1.3 Measuring and monitoring road safety

In Poland the Police provides yearly and monthly reports on road safety. These articles contain essential information on Polish roads. We learned from subsection Basic Definitions about the number of accidents, the number of killed and injured road users. All of these concepts assess road safety.

On the worldwide level there is the World Health Organization. This intuition was established on April 7 1948, and has more than 7 000 people working 150 country offices, in six regional offices and at their headquarters in Geneva, Switzerland (WHO, 2019). Their main goal is to coordinate and direct international health within the United Nations organization (WHO, 2019). In their report from 2018 on road safety we can learn that there are 1,35 million road traffic deaths each year (World Health Organization, 2018). Also that road traffic deaths are the number one cause of death for children and young adults 5-29 years of age and the number eight cause of death for people all ages (World Health Organization, 2018).

There is also the National Road Safety Council (pol. Krajowa Rada Bezpieczeństwa Ruchu Drogowego; KRBRD). All of the information from this paragraph comes from KRBRD (2019). The KRBRD was established on January 1, 2002 under the Road Traffic Act as an interministerial advisory and auxiliary body of the Council of Ministers in matters of road safety. The KRBRD determines the directions and coordinates the activities of the government administration in matters of road safety. The KRBRD is responsible for improving road safety. To carry out this task they propose state policy directions, develop road safety programs, commission scientific research, initiate and give opinions on legal acts in the field of road safety, initiate foreign cooperation as well as educational and informational activities, and cooperate with social organizations and non-governmental institutions.

1.1.4 Methods of measuring speeding violations

In Poland, the most popular method of ensuring road safety is speed controls conducted by the traffic police. They usually are on the side of the road where they measure passing vehicles velocity using laser radars as presented in the Figure 1.1.

Figure 1.1. Police Polish measuring speed

Source: Based on Kraśnik (2019).

Another popular method is police traffic in unmarked police vehicles. They drive behind vehicles and measure their speed.

Figure 1.2. Unmarked police vehicle

Source: Based on Interia (2019).

An example of such vehicle is provided in Figure 1.2.In addition to these methods speed is measured by speed cameras, they measure the speed of a passing car.

Figure 1.3. Speed camera

Source: Based on Flieger (2016).

An example of such vehicle is provided in Figure 1.3.In most cases when the speed is higher than 10 km/h of the speed limit a picture is taken of the car and the driver is issued a ticket.

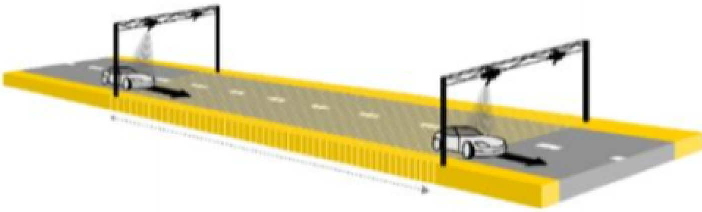

Figure 1.4. Average speed measuring device

Source: Based on Flieger (2016).

Also there are devices that detect the average speed on a given stretch of road, which will be called average speed measuring device, throughout the thesis.An example of such vehicle is provided in Figure 1.4. The machine registers the time a vehicle passes the beginning and the end of a segment. On the basis of this information the average speed is calculated.

1.2 Data sources on road safety in Poland

1.2.1 The General Director for National Roads and Motorways

The mission of the General Director for National Roads and Motorways is managing maintenance and development of national roads and motorways infrastructure in Poland by ensuring the best possible level of national roads, acting to constantly improve the level of road safety, minimizing the impact of the national road network on it's surroundings, the environment, and ensuring comfort of travel. Their strategical goals are: improving Poland's transport accessibility and connection with main transport corridors, increasing the safety of Polish roads, improving the comfort of traveling, increasing the efficiency of public spending and improving the Administrator of National Roads image. All of the information from this paragraph comes from GDDKiA (2019a).

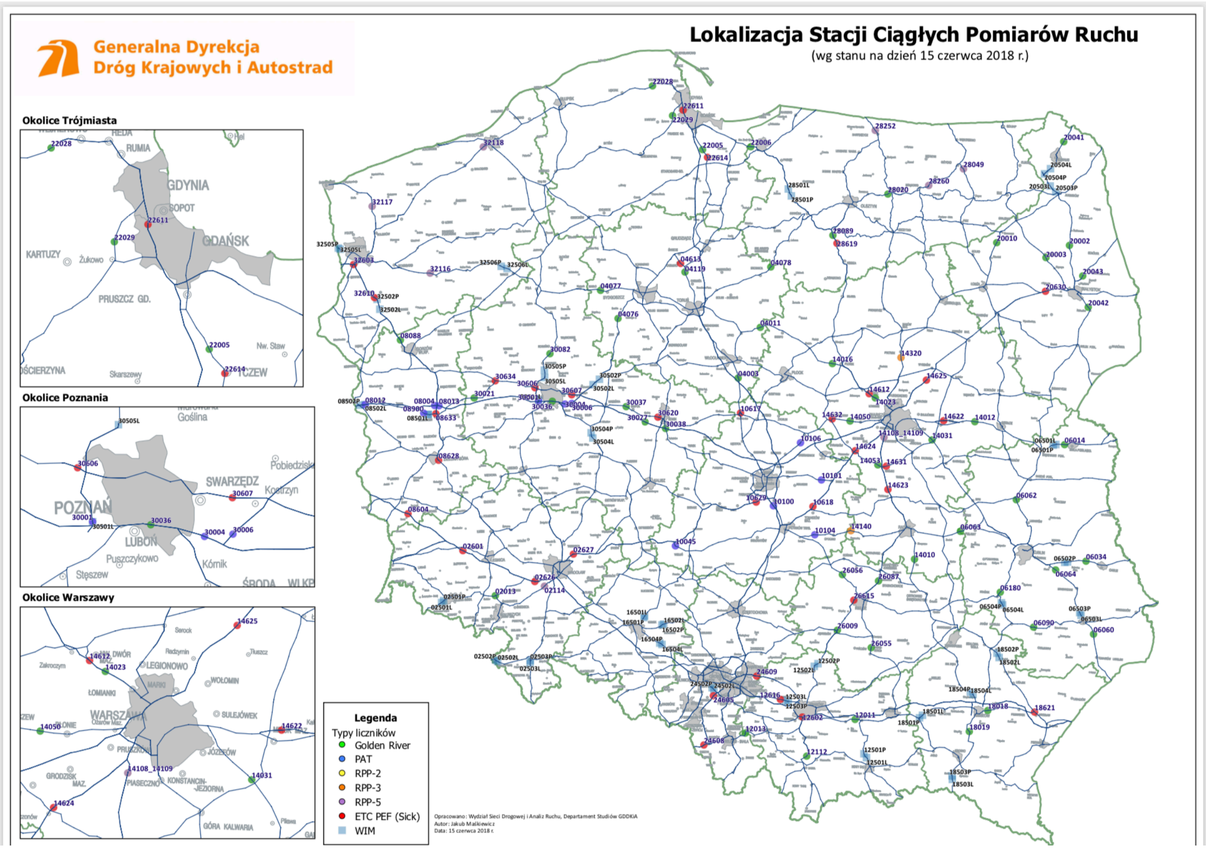

Figure 1.5. Location of GDDKiA monitoring stations in Poland

Source: Based on GDDKiA (2019b).

This organization has been analyzing the movement of vehicles since the 1970's. The data that has been collected is used for planning, design and prognosis. Currently this association has 103 monitoring stations across Poland, which collect data continuously. They use Verum RPP-5, Verum RPP-3, Verum RPP-2, PAT AVC 100, laser detectors from Sick company, Golden River Marksman 660 and 680 devices to gather information. The data from the locations on Figure 1.5 below are verified and analyzed on an ongoing basis, and once a year, a study summarizing the work of the entire system and presenting its results is created. The substantive unit responsible for supervising SCPR positions is the Faculty of Road Network and Traffic Analysis of the Department of Strategy and Studies. The results are presented in the form of summary reports for all positions and reports containing data specific to a given position (diagrams of weekly and daily traffic fluctuations represent averaged values for a given year). All of the information from this paragraph comes from GDDKiA (2019b).

On Figure 1.5 is a map showing the location of the counting devices. The PAT AVC 100 device is built into the road and measures traffic when a vehicle drives on it using induction loops / piezo sensors (CAT TRAFIC, 2019).

Figure 1.6. PAT AVC 100 device

Source: Based on CAT TRAFIC (2019).

The machine is presented in Figure 1.6. The machine collects data on the speed, vehicle type (8 possible types), the direction of travel, and allows measurements on all types of roads up to 8 lanes(CAT TRAFIC, 2019).

Another example of a vechicle counting machine used by the GDDIA is the Golden River Marksman 660 (see Figure 1.7).

Figure 1.7. Marksman 660

Source: Based on Schuhco (2019).

From the following Schuhco (2019) we read that:

> Golden River Marksman 660 provides the latest technology in traffic monitoring. Utilising inductive loops, the device counts and classifies vehicles, measures vehicle lengths, speed and the distance in time between them on up to 8 lanes (16 inductive loops). Parallel to the online output, data can also be saved in intervals or as individual values. The internal file structure facilitates the integration of the Marksman counter and classifier into a traffic management system. Owing to its low power consumption, the Marksman can be operated for weeks with the built-in battery, or permanently with solar panels.

1.2.2 The Centre for Automatic Traffic Supervision

Centrum Automatycznego Nadzoru nad Ruchem Drogowym (CANARD) in English The Center of Automatic Traffic Supervision is an organizational unit of the Main Inspectorate of Road Transport (CANARD, 2019). CANARD was created to conduct traffic supervision, also using devices it automatically registers violations of exceeding the speed limit or crossing a red light (CANARD, 2019).

Trzeszkowski (2014) presents information on the effectiveness of the implementation and operation of automatic traffic supervision. This report was prepared in connection with the realization of the „Construction of a central system of automatic traffic supervision" project, implemented by the Chief Inspectorate of Road Transport, co-financed by European Union from the European Regional Development Fund under Operational Program of Infrastructure and Environment. The main goals of this project were:

1. development of a detailed methodology for conducting road traffic studies,
2. implementation of road traffic recording devices in locations selected by GITD,
3. development of partial research results for selected locations of traffic recording devices,
4. development of final research results for all locations of traffic recording devices,
5. developing a methodology for assessing the effectiveness of the implementation and operation of the automatic traffic supervision system, allowing to make future assessments that take into account the state of road safety,
6. developing an assessment of the effectiveness of the implementation and operation of the automatic traffic supervision system,
7. syntheses of prepared documents.

From Trzeszkowski (2014) we read that the „Construction of a central system of automatic traffic supervision" project measured the effect of automatic traffic supervision by placing a speed cameras or average speed measuring devices. Data was collected before and after the introduction of automatic traffic supervision.The research was carried out in 52 sites across Poland. 40 locations where tested with speed detection cameras and 12 by average speed measuring device.

Figure 1.8. Location of speed cameras and average speed measuring devices in Poland

Source: Based on Flieger (2016).

In Figure 1.8 we see the locations of the cities, the yellow arrows indicate cities where speed cameras where introduced and the blue arrows indicate cities where average speed measuring devices where introduced . The sites selected by GITD were located in 13 voivodeships. The locations of SURs were placed in built-up areas and outside built-up areas. They were installed on the Polish national road network, excluding motorways, expressways and cities with poviat rights. Road traffic measurements and studies were carried out in a 24-hour cycle with division into ”daily” and ”night” sessions. Due to the change in the speed limit in the built-up area within 24 hours, in accordance with regulations, the time of conducting measurements and studies in the ”daily” period was 18 hours, from 5 a.m. and 11 p.m., while the ”night” period covered 6 hours, from 11 p.m. and 5 a.m.

Data was collected by a radar device equipped with a Doppler sensor (24.165 GHz), a real time clock, a RS232 interface, RAM flash drive, and a modem for data transmission. It also supplied with a battery and an optional solar panel battery. The device was calibrated only for approaching vehicles. It should be noted that the machine had the ability of collecting data automatically from up to 4 lanes of traffic and can measure speeds between 1 km/h and 255 km/h.

The device collected data on speed, type of vehicle (5 possible types), length, time interval between vehicles, date and time for each passing vehicle. The machine supplied data in a txt or vtf format. Measurement error of the device was up to 3 km/h for speeds up to 100 km/h and 3 % of the registered speed for speeds above 100 km/h, 5 % for vehicle classification and 1 % for counting vehicle totals. The appliances were mounted in such a way that the distance between the bottom edge and road surface was between 2.5 and 3.25 meters. Detailed results of traffic measurements after individual measurement sessions from each location are presented in individual measurement reports with recorded data generated by the measuring devices. Measurement reports were used to carry out detailed analyzes of the recording devices locations. Detailed analysis of each individual location was completed in separate studies.

Definitions regarding the ”Construction of a central system of automatic traffic supervision” study.

Definition 1.6 *Speed camera – a stationary recording device that records vehicles that exceed the speed limit on a controlled point of the road (Trzeszkowski, 2014).*

Definition 1.7 *Average speed measuring device – a system that records vehicles that have an average speed on a controlled road section higher than the speed limit (Trzeszkowski, 2014).*

Definition 1.8 *SUR –- within the meaning of art. 2 of the Road Traffic Law Act - a stationary device that records, reveals and saves images of vehicles when driver’s violate traffic regulations.(Trzeszkowski, 2014).*

Definition 1.9 *Built-up area – in accordance with art. 20 of the Road Traffic Law Act a built-up area is an area marked with appropriate road signs, where the speed limit is 50 km / h between 5 a.m. and 11 p.m. and the speed limit is 60 km / h between 11 p.m. and 5 a.m. (Trzeszkowski, 2014).*

Definition 1.10 *Measurement report - an individual document prepared for a given measurement site, which contains data on the intensity, structure of road traffic, registered vehicle speeds and the date and place of road traffic studies. The report has a place to record and sketch any observations during the deployment of measuring devices(Trzeszkowski, 2014).*

Information on the ”Construction of a central system of automatic traffic supervision” project present in this subsection can be read from Trzeszkowski (2014).

1.2.3 The Polish Police

The Polish Police provides yearly reports on road safety. Police units register traffic incidents that have occurred or have commenced on a public road, in a traffic area or in a residential area, involving at least the movement of one vehicle. Traffic incidents are recorded in the road accident card, the formula of which is specified in the annex of Gajewski (2012). In the case of an event where there is a casualty, a photocopy of the accident site is taken and drawn up on the road incident card. In the event of a traffic incident, where a fine was imposed or a caution was issued, the policeman who imposed the fine or caution fills in the road incident card. The completed road incident card together with the required photocopy, is entered into the computer system. We read all of the information present in this paragraph according to Gajewski (2012).

Organizational units of poviat (city) police, enter data into the National Police Information System directly from access points located in the poviat (municipal) police stations, based on the road incident card. Organizational units of the poviat (city) police competent in the field of entering data into the computer system, store road incident card for a period of 2 years. We read all of the information present in this paragraph according to Bieńkowski (2006).

In this report from 2018 we can find information general information on motorization. For example the number of motor vehicles, including the amount of cars, trucks or motorcycles. Also facts about the number of road accidents, injuries and causalities are presented on the national and voivedship level. We can also find information regarding road accidents, injuries and casualties on a monthly, day of week and time of day level, and also depending on weather conditions. In this report we can also find facts on the site a road accident happened, for example whether it occurred on a parking, type of road or bridge. The article also provides information on the types of road accidents. For instance the amount of vehicles that were involved, the type of impact that occurred, and types of run overs. From this report we can also learn about the causes of road accidents, although there is substantially more information enclosed in this report. We read all of the information present in this paragraph according to Polish Police (2019).

1.2.4 The Organisation for Economic Co-operation and Development

The Organisation for Economic Co-operation and Development short OECD was established in 1961 with their headquarters being in Paris, France. The mission of this institution is to advocate policies that will enhance the social and financial well-being of the worlds population. Currently the OECD is focused on supporting governments with: strengthening confidence in markets and organizations that make them work, economic improvement, advancement of emerging economies, re-establishing healthy national finances for continuous economic improvement in the future and guaranteeing that people can acquire skills to work in productive and gratifying jobs. We read all of the information present in this paragraph according to OECD (2019a).

The International Transport Forum short ITF was established on 18 May 2006 by ministers from 43 countries. The ITF with 59 member countries, is administratively unified with the OECD, yet politically self-governing (ITF, 2019). From this website we can read that this organization coordinates the Annual Summit of transport ministers and functions as a think tank for transport administration. ITF is the only global body that covers all transport modes and it is administratively integrated with the OECD, yet politically autonomous (ITF, 2019). From the following Forum (2017) we read that:

> The International Transport Forum collects data on transport statistics on annual basis from all its Member countries. Data are collected from Transport Ministries, statistical offices and other institution designated as official data source. Although there are clear definitions for all the terms used in this survey, countries might have different methodologies to calculate tonne-kilometre and passenger-kilometres. Methods could be based on traffic or mobility surveys, use very different sampling methods and estimating techniques which could affect the comparability of their statistics. Also, if the definition on road fatalities is very clear and well applied by most countries, this is not the case for road injuries. Indeed, not only countries might have different definitions but the important under reporting of road injuries in most countries can distort analysis based on these data.

1.3 Traffic safety in Poland

1.3.1 Multinational comparisons

According to European Commission (2018) the European Union can boast the safest roads across the world. The last two decades have been very progressive regarding road safety in the European Union, because from 2001 to 2010 fatal crashes fell by 43 % and between 2010 and 2017 another 20 % we read from this report. Although in recent years the decrease in fatality rate has slowed down, in 2017 the fatality rate in the European Union was the lowest ever at 49 causalities per million inhabitants (European Commission, 2018). To put this into perspective we 174 deaths per million worldwide, 106 deaths per million in the USA and 93 deaths per million in geographical Europe(European Commission, 2018).

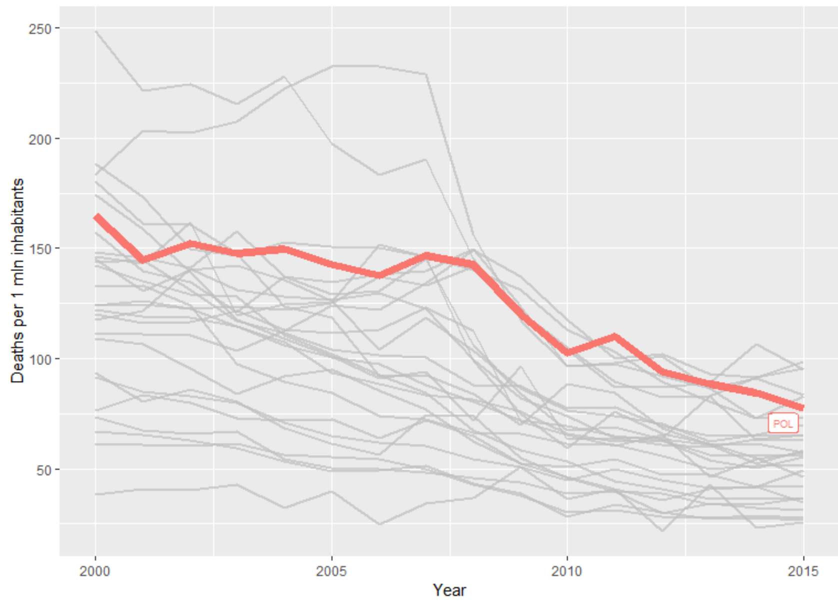

Figure 1.9. Deaths per 1 mln inhabitants across time in EU countries

Source: Own elaboration based on OECD data.

We would like to measure the influence of automatic traffic supervision in Poland. That is why we will provide some information on this country in terms of traffic safety below. On Figure 1.9 we see deaths per 1 million inhabitants across the European Union in 2015. Poland's position is 22nd overall, so there is much room for improving the safety of roads. We would also like to see whether the country improved between 2000 and 2015.

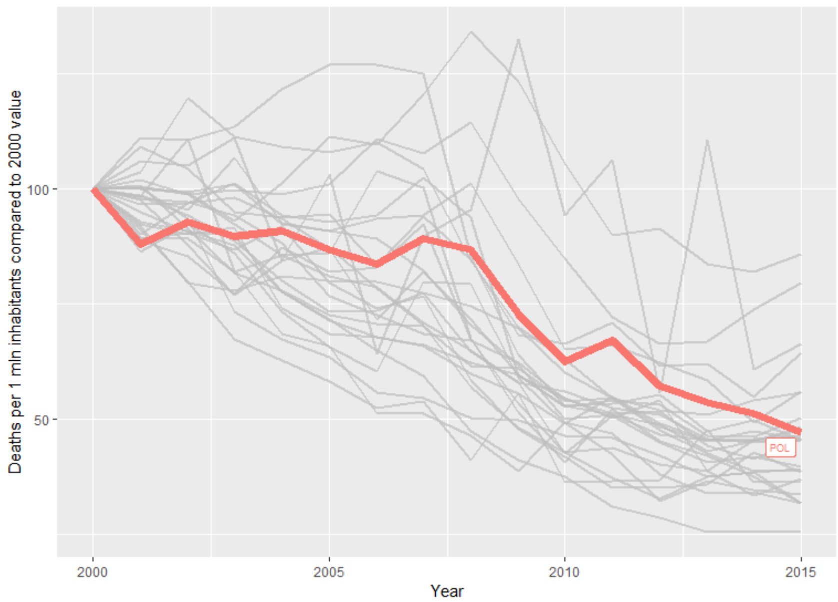

Figure 1.10. Deaths per 1 mln inhabitants compared to 2000 value across time in EU countries

Source: Own elaboration based on OECD data.

On Figure 1.10 we can see Poland has improved in terms of Deaths per 1 million inhabitants. It's position in terms of improvement is 17th compared to other European Union countries.

Both of these graphs show that there is still much to be done in making the roads of Poland safer. One of the methods is trying to decrease the average speed on roads. This is done by introducing automatic traffic supervision, which we will try to measure the affect it has on speed.

1.3.2 Detailed information regarding Poland

In this section we present detailed information regarding Poland. First we present the number of deaths on Polish roads.

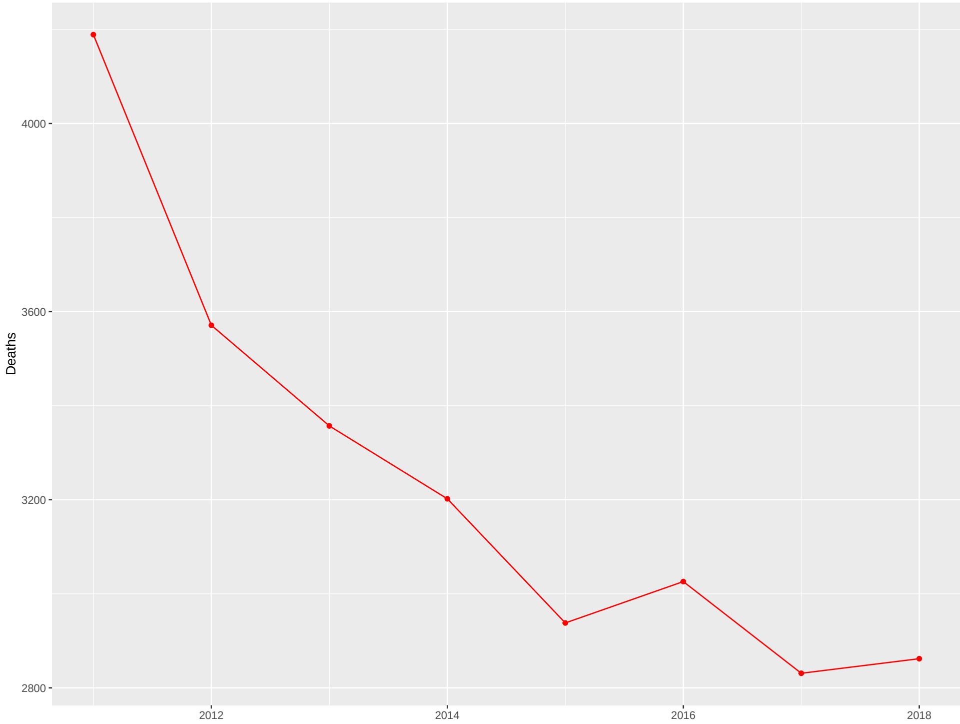

Figure 1.11. Road accident deaths in Poland

Source: Source: Own elaboration based on Polish Police data.

Speed cameras were introduced on July 1 2011 in order to control traffic. As we see in Figure 1.11 there was a sharp decline in road accident deaths between 2011 and 2015. From 2016 municipal and regional guards were had their right to use speed cameras taken away. As we can see on the figure above after this event the decrease of road accident deaths has slowed down.

Voivodeship	Deaths	Deaths per 1 mln inhabitants*
Śląskie	3222	48
KSP**	1763	53
Podkarpackie	1481	59
Pomorskie	2504	63
Małopolskie	3404	66
Dolnośląskie	2148	70
Wielkopolskie	3232	75
Zachodniopomorskie	1182	76
Lubuskie	663	78
Kujawsko - pomorskie	970	82
Opolskie	705	82
Lubelskie	1216	84
Podlaskie	672	86
Łódzkie	3759	93
Warmińsko-mazurskie	1281	98
Świętokrzyskie	1201	102
Mazowieckie (without KSP)	2271	117

Table 1.1. Road accident deaths in Poland

Source: Own elaboration based on Polish Police data.

In Table 1.1 * means that deaths per 1 mln inhabitants were calculated from GUS population data from 30/06/2018, while ** symbolizes Warsaw and subordinate counties to the Capital Police Station. In Table 1.1 we observe that Śląskie Voivodeship can boast the safest roads in Poland in 2018. We can also notice the the most dangerous Voivodeship - Mazowieckie (without KSP) has over twice as many deaths per 1 mln inhabitants compared to the safest - Śląskie. For 2018 Poland had 75 deaths per 1 mln inhabitants.

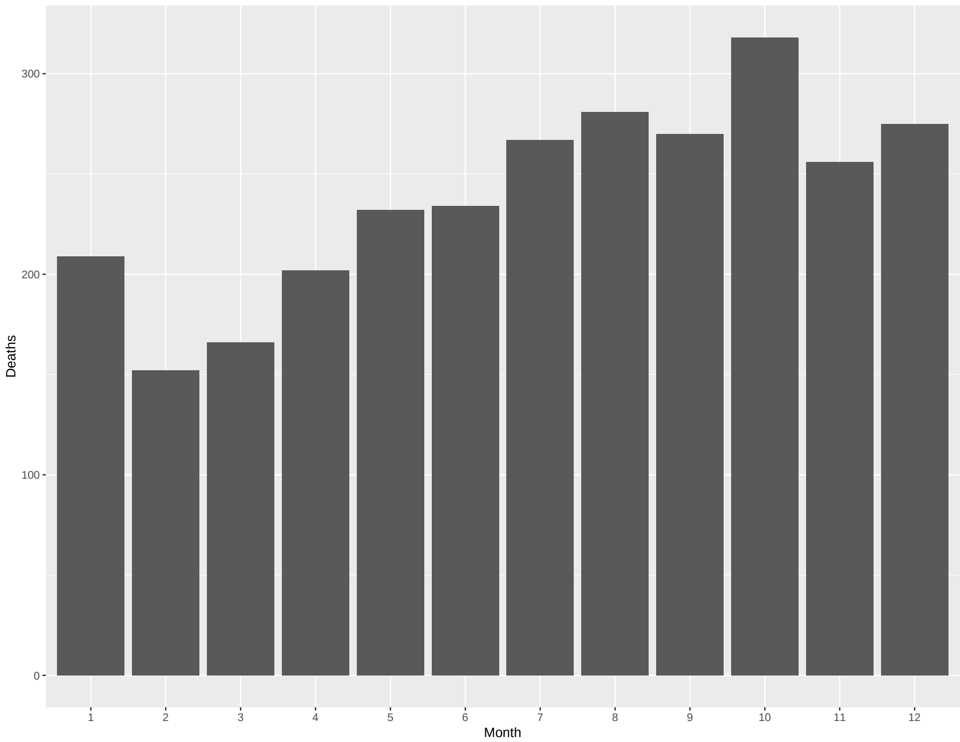

Figure 1.12. 2018 Monthly road accident deaths in Poland

Source: Own elaboration based on Polish Police data.

We can see that the most road accident deaths occurred in October, May and July. A large number of accidents in autumn months are caused by deteriorating weather conditions making road conditions worse and in the summer, traffic increases due to holiday trips (Polish Police, 2019).

Day of Week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Deaths	370	375	382	389	462	465	419

Table 1.2. Weekday road accident deaths in Poland

Source: Own elaboration based on Polish Police data.

As we can see in Table 1.2 most deaths occur on the weekend, this might have to do with the fact that there is a higher intoxication level during these days.

Atmospheric conditions	Deaths
Good weather conditions	1825
Overcast	597
Rainfall	355
Snowfall, hail	64
Blinding sun	56
Fog, smoke	55
Strong wind	33

Table 1.3. Weather conditions road accident deaths in Poland

Source: Own elaboration based on Polish Police data.

Most deaths happened under good weather conditions. In good weather conditions, the drivers feel more comfortable, develop faster speeds, which in the case of an accident gives more tragic results(Polish Police, 2019).

Accident reason	Driver	Pedestrian	Other	More than one person	Passenger
Deaths	2177	348	293	39	5
Percent	76.1	12.2	10.2	1.4	0.2

Table 1.4. Accident reason deaths in Poland

Source: Own elaboration based on Polish Police data.

From Table 1.4 we see that the behavior of individual groups of road users, affect the occurrence of road accidents the most, other factors being definitely less important making up around 10.2 % of all road accidents (Polish Police, 2019).

Driver cause	Deaths
Not adapting speed to traffic conditions	778
Not yielding right of way	322
Other	307
Incorrect maneuvering	219
Not yielding right of way for pedestrian on pedestrian crossing	216
Incorrect overtaking	202
Fatigue, drowsiness	76
Failure to maintain a safe distance between vehicles	57

Table 1.5. Driver cause of death in Poland

Source: Own elaboration based on Polish Police data.

Not adapting speed to traffic conditions is the main cause of deaths with the driver being the perpetrator of the accident. This information shows us that driving with a reduced velocity might help decrease the death toll on Polish roads.

1.4 Conclusions

Summarizing there are many definitions relating to quantifying road safety. Road safety can be measrued by the number of accidents, injured or killed road users, and by the accident rate. The "Krajowa Rada Bezpieczeństwa Ruchu Drogowego" (KRBRD) is an organization that monitors road safety on a Polish level and the World Health organization monitors road safety on a worldwide level. There are many factors that influence road safety. For example: excessive speed, month, day, time, weather, amount of daylight and age. Velocity is placed as one of the most important factors influencing road safety. The main methods of measuring speeding violations in Poland are traffic police, police in unmarked vehicles, speed cameras and average speed measuring device. The main provider of road safety information in Poland is the Polish Police. They produce yearly reports with information on deaths, accidents, injuries and much more. Canard an organizational unit of the Main Inspectorate of Road Transport realized the „Construction of a central automatic traffic monitoring system" project in which they measured the effect of automatic traffic supervision by placing a speed cameras or average speed measuring devices. The GDDIA analyzes the movement of traffic in Poland in order to improve the roads in this country. The International Transport Forum at the OECD collects road safety data from member countries. Unfortunately Poland position in 2015 in terms of deaths per 1 mln inhabitants is not the best in Europe having the 22nd position. In terms of improvement in deaths per 1 mln inhabitants from the year 2000 Poland is 17th in Europe. As we can see from these statistics there much more room for improvement. From 2011 to 2015 the amount of road accident deaths had declined strongly, but from 2016 the decline slowed down. From Polish Police (2019) we read that Śląskie Voivodeship can boast the safest roads in Poland in 2018. When analyzing the driver cause of accident we can learn that not adapting the speed to traffic conditions is the main reason of deaths. Next we would like to present need theory in order to evaluate the effect of speed measruing systems.

Chapter 2

Casual models for observational studies

2.1 Causality in econometrics – selected definitions

Many researchers want to measure the effect of an intervention. For example a scientist looking at the effect of certain medicine or a the effect of the change in minimum wage. One of the key subjects of econometrics is causality, which is presented in definition 2.1.

Definition 2.1 *Causality is tied to an action (or manipulation, treatment, or intervention), applied to a unit. A unit here can be a physical object, a firm, an individual person, or collection of objects or persons, such as a classroom or a market, at a particular point in time. For our purposes, the same physical object or person at a different time is a different unit. From this perspective, a causal statement presumes that, although a unit was (at a particular point in time) subject to, or exposed to, a particular action, treatment, or regime, the same unit could have been exposed to an alternative action, treatment, or regime (at the same point in time) (Imbens & Rubin, 2015).*

Causality can also be defined as in defition 2.2.

Definition 2.2 *"causality (Merriam-Webster, 2019):*

1. *a causal quality or agency*
2. *the relation between a cause and its effect or between regularly correlated events or phenomena"*

Another key concept regarding the estimation of an intervention or treatment is casual inference, which is defined in definition 2.3. Although, an essential difficulty of causal inference is that we can only notice one of the potential results for a specific subject (Imbens & Rubin, 2015).

Definition 2.3 *Causal inference is fundamentally a missing data problem and, as in all missing data problems, a key role is played by the mechanism that determines which data values are observed and which are missing. In causal inference, this mechanism is referred to as the assignment mechanism, the mechanism that determines levels of the treatment taken by the units studied (Imbens & Rubin, 2015).*

Causality can also be defined as in Vinacke (2019).

Definition 2.4 *Causal inference - one reasons to the conclusion that something is, or is likely to be, the cause of something else. For example, from the fact that one hears the sound of piano music, one may infer that someone is (or was) playing a piano. But although this conclusion may be likely, it is not certain, since the sounds could have been produced by an electronic synthesizer.*

A common way to measure the effect of a treatment is a randomized (controlled) trial, where each participant is randomly assigned to a control group or treatment group. Another method of measuring an intervention is a natural experiment defined in definition 2.5.

Definition 2.5 *Natural experiment, observational study in which an event or a situation that allows for the random or seemingly random assignment of study subjects to different groups is exploited to answer a particular question. Natural experiments are often used to study situations in which controlled experimentation is not possible, such as when an exposure of interest cannot be practically or ethically assigned to research subjects. Situations that may create appropriate circumstances for a natural experiment include policy changes, weather events, and natural disasters. Natural experiments are used most commonly in the fields of epidemiology, political science, psychology, and social science (Messer, 2019).*

From natural experiments we can obtain panel data defined in definition 2.6.

Definition 2.6 *Panel data, also known as longitudinal data or cross-sectional time series data in some special cases, is data that is derived from a (usually small) number of observations over* *time on a (usually large) number of cross-sectional units like individuals, households, firms, or governments. In the disciplines of econometrics and statistics, panel data refers to multi-dimensional data that generally involves measurements over some period of time. As such, panel data consists of researcher's observations of numerous phenomena that were collected over several time periods for the same group of units or entities. For example, a panel data set may be one that follows a given sample of individuals over time and records observations or information on each individual in the sample (Moffatt, 2019).*

We also present the definition of a confounder in definiton 2.7.

Definition 2.7 *A confounder can be defined as a pre-exposure covariate C for which there exists a set of other covariates X such that effect of the exposure on the outcome is unconfounded conditional on (X,C) but such that for no proper subset of (X,C) is the effect of the exposure on the outcome unconfounded given the subset (VanderWeele & Shpitser, 2013).*

2.2 Types of causality models

Generally, economists cannot conduct experiments in the way that laboratory scientists or clinical researchers can. Nevertheless, economists can often observe natural experiments, that is, identifiable discrete shifts in the economic environment, such as passage of a new law, deployment of a new invention or technology, implementation of a new economic or social policy, or a shift in industry behavior, such as a merger or the operation of a cartel. The effects of such natural experiments are often of keen interest to economists (White, 2005).

According to Craig, Katikireddi, Leyland, and Popham (2017) there are many approaches to evaluating natural experiments: instrumental variables, synthetic controls, interrupted time series, regression adjustment, prepost, propensity scores, regression discontinuity, and difference-in-differences. We will discuss several of the aforementioned methods in the following sections.

2.2.1 Basic setup

In this subsection we present theory about the effect of modifying treatment status on some observed outcome variable. The idea of of potential and realized outcomes are deeply rooted in economics. Potential outcomes are used to describe causal parameters.

Let Y_w be the potential value of the result when random variable W that denotes exposition to intervention is set to w. We can also learn that Y_w is a random variable with a distribution over the population, for each value of w in the backing of W. The realized outcome - Y is equivalent to Y_w when the value of the treatment is equal to w for that unit in the population, at the same time other potential outcomes $Y_{w'}$ with $w' \neq w$ continue to be counterfactual. From the last sentence we see that the realized outcome for each specific unit relies upon only on the value of the treatment of that unit, and not on the treatment or on outcome values of other units. The previous statement is commonly introduced as "Stable Unit Treatment Value Assumption" or in short SUTVA (Rubin, 1980).

In studies scientists may be attentive to a multiplicity of treatments and outcomes, also we consider Y and W as scalar random variables. We can also learn that populations that are affected by policy intervention are represented by covariates, X, a $k \times 1$ vector of variables that are predetermined relative to the treatment. X and W may not be independent, the reason being, because X causes W, or possibly they receive common causes, therefore he value of X cannot be altered by active manipulation of W. Very often X has attributes of the units evaluated before W is recognized. The theory presented in this subsection on the DID estimator focuses on a binary treatment $W \in \{0,1\}$, although the notation allows the values assigned to the treatment to be greater than two. $W = 0$ denotes not exposed to intervention, while $W = 1$ denotes exposed to intervention. The difference Y_1-Y_0 represents the treatment effect

$$Y = WY_1 + (W-1)Y_0, \tag{2.1}$$

where W - value of the treatment by the random variable, Y is observed outcome variable, W denotes exposition to intervention, Y_1 is outcome variable when $W = 1$ and Y_0 denotes outcome variable when $W = 0$.

Equation 2.1 is often called "the fundamental problem of causal inference". Unit-level treatment effect Y_1-Y_0 depends on both values of W, that is why we cannot identity Y_1-Y_0 from detecting (Y,W,X) .

In most empirical settings assumptions needed to identify unit-level treatment effects are not possible to obtain. That is why estimands of program evaluation are attributes of the joint distribution of (Y_1,Y_0,W,X) in a population or sample. We also learn that an estimand is casual when it depends on the distribution of potential results (Y_1,Y_0), beyond its reliance on the distribution of (Y,W,X). Also, the the average treatment effect (ATE) is described by equation

2.2 and the average treatment affect on the treated is described by equation 2.3.

$$\tau_{ATE} = E[Y_1 - Y_0], \tag{2.2}$$

$$\tau_{ATET} = E[Y_1 - Y_0 | W = 1]. \tag{2.3}$$

We read all of the theory on the basic setup present in this subsection according to Abadie and Cattaneo (2018).

2.2.2 Propensity score matching

In observational studies investigators have no control over treatment assignment. That is why large differences on observed covariates in the treated and untreated group may occur, leading to biased estimates of treatment effects. Comparisons of results from intervention and non-intervention groups may be misleading. On the contrary in a randomized experiment, on average there should be no systematic discrepancies in obsereved and unobsereved covariates, because of randomization of units to separate treatments. The complication of biased estimates of treatment effects in observational studies may be partially evaded if information on measured covariates is integrated into the study design (e.g. matched sampling) or into estimation of the treatment influence (e.g. stratification or covariance adjustment). Conventional approaches of adjustment (e.g. covariance adjustment, stratification and matching) are usually restricted since they can only use a limited amount of covariates for adjustment. Nevertheless propensity scores, which provide a scalar summary of the covariate information, do not have this restriction. The propensity score for an individual, defined as the conditional plausibility of being treated given the individual's covariates, can be applied to balance the covariates in the treated and untreated group, and therefore reducing biased estimates. Instinctively, the propensity score is a calculation of probability that a unit would have been treated utilizing only their covariate scores. From Rosenbaum and Rubin (1983), with thorough data, we learn that the propensity score for subject $i = 1, ..., N$ as the conditional plausibility of selection to a specific treatment $(Z_i = 1)$ versus control $(Z_i = 0)$ given a vector of observed covariates, x_i :

$$e(x_i) = \text{pr}(Z_i = 1 | X_i = x_i), \tag{2.4}$$

where it is accepted that, given the X's, the Z_i are independent:

$$\text{pr}(Z_1 = z_1, ..., Z = z_N | X_1 = x_1, ..., X_N = x_N) = \prod_{i=1}^{N} e(x_i)^{z_i} \{1 - e(x_i)\}^{1-z_i}. \tag{2.5}$$

According to Rosenbaum and Rubin (1983) the function $e(x)$ is named the propensity score, meaning the inclination towards exposure to specific treatment $(Z_i = 1)$ given the observed covariates x_i.

In the propensity score matching method we can create a 'quasi-randomized' experiment. When we have one unit in the treated group and one unit in the control group with the same propensity score, we can assume that they both had the same probability of being in the treatment or control group. Comparing to a controlled experiment, the randomization, which appoints pairs units to treatment and control groups, is superior than the propensity score matching method because it does not rely upon on the researcher conditioning on a specific set of covariates. From the information above we have learned that propensity scores are mainly used to weaken bias and enhance accuracy. The three most common approaches that use the propensity scores are regression adjustment, stratification (subclassification) and matching. Each of these methods are ways to make an adjustment for covariates before (stratification and matching) or during (regression adjustment and stratification) the measurement of the treatment effect. The propensity score is computed using the same approach for all of these techniques but once it is calculated it is applied differently. We read all of the theory on propensity score matching present in this subsection according to d'Agostino (1998).

2.2.3 Regression discontinuity

The regression discontinuity (RD) design allows investigators to acquire knowledge about causal effects in environments where the treatment is not explicitly randomized and unobservable influences cannot be ruled out. This approach to evaluating natural experiments is applicable when each subject obtains a score, also named a running variable or index, and only subjects whose score is higher than a known cutoff point are appointed to treatment status, while the others are appointed to control status. In the regression discontinuity design the assignment mechanism is $W = 1(X \geq c)$, where c stands for the cutoff point, W stands for exposition to treatment, and X stands for the score.

The main idea in this technique is that subjects near the cutoff point are comparable. We assume that units do not have the capability of accurately manipulating their score in order to consistently appoint themselves higher or lower than the cutoff point. This is an important identifying assumption in the regression discontinuity design. There is a range of RD designs and closely related frameworks:

1. Sharp RD - environments where actual treatment condition and treatment appointment resolved by the value of the running variable proportionate to the cutoff, coincide. This is comparable to flawless compliance in randomized experiments.

2. Fuzzy RD - environments where compliance with treatment appointment, resolved by the value of the running variable, is flawed. The previously mentioned is similar to the instrumental variable environment but for units with values of the running variable near the cutoff.

3. Multi-Score and Geographic RD - environments where treatment appointment relies on more than one score variable (see Papay, Willett, and Murnane (2011), Keele and Titiunik (2015)).

4. Kink RD - sharp or fuzzy environments where the object concerned is the derivative rather than the level of the mean result close or at the same spot as the cutoff point (see Card, Lee, Pei, and Weber (2015)).

5. Multi-Cutoff RD - environments where treatment appointment relies on more than one cutoff point (see Cattaneo, Titiunik, Vazquez-Bare, and Keele (2016)).

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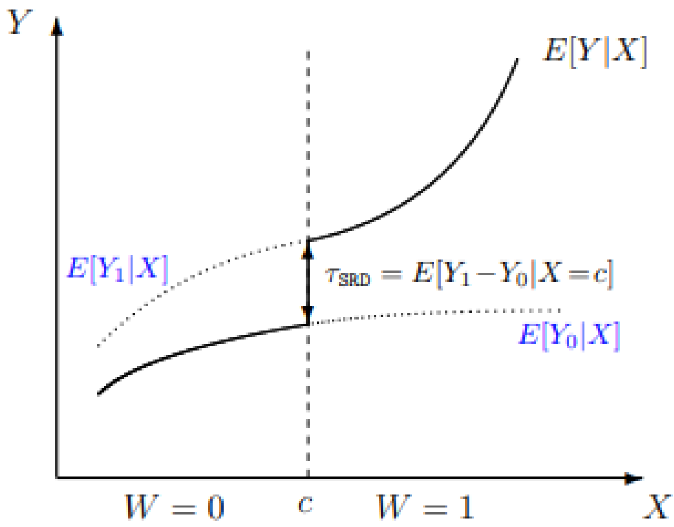

Figure 2.1. Regression Discontinuity Design

Source: Based on Abadie and Cattaneo (2018)

The most popular parameter of interest is in the sharp regression discontinuity design with a continuously distributed score is τ_{SRD}.

$$\tau_{SRD} = E[Y_1 - Y_0|X = c] = \lim_{x \downarrow c} E[Y|X = x] - \lim_{x \uparrow c} E[Y|X = x] \tag{2.6}$$

which complements to the mean causal treatment influence at the score level $X = c$. On Figure 2.1 we see a visual depiction of the regression discontinuity design. The parameter of interest is the jump at the point $X = c$, where treatment appointment alters discontinuously. When $X \geq c$ then units are appointed to treatment group $W = 1$ and $E[Y_1|X = x]$ is observed. When $X < c$ then units are appointed to control group $W = 0$ and $E[Y_0|X = x]$ is observed.

$\lim_{x \downarrow c} E[Y|X = x] - \lim_{x \uparrow c} E[Y|X = x]$ is the essential notion of comparison between units with very close values of the score but on opposite sides of the cutoff. The original regression discontinuity design can be attributed to Thistlethwaite and Campbell (1960), while in Hahn, Todd, and Van der Klaauw (2001) the RD desgin was formalized from a continuity-at-the-cutoff perspective. Particularly τ_{SRD} is nonparametrically identified, when under regularity conditions, the regression functions $E[Y_1|X = x]$ and $E[Y_0|X = x]$ are continuous at $x = c$. From the continuity conditions we read that the mean response of units merely beneath the cutoff point give us a similar approximation of the mean response, that would have been observed, of units merely higher than the cutoff point, had they not been appointed an intervention. We read all of the theory on regression discontinuity present in this subsection according to Abadie and Cattaneo (2018).

2.3 The difference-in-differences estimator

2.3.1 Basic setup

"Difference in Differences treatment effects (DID) have been widely used when the evaluation of a given intervention entails the collection of panel data or repeated cross sections" (Villa, 2012). "The difference in difference (DID) design is a quasi-experimental research design that researchers often use to study causal relationships in public health settings where randomized controlled trials (RCTs) are infeasible or unethical" (Wing, Simon, & Bello-Gomez, 2018).

Researchers in many practical studies encounter the obstacle of the probable existence of unobserved confounders. Difference-in-differences models, in theses studies, aim to achieve identification by restricting the way in which unobserved confounders influence the results of interests over time. We examine the panel regression model equation 2.7

$$Y_{it} = W_{it}\tau_{it} + \mu_i + \delta_t + \varepsilon_{it}, \tag{2.7}$$

where Y_{it} is observed outcome variable, W_{it} denotes observed exposition to intervention, τ_{it} is unit-level treatment effect, μ_i is time invariant confounder, δ_t denotes time effect, common across units and ε_{it} causes of the outcome that are unrelated to selection for treatment.

W_{i1} and μ_i are not independent because μ_i is a time invariant confounder. Taking into account 2.1 and 2.7, we receive 2.8 and 2.9 that describe potential results indexed by time period t.

$$Y_{0it} = \mu_i + \delta_t + \varepsilon_{it}, \tag{2.8}$$

and

$$Y_{1it} = \tau_{it} + \mu_i + \delta_t + \varepsilon_{it}. \tag{2.9}$$

We consider two time periods: $t = 0$ being the pre-intervention period, ($W_{i0} = 0$ for all i), and $t = 1$ being the post-treatment period, when a certain group is exposed to the intervention.

Next we present unit-level treatment effect equation 2.10.

$$\tau_{it} = Y_{1it} - Y_{0it} \tag{2.10}$$

We assume that ε_{it} are causes of the result that are unassociated to selection for intervention, so we receive 2.11.

$$E[\varepsilon_{it}|W_{it}] = E[\varepsilon_{it}] \tag{2.11}$$

This requirement can be reduced to 2.12,

$$E[\Delta\varepsilon_{i1}|W_{it}] = E[\Delta\varepsilon_{i1}] \tag{2.12}$$

where Δ is the first difference operator, so we obtain 2.13.

$$\Delta\varepsilon_{i1} = \varepsilon_{i1} - \varepsilon_{i0} \tag{2.13}$$

Next we receive estimations of differences of results in the two time periods :

$$\begin{aligned}
E[Y_{i1}|W_{i1}=1] &= E[\tau_{i1}|W_{i1}=1] + E[\mu_i|W_{i1}=1] + \delta_1 + E[\varepsilon_{i1}]\\
E[Y_{i0}|W_{i1}=1] &= \phantom{E[\tau_{i1}|W_{i1}=1] +{}} E[\mu_i|W_{i1}=1] + \delta_0 + E[\varepsilon_{i0}]\\
E[Y_{i1}|W_{i1}=0] &= \phantom{E[\tau_{i1}|W_{i1}=1] +{}} E[\mu_i|W_{i1}=0] + \delta_1 + E[\varepsilon_{i1}]\\
E[Y_{i0}|W_{i1}=0] &= \phantom{E[\tau_{i1}|W_{i1}=1] +{}} E[\mu_i|W_{i1}=0] + \delta_0 + E[\varepsilon_{i0}].
\end{aligned}$$

In the difference-in-difference model the effect of the unobserved confounders on the mean of the result variable is additive and does not alter in time. Under the condition of the previous statement being true we receive:

$$\begin{aligned}
\tau_{ATET} &= E[\tau_{i1}|W_{i1}=1]\\
&= [E[Y_{i1}|W_{i1}=1] - E[Y_{i1}|W_{i1}=0]] - [E[Y_{i0}|W_{i1}=1] - E[Y_{i0}|W_{i1}=0]]\\
&= [E[\Delta Y_{i1}|W_{i1}=1] - E[\Delta Y_{i1}|W_{i1}=0]]
\end{aligned} \tag{2.14}$$

The justification for the name difference-in-difference is presented in 2.14. In panel data regression with an environment with before and after intervention observations for the same units, the right hand side of 2.14 is equivalent to the regression coefficient on W_{i1} in a regression of ΔY_{i1} on W_{i1} and a constant. Also, we see that τ_{ATET} is defined by the post-treatment period. The common trends assumption implied by equation 2.9 generates identification in the difference-in-difference model. Next from 2.9 and 2.12 we receive:

$$E[\Delta Y_{0i1}|W_{it}=1]=E[\Delta Y_{0i1}|W_{it}=0] \tag{2.15}$$

From equation 2.15 we learn that in the absence of intervention , the mean result for the exposed to treatment and the mean result for the unexposed to treatment would have encountered the same variation over time.

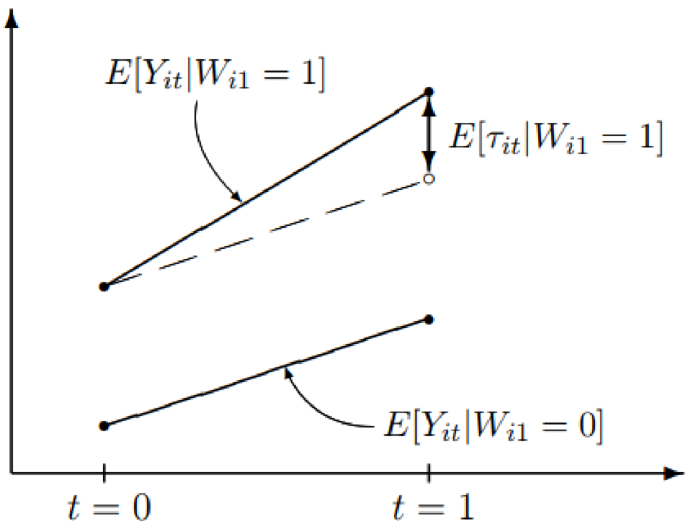

Figure 2.2. Identification in a difference-in-differences Model

Source: Based on Abadie and Cattaneo (2018).

Figure 2.2 presents a visual depiction how identification functions in the difference-in-difference model. The dashed line represents the mean change that the intervention group would have experienced without the intervention. The control group is usually a group of units unexposed to treatment selected to reproduce the counterfactual trajectory of the result for the treatment group. We would also like to point out that the common trend assumption in 2.15 is not invariant to nonlinear conversions of the dependent variable. Assuming that 2.15 is true when the result is a wage rate evaluated in levels, then the same equation will not be true for wages calculated in logs. From the last two sentences we can deduct that identification in a difference in differences model is not invariant to nonlinear conversions in the dependent variable.

The common trends assumption from 2.15 is a vigorous restriction, which should be evaluated in empirical settings. The validity of this assumption can be assessed using 1. multiple pre-treatment periods (see Abadie and Dermisi (2008)), or 2. using population groups that have no possibility of being exposed to intervention (see Gruber (1994)). In both of theses evaluation methods, a difference in differences estimate of the influence of a placebo intervention, is used as an inspection for common trends assumption. When using multiple pre-intervention periods to asses the common trend restriction the placebo estimate is calculated using the pre-treatment data only and assess the influence of a non-existent intervention occurring before the actual treatment period. The common trend assumption before the treatment does not hold when the null effect of the placebo treatment is rejected. The second method is comparable, but uses an estimation acquired for a population group known not to be susceptible to undergo the treatment. The probability of 2.15 being accurate may be investigated if the control and intervention groups are contrasting in the distribution of characteristics that are known or suspected to influence the result trend.

There have been various modifications to the basic difference in difference model proposed in literature. For example the model instinctively develops into a fixed-effects regression in settings with more than two periods, and/or models with unit-specific linear trends (see Bertrand, Duflo, and Mullainathan (2004a)). Reasonably the requirements of data should be higher when estimating models with many time periods and/or trends. We would also like to mention two more approaches to DID estimation. The first one being a generalization of the difference in differences model for the occurrence when covariates define the differences in the trends of the result variable between exposed to intervention and unexposed to intervention (Abadie, 2005). The outcome estimators adjust the distribution of the covariates between the exposed to intervention and unexposed to intervention using propensity score weighting. The second approach from Athey and Imbens (2006) presents a generalization of the difference in differences model to the instance when Y_{0it} is nonlinear in the unobserved confounder μ_i. Identification in this model is generated by strict monotonicity of Y_{0it} with respect to μ_i and from the assumption that the distribution of μ_i is time invariant for the exposed to intervention and unexposed to intervention. A benefit of this method is that it presents an identification outcome that is robust to monotonic transformations of the result variable, for example levels, Y_{it} vs. $\log s, \log(Y_{0it})$. We read all of the theory on the difference-in-difference method present in this subsection according to Abadie and Cattaneo (2018).

In order to identify to understand complex models and different patterns in data we present the definition of marginal effects in definition 2.8.

Definition 2.8 *A marginal effect of a given variable is, the slope of the regression surface with respect to a given covariate. The marginal effect communicates the rate at which y changes at a given point in covariate space, with respect to one covariate dimension and holding all covariate values constant. This quantity is particularly useful because it is intuitive — it is simply a slope — and because it can be calculated from essentially any set of regression estimates. To calculate marginal effects requires the application of partial derivatives. A marginal effect is, in essence, the slope of multi-dimensional surface with respect to one dimension of that surface.Marginal effects are a particularly useful quantity of interest because, in the case of OLS, they translate the coefficients estimated from any model parameterization back into the quantity that is expressed by coefficients in any unconditional model: namely the marginal contribution of x to the outcome (Leeper, 2017).*

We also present the definition of the generalized variance inflator factor (GVIF) in definition 2.9 in order to diagnose collinearity.

Definition 2.9 *The generalized variance inflator factor (GVIF) defined by Fox and Monette (1992) is the measure of the impact of collinearity on the square of the length of the joint confidence region (two or more coefficients).*

$$GVIF = \frac{|R_1||R_2|}{|R|}, \tag{2.16}$$

In equation 2.16 R_1 is the correlation matrix of a particular set of regressors, R_2 is the correlation matrix of the rest of the regressors,and R is the correlation matrix of all the regressors (Salmerón Gómez, García Pérez, López Martín, & García, 2016).

2.3.2 Examples of difference-in-differences estimators

All of the information from this subsection comes from Angrist and Pischke (2008). This book presents one the most famous most famous difference-in-difference studies. It was conducted by Card and Krueger in 1994, and tried to asses whether or not the change in minimum wage in New Jersey will affect employment. These researches wrote an article in 1994 - (Card & Krueger, 1994). Standard economic theory suggests us that higher minimum wages increase unemployment. New Jersey raised the state minimum from \$ 4.25 to \$ 5.05. Card and Kruger accumulated data in February 1992 and in November 1992 from fast food restaurants in New Jersey and from the same type of restaurants in eastern Pennsylvania, where the minimum wage remained unaltered at \$ 4.25 during this time span. The researches used this data to estimate the effect of the increase of minimum wage in New Jersey using the difference-in-difference method. The results from this study are presented below.

Variable	PA	NJ	Difference, NJ-PA
FTE employment before, all available observations	23.33	20.44	-2.89
	(1.35)	(0.51)	(1.44)
FTE employment after, all available observations	21.17	21.03	-0.14
	(0.94)	(0.52)	(1.07)
Change in mean FTE employment	-2.16	0.59	2.76
	(1.25)	(0.54)	(1.36)

Table 2.1. Average employment per store before and after the New Jersey minimum wage increase

Source: Based on Card and Krueger (1994).

Table 2.1 presents results from the Card and Krueger study. We can observe mean full-time equivalent (FTE) employment at fast food restaurants in New Jersey and Pennsylvania before and after the increase of minimum wage in New Jersey. In parentheses standard errors are presented.

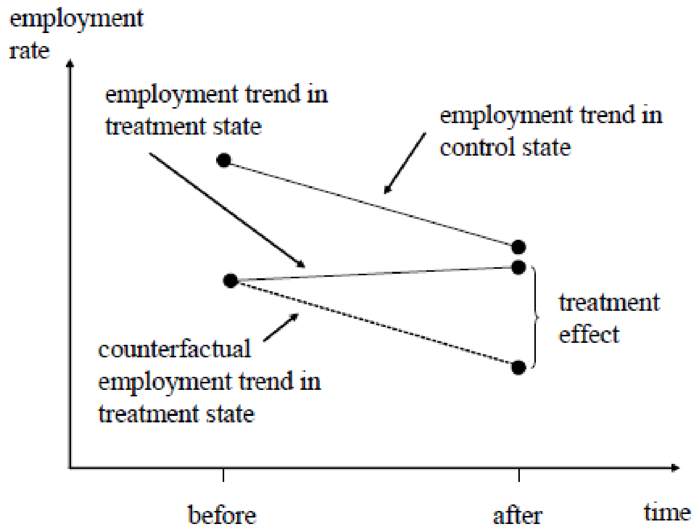

Figure 2.3. Causal effects in the differences-in-differences model in Card and Krueger study

Source: Based on Angrist and Pischke (2008).

According to the parallel trend assumption, in November the employment in New Jersey should decrease in the same amount as in Pennsylvania, but it increases. The rise in employment with higher minimum wages is contrary to standard economic theory. On Figure 2.3 we see a visual presentation of the Card and Kruger study using the differences-in-differences model.

2.4 Robust standard errors for difference-in-differences estimators

One of the assumptions of the ordinary least squares method is that the variance of the errors is homoscedastic. To test whether or not this assumption is fullfilled is to conduct the Breusch-Pagan test. If the p-value is below an appropriate threshold than we reject the null hypothesis of homoskedasticity and assume heteroskedasticity of the errors. We would also like to mention that when data is clustered, for example by city, heteroskedasticity can also be present. For this reason we present information on adjusting standard errors for clustering.

We examine a framework where we model a scalar result Y_i in terms of a binary covariate $W_i \in 0, 1$, with the units belonging to clusters, with the cluster for unit i symbolized by $C_i \in$

$1,\ldots,C$. We assess the linear model present in equation 2.17

$$Y_i = \alpha + \tau W_i + \varepsilon_i = \beta^\top X_i + \varepsilon_i, \tag{2.17}$$

where $\beta^\top = (\alpha, \tau)$ and $X_i^\top = (1, W_i)$, utilizing least squares we receive equation 2.18

$$\hat{\beta} = \arg\min_{\beta} \sum_{i=1}^{N} (Y_i - \beta^\top X_i)^2 = (X^\top X)^{-1}(X^\top Y). \tag{2.18}$$

In the model-based outlook, the N-vector ε with ith element equivalent to ε_i, is looked at as the stochastic component. The N-vector C with ith element equivalent to C_i and the $N \times 2$ matrix X with ith row equivalent to $(1, W_i)$ are looked at as non-stochastic. Therefore keeping fixed W and C, the reiterated sampling thought investigation is redrawing the vectors ε

$$E[\varepsilon | X, C] = 0. \tag{2.19}$$

Usually equation 2.19 and equation 2.20 are imposed on the first two moments of ε.

$$E[\varepsilon\varepsilon^\top | X, C] = \Omega. \tag{2.20}$$

This leads to equation 2.21 for the variance of the ordinary least squares estimator

$$V(\hat{\beta}) = (X^\top X)^{-1}(X^\top \Omega X)(X^\top X)^{-1}. \tag{2.21}$$

The primary assumption, in the framework without clustering, is that Σ is diagonal. In case where we assume homoskedasticity the variance is the standard OLS variance in equation 2.22

$$V_{OLS} = \sigma^2 (X^\top X)^{-1}, \tag{2.22}$$

where $\sigma = \Omega_{ii} = V(\varepsilon_i)$ for all i. Scientists frequently acknowledge general heteroskedasticity and use the robust Eicker-Huber-White (EHW) variance present in equation 2.23 (White, 2014; Eicker, 1967; Huber et al., 1967)

$$V_{EHW}(\hat{\beta}) = (X^\top X)^{-1}\left(\sum_{i=1}^{N} \Omega_{ii} X_i X_i^\top\right)(X^\top X)^{-1}. \tag{2.23}$$

In frameworks with clusters of units, the acceptance that Σ is diagonal is usually looked as not valid. We read all of the theory on regression discontinuity present in this subsection according to Abadie and Cattaneo (2018).

On the other hand Kloek (1979), Moulton and Randolph (1989), and Moulton et al. (1990) apply the homoskedastic design present in equation 2.24.

$$\Omega_{ij} = \begin{cases} 0 & \text{if } C_i \neq C_j, \\ \rho\sigma^2 & \text{if } C_i = C_j, i \neq j, \\ \sigma^2 & \text{if } i \neq j. \end{cases} \tag{2.24}$$

Assuming the clusters are the same size we obtain the variance for the slope coefficient τ present in equation 2.25

$$V_{kloek}(\hat{\tau}) = V_{OLS} \times (1 + \rho_\varepsilon \rho_W \frac{N}{C}), \tag{2.25}$$

where ρ_ε and ρ_W are the within-cluster correlation of the errors and covariates. Scientists for example Liang and Zeger (1986), Bertrand, Duflo, and Mullainathan (2004b), and Stock and Watson (2008) regularly relax this model by acknowledging the Ω_{ij} for pairs (i, j) with $C_i = C_j$ to be unrestricted. By allowing the units to be ordered by cluster, and allowing the $N_c \times N_c$ submatrix of Ω analogous to the units from cluster c be symbolized by Σ_c, and the submatrix of X analogous to cluster c by X_c we receive equation 2.26

$$V_{LZ}(\hat{\beta}) = (X^\top X)^{-1} (\sum_{c=1}^{C} X_c^\top \Omega_c X_c)(X^\top X)^{-1}. \tag{2.26}$$

Equation 2.26 can be looked at as the extension to robust variance estimator from the least squares variance, used in the occurrence with clustering

$$\hat{V}_{EHW}(\hat{\beta}) = (X^\top X)^{-1} \Big(\sum_{i=1}^{N} (Y_i - \hat{\beta}^\top X_i)^2 X_i X_i^\top \Big) (X^\top X)^{-1}. \tag{2.27}$$

The estimated variant of the Eicker-Huber-White variance is present in equation 2.27.

$$\hat{V}_{LZ}(\hat{\beta}) = (X^\top X)^{-1} \Bigg(\sum_{c=1}^{C} \Big(\sum_{i:C_i=c} (Y_i - \hat{\beta}^\top X_i) X_i \Big) \Big(\sum_{i:C_i=c} (Y_i - \hat{\beta}^\top X_i) X_i \Big)^\top \Bigg) (X^\top X)^{-1} \tag{2.28}$$

The estimated variant of the LZ variance is present in equation 2.27. We read all of the theory on robust standard errors present in this subsection according to Abadie, Athey, Imbens, and Wooldridge (2017).

2.5 Conclusions

Causality is an important subject in econometrics. Many researches want to know whther or not an intervention is succesful, that is why randomized controlled trial are performed. When it is not possible to conduct this kind of study scientists try conduct an natural experiment. The basic setup assumes binary treatment exposed to intervention and unexposed to intervention.

Propensity score matching is method that helps with estimating the effect by balancing the covariates in the treatment and control group. This method helps with obtaining unbaised calculations, although the randomization in a controlled experiment is better due to the researcher not conditioning on a specific set of covariates.

Regression discontinuity is also a method allowing investigators to obtain information on casual effects. This approach is based on a cutoff point where subjects higher than this point are assigned to test group while the other subjects are appointed to the control group.

The difference in difference method is commonly used in panel data and cross sections. It is used in order to gain knowledge on effects of treatment. This method controls for time trends by comparing the intervention group with treatment group. One of the main assumptions of this approach is the parallel trend assumption. A popular example of the difference in difference estimation was conducted by Card and Krueger in 1994. These researcher measured the effect of raising the minimum wage. The results of this study were contrary to standard economic theory, because the employment increased, instead of decreasing. When heteroscedasticity is present, robust standard errors are calculated in order to obtain errors with consistent variance. This method can also be extended for clustered data.

In the next chapter we will apply difference-in-differences estimator with clustered standard errors to estimate the impact of automatic traffic supervision on vehicle speed.

Chapter 3

Empirical evaluation of the effectiveness of automatic speed measurement

3.1 The Centre for Automatic Traffic Supervision – exploratory data analysis

The Centre for Automatic Traffic Supervision collected data during the „Construction of a central system of automatic traffic supervision” project, which took place from February 2015 to April 2016. Data were collected before and after the introduction of speed cameras (SC) and average speed measuring devices (AMD). Data was provided in excel files that were later combined using R programming language.

city	measurement_date	length_vehicle	vehicle_type	radar_type	speed	time_5_23
Przerzeczyn-Zdroj	2015-03-05T21:43:27Z	476	Samochod osobowy	none	53	50
Przerzeczyn-Zdroj	2015-03-05T21:43:56Z	418	Samochod osobowy	none	58	50
Przerzeczyn-Zdroj	2015-03-05T21:43:57Z	884	Ciezarowki	none	54	50
Przerzeczyn-Zdroj	2015-03-05T21:43:59Z	830	Ciezarowki	none	57	50
Przerzeczyn-Zdroj	2015-03-05T21:44:10Z	1291	Ciezarowka z przyczepa	none	63	50
Przerzeczyn-Zdroj	2015-03-05T21:44:12Z	1217	Ciezarowka z przyczepa	none	69	50

Figure 3.1. Canard data - example

Source: Canard data source.

In Figure 3.1 we see an example of the original data. One of the first tasks during data preparation was taking out separately the day and the time of the measurement from column measurement_date.

```
data <- data %>% mutate(
day = as.Date(measurement_date,format = "%Y-%m-%d"),
time = format(as.POSIXct(strptime(measurement_date ,"%Y-%m-%dT%H:%M:%SZ",tz
    ="")) ,format = "%H:%M:%S"))
```

Listing 3.1. Canard data preparation

In Listing 3.1 we see the code that was used in order to obtain the day and the time of the measurement. On Figure 1.8 from chapter one we see the locations of the cities that were tested with automatic traffic supervision and on Figure 3.2 we see when the measurements took place.

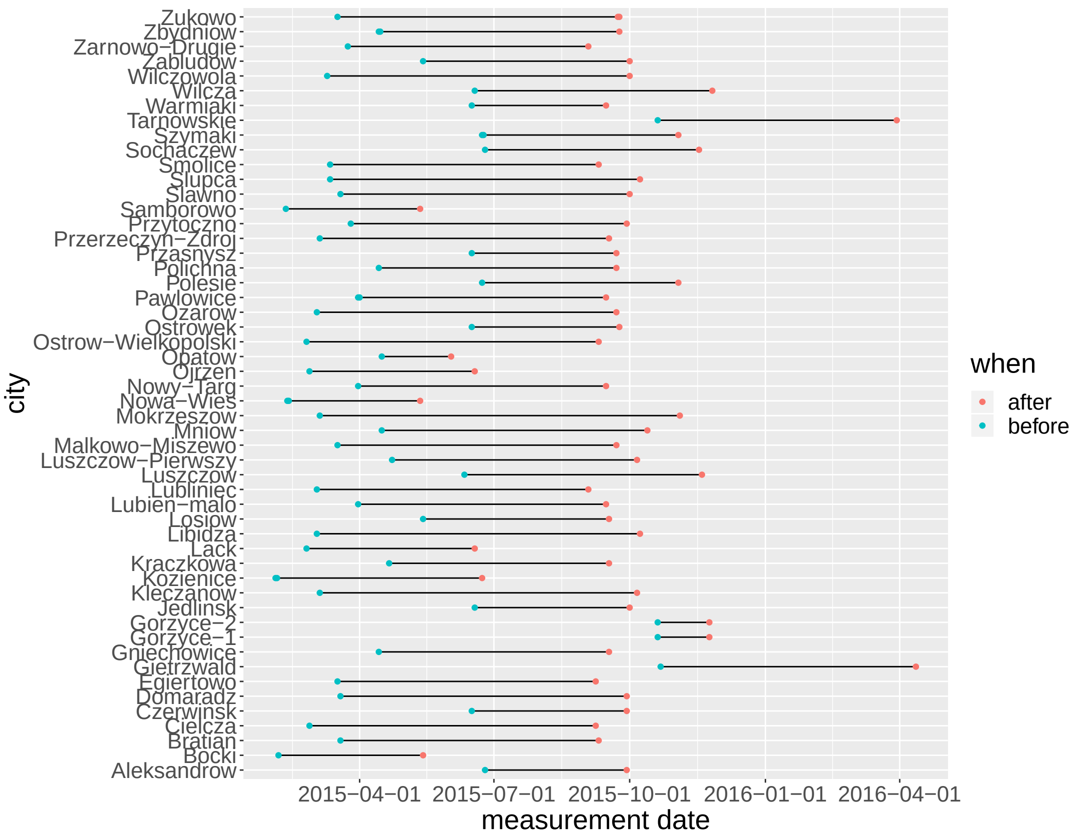

Figure 3.2. Measurements cities in Canard project

Source: Own elaboration based on the Canard data. Note: before – before installing the monitoring system; after – after installing the monitoring system.

With prepared data we analyzed the share and count of vehicles before and after the installation of speed cameras.

Table 3.1. Vehicle count and share before and after speed camera measurement device

vehicle	count in no radar	count in speed camera	share in no radar	share in speed camera
Car	133927	138997	61%	60.6%
Truck with trailer	28477	31943	13%	13.9%
Van	30932	30235	14.1%	13.2%
Truck	23641	24132	10.8%	10.5%
Two-wheeled vehicle	2513	3243	1.1%	1.4%
Other	73	673	0%	0.3%

Source: Own elaboration based on Canard data.

In Table 3.1 we see that the share and count of specific vehicles (except other vehicle types) in cities that were tested with speed cameras are consistent. We also analyzed the share and count of vehicles before and after the installation of average speed measuring devices.

Table 3.2. Vehicle count and share before and after average speed measurement device

vehicle	count in no radar	count in avg speed device	share in no radar	share in avg speed device
Car	39687	38704	61%	60.6%
Truck with trailer	10179	10106	13%	13.9%
Van	7774	6851	14.1%	13.2%
Truck	5946	5657	10.8%	10.5%
Two-wheeled vehicle	629	455	1.1%	1.4%
Other	31	18	0%	0.3%

Source: Own elaboration based on Canard data.

In table 3.2 we also can observe that the share and count of specific vehicles (except other vehicle types) in cities that were tested with average speed measuring devices are consistent. From both of these tables we can observe that the number of observations for cities that were tested with speed cameras is much higher, the reason for this is 40 cities tested for SC and 12 for AMD.

3.2 The General Director for National Roads and Motorways – exploratory data analysis

The General Director for National Roads and Motorways collects data on the movement of vehicles in given monitoring stations on an ongoing basis. This institution provided us with data for 2015, 2016 and 2017 from: Złota - Built-up area, Kruszów - road with 2 lanes in each direction, Poznań - S11 expressway, Poznań - S5 expressway, and Poznań - A2 highway. Data on these monitoring stations were provided in daily txt format files. We can see an example in Figure 3.3.

// 2	Device	Site	Year	Month	Day	Hour	Minute	Second	Lane	Speed	Profile	Typ						
// 3	Device	Site	Year	Month	Day	Hour	Minute	Second	Lane	Speed	Profile	Typ	Gap					
// 4	Device	Site	Year	Month	Day	Hour	Minute	Second	Lane	Speed	Length	VehTyp	VehGap	AxleNo	A-Typ	A-Left	A-Right	A-Gap
// 32	Device	Site	Year	Month	Day	Hour	Minute	Second	Temp									
32	272	1	2015	4	5	0	0	0	1068									
4	272	1	2015	4	5	0	1	49	1	126	46	1	1997	0				
4	272	1	2015	4	5	0	3	29	1	108	43	1	1997	0				
4	272	1	2015	4	5	0	4	21	1	81	165	6	1997	0				
4	272	1	2015	4	5	0	4	23	1	87	170	6	622	0				
4	272	1	2015	4	5	0	4	39	4	47	4	1	1997	0				
4	272	1	2015	4	5	0	4	55	1	126	53	2	1997	0				
4	272	1	2015	4	5	0	5	46	3	83	44	1	1997	0				
4	272	1	2015	4	5	0	6	11	1	73	157	6	1997	0				
4	272	1	2015	4	5	0	6	13	2	115	59	2	1997	0				
4	272	1	2015	4	5	0	6	14	3	86	163	6	1997	0				
4	272	1	2015	4	5	0	6	20	1	73	156	6	1997	0				
4	272	1	2015	4	5	0	7	7	1	91	44	1	1997	0				
4	272	1	2015	4	5	0	7	16	1	99	46	1	1997	0				

Figure 3.3. Control group data - example

Source: GDDKiA data source.

All of the daily files were in monthly folders and all of the monthly folders were in monitoring station specific files. In order to conduct analysis and take out necessary data, we had to write R code for the data preparation part. In Listing 3.2 we see that in order to convert many daily files to one table, we had to write a nested loop that first exports data from each daily file and the end result is one table. Also in Figure 3.3 we see that in order to obtain data and time variables we had to combine the Year, Month, and Day columns for date and Hour, Minute, and Second columns for time. The code needed for this part is visible in Listing 3.2. Also, we had to manually insert the speed limit for the cities from the GDDKiA data source.

After preparing the data we conducted an analysis of the data in 2015. In table 3.3 we see how the average vehicle speeds differ in given monitoring stations. Table 3.3 shows us that the speed differs according to city and vehicle.

```
file_paths <- list.files(path = file_dir)
file_dir_month <- vector()
POZNAN_S5_Data_2015 <- data_frame()

```

```
for (j in 1:length(file_paths)) {

file_dir_month[j] <- paste0(file_dir,"/",file_paths[j],"/txt")

for ( i in 1:length(list.files(path =  file_dir_month[j]))) {

file_paths_month <- list.files(path = file_dir_month[j])

data_day <- read_table2(paste0(file_dir_month[j],"/",
 file_paths_month[i]) ,col_names = F, skip =2)

data_day <- data_day %>%
      select(2:15) %>%
      setNames(as.character(data_day[1,3:16])) %>%
      slice(-1:-3) %>%
      mutate(Speed = as.numeric(Speed),
             Date = paste0(Year,"-",Month,"-",Day),
             city="POZNAN_S5",
             Date=as_date(Date,tz="Europe/Warsaw" ,format = "%Y-%m-%d"))
                %>%
      mutate_at(vars(Hour,Minute,Second), as.numeric) %>%
      mutate(Hour = ifelse(Hour <10, paste0("0",Hour), Hour),
             Minute = ifelse(Minute <10, paste0("0",Minute), Minute),
             Second = ifelse(Second <10, paste0("0",Second), Second),
             Time = paste0(Hour,":",Minute,":",Second),
             Time = as.hms(Time),
             speed_limit = "120") %>%
      select(city, Date, Time, VehTyp,speed_limit, Speed)

  POZNAN_S5_Data_2015 <- bind_rows(data_day,POZNAN_S5_Data_2015) }}
```

Listing 3.2. GDDKiA data preparation

The reason for this being are different speed limits in cities and different speed limits for specific vehicles. The speed limit for cars, vans and motorcycles in Kruszów is 100 km/h, Poznan S11 and Poznan S5 (expressways) is 120 km/h and Poznan A2 is 140 km/h (highway). For cars with trailers, trucks, trucks with trailers and some buses the speed limit is always 80 km/h. For buses with special equipment the speed limit is 100 km/h only in Poznan A2. In Złota the speed limit for every vehicle type 50 km/h from 5:00 a.m. to 11 p.m. and 60 km/h from 11 p.m. to 5 a.m.

Table 3.3. Average vehicle types speed in cities based on the GDDKiA data

Vehicle type	Kruszow	Poznan A2	Poznan S11	Poznan S5	Zlota
Car	88.24	131.81	109.73	110.83	68.26
Van	91.68	120.74	98.80	101.41	68.04
Car with trailer	77.76	100.45	89.99	91.88	67.53
Truck	78.70	95.25	86.12	85.50	66.77
Truck with trailer	77.77	90.52	83.04	81.89	73.48
Truck with semi-trailer	70.85	84.54	80.03	80.96	69.77
Bus	70.89	95.71	79.83	86.27	64.32
Motorcycle	73.75	146.73	112.03	83.60	77.55

Source: Own elaboration based on GDDKiA data source.

We also analyzed the average speed for each month for Złota, Kruszow, Poznan A2, Poznan S11 and Poznan S5. In Figure 3.4 we can notice that the average speed in months in Poznan S11 and Poznan S5 are similar because of the same speed limit. Also we can observe that Poznan A2 has greater average velocities because of higher speed limits and Kruszow and Złota have decreased mean speeds due to a lower speed limits. The average velocities for months in the cities presented do not differ from each other substantially expect city Złota. Most likely there had to be some kind of modification that caused the sudden drop.

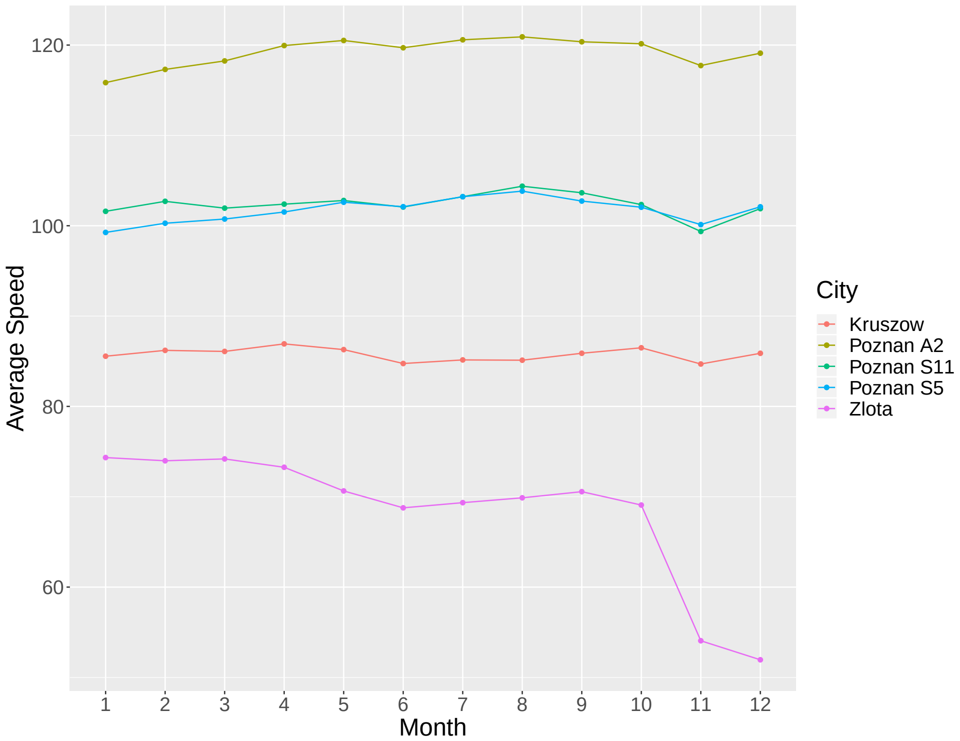

Figure 3.4. Average speed in city in months

Source: Own elaboration based on GDDKiA data.

For 2015 the number of observations was: Złota - 1 838 702, Kruszów - 13 373 048, Poznań - 9 748 695, Poznań - 7 500 773, and Poznań - 14 339 501.

3.3 Visual inspection of the effect of speed measurement systems on average speed

The goal of speed surveillance systems is to make sure drivers drive according to the speed limit. With prepared data, from the Canard data source, we visually inspected the effect of speed measurement systems on average speed in Poland. We would also like to note that we filtered out the other vehicle type due small number of observations.

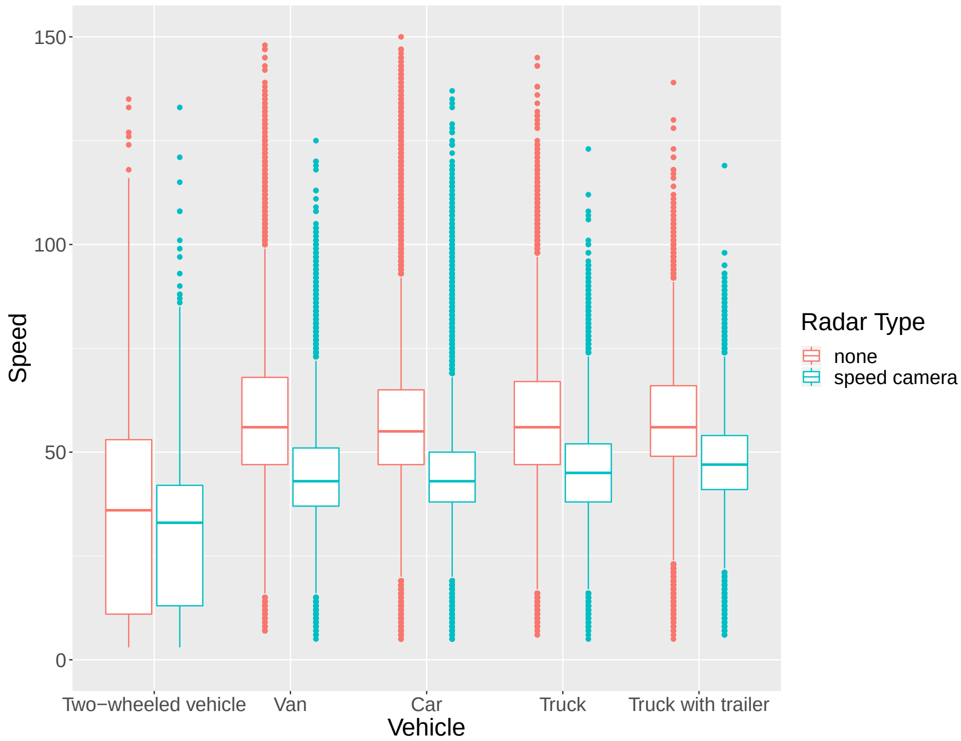

Figure 3.5. Box plot vehicles - before/after speed cameras

Source: Own elaboration based on Canard.

On Figure 3.5 we see the visual effect of introducing speed cameras. From Figure 3.5 we can recognize a decrease of median speed for every vehicle type. We also looked at he visual effect of the introduction of average speed measuring devices. On Figure 3.6 we can observe a decrease of median speed for every vehicle type.

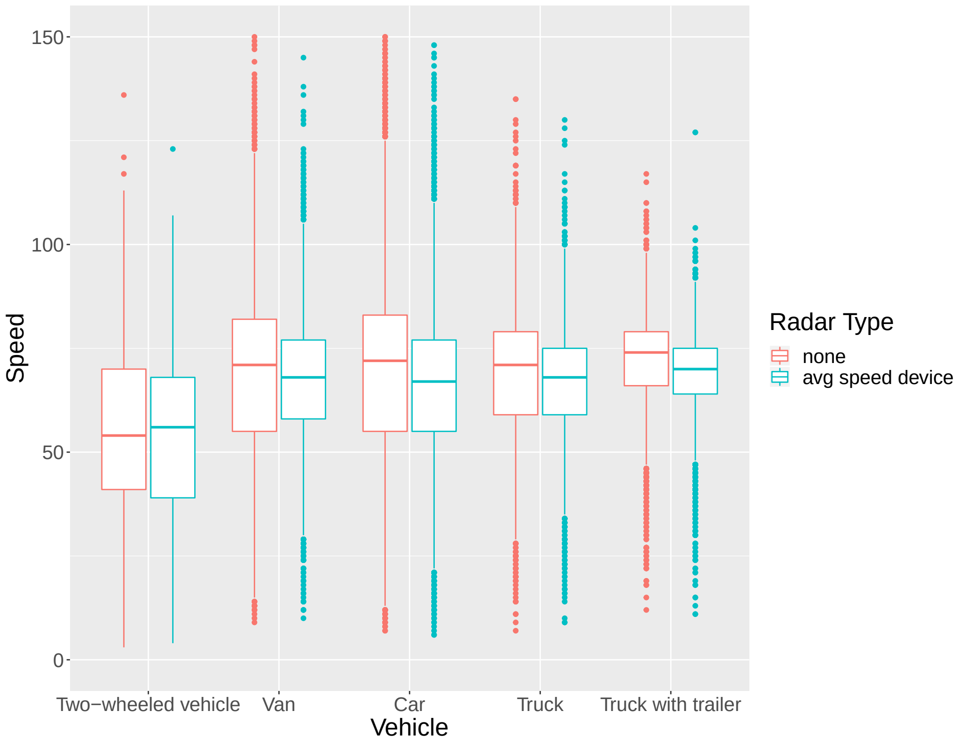

Figure 3.6. Box plot vehicles - before/after average speed measuring devices

Source: Own elaboration based on Canard data.

Comparing Figure 3.6 with Figure 3.5 we can visually detect that the effect of speed cameras was greater than average speed measuring devices.

The average speed of vehicles when there was no speed camera was 57.09 km/h but when the speed camera was present the speed decreased to 44.5 km/h. In table 3.4 we also see how the speed altered for different vehicle types.

Table 3.4. Average speed of vehicles measured by the speed cameras according to the CANARD data

Vehicle	no speed camera (km/h)	speed camera (km/h)
Car	57.12	44.00
Truck	57.44	45.29
Truck with trailer	56.98	47.55
Van	58.64	44.33
Two-wheeled vehicle	35.09	33.03

Source: Own elaboration based on Canard data.

From Table 3.4 we can notice a decrease of average speed for every vehicle type. The smallest decrease was for two-wheeled vehicles, this might be due to the fact that before the introduction of speed cameras they were already driving slow. The reason most likely for this is that bikes and scooters do not develop high velocities.

The average speed of vehicles when there was no average speed measuring device was 70.75 km/h but when the average speed measuring devices was present the speed decreased to 66.79 km/h. In Table 3.4 we also see how the speed altered for different vehicle types.

Table 3.5. Average speed for the vehicles measured by the average speed measuring device according to the CANARD data

Vehicle	no speed camera (km/h)	speed camera (km/h)
Car	71.11	66.38
Truck	69.34	66.85
Truck with trailer	71.75	68.46
Van	70.11	67.74
Two-wheeled vehicle	52.7	50.25

Source: Own elaboration based on Canard data.

Like in Table 3.4 in Table 3.5 we can observe a decrease of average speed for every vehicle type. Also, two-wheeled vehicle have the lowest average velocities. Although the difference between Table 3.4 and Table 3.5 is that the decrease of average speed for given vehicle types is lower. When comparing the average speeds for speed cameras and average speed measuring device we notice substantial discrepancy. This is due to the fact that more cities with higher speed limits where tested with the average speed measuring device. Also when comparing the averages before and after the introduction of surveillance equipment we notice that the average speed decreased considerably more after installing speed cameras.

We analyzed the distribution of speed intervals before and after installing speed cameras. On Figure 3.7 we see that the number of vehicles driving with higher speeds decreases after the introduction of speed cameras. We can notice a very high increase in the number of vehicles driving with speeds between 30 km/h and 40 km/h. This also shows a influence of the introduction of speed cameras.

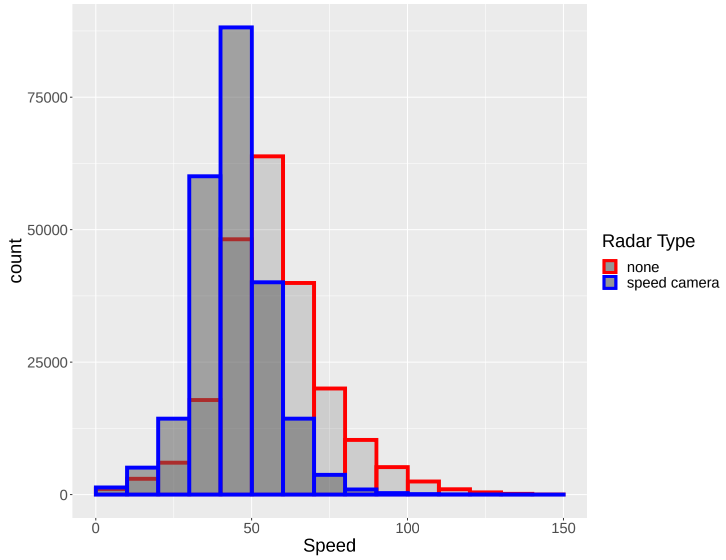

Figure 3.7. Distribution of speed – before/after installing the speed cameras devices

Source: Own elaboration based on Canard data.

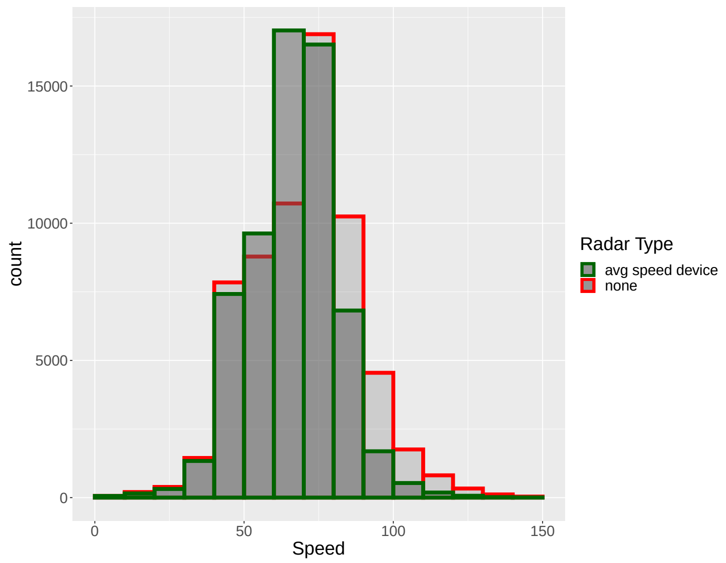

Figure 3.8. Distribution of speed - before/after installing the average speed measuring devices

Source: Own elaboration based on Canard data.

We analyzed the distribution of speed intervals before and after installing average speed measuring devices. On Figure 3.8 we see that the number of vehicles driving with higher speeds decreases after the introduction of average speed measuring devices. We can notice a very high increase in the number of vehicles driving with speeds between 60 km/h and 70 km/h. This also shows a influence of the introduction of average speed measuring devices.

Comparing Figure 3.8 with Figure 3.7 we notice that the count of vehicles driving in certain speed intervals did not change as much as in the speed camera case. Also we see that the distribution is centered around greater speeds in Figure 3.8 compared to Figure 3.7. The reason for this are higher speed limits in locations tested for average speed measuring devices.

3.4 Estimation of the effect of speed measurement systems on average speed of vehicles

3.4.1 Aligning data from CANARD and GDDKiA

Comparing the average and median before and after the introduction of the surveillance systems, from the Canard data source analysis, we see that speed cameras and average speed measuring devices cause a decrease in average speed on Polish roads. The drawback of just comparing before and after is that this method does not control for time trends and also the same communities are analyzed. From Figure 3.4 in the absence of intervention we can observe that the time trends for the monitoring stations, in the GDDKiA data source, do not differ from each other substantially, expect for city Złota. The set up of this research with the Canard data source being the treatment group and the GDDKiA data source being the control group has the characteristics of a natural experiment. A method that controls for time trends and enables to compare different communities in a natural experiment is the difference in difference method. In order to estimate the effect of speed measurement systems on average speed, substantial data preparation work was needed. We had to integrate Canard data (treatment group) with GDDKiA data (control group). The greatest obstacle when combining these two data sources was unifying vehicle types. We unified the vehicle types present in the GDDKiA data source in order for them to be consistent with the vehicle types in the Canard data source.

Table 3.6. Unification of vehicle types

Canard	GDDKiA
Car	Car
Truck with trailer	Truck with trailer
Truck with trailer	Truck with semi-trailer
Van	Van
Truck	Truck
Two-wheeled vehicle	Motorcycle
Other	Bus
Other	Car with trailer
Other	Other

Source: Own elaboration based on Canard and GDDKiA data.

In 3.6 we show how the unification of vehicle types was conducted. The next part needed to evaluate the effectiveness of automatic speed measurement was to filter out cities in the Canard data source. First, for the evaluation of speed cameras, we filtered out cities that had measurements without speed camera after April 2015. Second, for the evaluation of average speed measuring devices, we filtered out cities that had measurements without average speed measuring device after June 2015. We did this in order to achieve a before treatment and after treatment structure of the data and also to obtain similar dates for measurements. Next we had to take out measurements from the GDDKiA data source that had the same dates as measurements for speed cameras and average speed measuring device in the Canard data source. Then we combined both data sources and created two tables one for the speed camera model and one for average speed measuring device model. In both of these tables we adjusted the speed limit according to vehicle type and the time. We also filtered out other and two-wheeled vehicles due to incompatibility of these vehicle types. We also filtered out city Złota due to inconsistencies across months visible in Figure 3.4. For the control group for assessing the influence of speed cameras we only took Kruszow, because Poznan A2, Poznan S11 and Poznan S5, had too big road characteristic differences compared to the cities where speed cameras where introduced. For measuring the influence of average speed measuring devices for the control group we took into account Poznan A2, Poznan S11, Poznan S5 and Kruszow.

3.4.2 Model for the Speed Camera measurement detive

In order to to evaluate the efficiency of speed cameras we created a difference-in-differences regression model. In the basic difference-in-differences set up two time periods and two groups are taken into account. In our setup we took into account multiple time periods and multiple groups. The time periods are months and the groups are speed limits in given cities. The speed limits are group specific for the treatment and control group. Before intervention months were: February, March, April and after intervention months were : May, June, September, October and November. The treatment group were cities where speed limits equal 40 km/h, 50 km/h, 60 km/h, 70 km/h and 90 km/h. The Control group was Kruszow where speed limits equal 80 km/h and 100 km/h. In our analysis we calculated weighted linear regression, were each weight was an observation of the same type. The covariates in this set up are vehicle, day of day of week and time of day. In our model for levels in variables vehicle, speed limit, month, day of week, hour we compared every level to the overall mean of means (contr.Sum function in R programming language), which is visible in Listing 3.3.

```
lm(formula = speed ~ radar*vehicle + speed_limit + month + week +time ,
         data  = did_data_speed_camera,
         weights = n,
        contrasts = list( vehicle = "contr.Sum", speed_limit = "contr.Sum",
             month = "contr.Sum", week  = "contr.Sum", time = "contr.Sum"))
```

Listing 3.3. Speed camera model

In Table 3.5 we also see our speed camera model equation where the radar*vehicle term symbolizes the cross between radar and vehicle. This is the same as radar + vehicle + interaction of vehicle and radar. In the model summary 3.8 we see coefficients and in parentheses standard errors, for the default and robust version. Also in 3.8 $*$ symbolizes $p < 0.1$, $**$ symbolizes $p < 0.05$ and $***$ symbolizes $p < 0.01$.

Table 3.7. Speed camera model – collinearity measur

Variable	GVIF	Df	GVIF$^{1/(2*Df)}$
radar	3.43	1.00	1.85
vehicle	16.15	3.00	1.59
speed_limit	26.87	6.00	1.32
month	1.88	7.00	1.05
day_week	1.43	2.00	1.09
time	1.22	23.00	1.00
radar:vehicle	4.31	3.00	1.28

Source: Own elaboration based on Canard and GDDKiA.

We tested whether or not the variables are collinear. We interpreted the GVIF$^{1/(2*Df)}$ estimate because the variables are categorical. As we can see from Table 3.7 that the variables are not collinear.

Next we conducted the Breusch-Pagan test to see whether or not the variance of the residuals is constant. After conducting this test we had to reject the null hypothesis of homoskedasticity and assume heteroskedasticity. Next using clustered covariance matrices with HC1 estimation we assesed robust standard errors. We clustered observations by city and obtained robust standard errors that are visible in Table 3.8. From Table 3.8 we see that the standard errors are now larger than before and also the significance for given variable levels has changed. From 3.8 we can observe that in the presence of speed cameras the estimated average decrease of speed is 12.75 km/h, we also see that this estimate is statistically significant, also after calculating robust standard errors. This shows that speed cameras have a relevant effect on lowering the speed on Polish roads. We can also observe that speed cameras have a different impact on vehicle types, so we calculated marginal effects using code present in Listing 3.4.

```
margins(speed_camera_model,
                 variables = ”radar”,
                 vcov = vcovCL(m3, cluster = ~city),
                 at = list(vehicle = c(”Truck”,”Truck with trailer”,”
                    Van”,”Car”)))
```

Listing 3.4. Speed camera - marginal effects code

The result of Listing 3.4 can be seen in Table 3.9. From Table 3.9 we notice that speed cameras have different effects on different vehicle types.

Table 3.8. Speed camera model – estimation results

	Dependent variable:	
	speed	
	default se	robust se
	(1)	(2)
Constant	68.42*** (0.18)	68.42*** (0.67)
radarspeed camera	−12.75*** (0.21)	−12.75*** (1.06)
vehicle Truck	2.27*** (0.16)	2.27*** (0.57)
vehicle Truck with trailer	−3.03*** (0.16)	−3.03*** (0.61)
vehicle Van	1.06*** (0.15)	1.06*** (0.37)
speed_limit 40	−14.54*** (0.49)	−14.54*** (0.90)
speed_limit 50	−13.46*** (0.18)	−13.46*** (1.14)
speed_limit 60	−6.31*** (0.39)	−6.31*** (1.03)
speed_limit 70	2.22*** (0.23)	2.22 (3.48)
speed_limit 80	7.72*** (0.26)	7.72*** (0.62)
speed_limit 90	1.56** (0.71)	1.56* (0.87)
month 2	−1.35*** (0.09)	−1.35 (0.87)
month 3	0.45*** (0.08)	0.45 (1.00)
month 4	−1.19*** (0.10)	−1.19* (0.70)
month 5	1.34*** (0.15)	1.34** (0.52)
month 6	−1.67*** (0.12)	−1.67*** (0.35)
month 9	−0.48*** (0.08)	−0.48 (0.46)
month 10	1.84*** (0.11)	1.84* (1.11)
day_week 2	−0.69*** (0.06)	−0.69 (0.57)
day_week 3	0.59*** (0.09)	0.59 (0.56)
hour 0	0.95*** (0.29)	0.95*** (0.05)
hour 1	1.11*** (0.30)	1.11*** (0.04)
hour 2	0.75** (0.31)	0.75*** (0.07)
hour 3	0.96*** (0.29)	0.96*** (0.05)
hour 4	0.31 (0.26)	0.31** (0.14)
hour 5	1.02*** (0.20)	1.02* (0.53)
hour 6	0.20 (0.16)	0.20 (0.47)
hour 7	0.18 (0.14)	0.18 (0.58)
hour 8	−0.22 (0.14)	−0.22 (0.24)
hour 9	−0.64*** (0.14)	−0.64*** (0.16)
hour 10	−0.41*** (0.15)	−0.41* (0.21)
hour 11	−0.50*** (0.15)	−0.50*** (0.12)
hour 12	−0.37** (0.14)	−0.37*** (0.12)
hour 13	−0.32** (0.14)	−0.32*** (0.12)
hour 14	−0.46*** (0.14)	−0.46*** (0.14)
hour 15	−0.51*** (0.14)	−0.51* (0.30)
hour 16	−0.43*** (0.14)	−0.43 (0.30)
hour 17	−0.62*** (0.14)	−0.62*** (0.06)
hour 18	−0.88*** (0.15)	−0.88*** (0.18)
hour 19	−1.05*** (0.16)	−1.05*** (0.34)
hour 20	−0.35* (0.18)	−0.35 (0.33)
hour 21	0.20 (0.20)	0.20 (0.54)
hour 22	0.52** (0.22)	0.52 (0.59)
radarspeed camera:vehicle Truck	−2.68*** (0.32)	−2.68*** (0.64)
radarspeed camera:vehicle Truck with trailer	5.21*** (0.30)	5.21*** (0.57)
radarspeed camera:vehicle Van	−2.07*** (0.29)	−2.07*** (0.36)
Observations	238,395	238,395
R^2	0.49	0.49
Note:		*p<0.1; **p<0.05; ***p<0.01

Source: Own elaboration based on Canard and GDDKiA data.

Table 3.9. Speed camera model - marginal effects

factor	vehicle	AME	SE	z	p	lower	upper
radarspeed camera	Truck	-15.44	1.33	-11.64	0.00	-18.04	-12.84
radarspeed camera	Truck with trailer	-7.55	1.05	-7.21	0.00	-9.60	-5.50
radarspeed camera	Van	-14.83	1.14	-12.96	0.00	-17.07	-12.59
radarspeed camera	Car	-13.20	1.14	-11.58	0.00	-15.44	-10.97

Source: Own elaboration based on Canard and GDDKiA data.

Also we can notice that cars on average decrease their speed by over 13 km/h in the presence of a speed camera. We read from Polish Police (2019) that not adapting speed to traffic conditions was the most common cause of death. Also we read from (Polish Police, 2019) that the most common vehicle type of the perpetrator of an accident were cars, which caused 1547 deaths (71,1%).

3.4.3 Average speed measuring device model

In order to to evaluate the efficiency of average speed measuring devices we created a difference-in-differences regression model. Like in the speed camera model we take into account multiple time periods and multiple groups. The time periods are months and the groups are speed limits in given cities. The speed limits are group specific for the treatment and control group. Before intervention months were: May, June and after intervention months were : September, October and November. The treatment group were cities where speed limits equal 50 km/h, 60 km/h, 70 km/h and 90 km/h. The Control group were Poznan A2, Poznan S11, Poznan S5 and Kruszow where speed limits equal 80 km/h, 100 km/h, 120 km/h, and 140 km/h. In our analysis we calculated weighted linear regression, were each weight was an observation of the same type.

```
lm(formula = speed ~ radar*vehicle + speed_limit + month + week +time ,
         data  = did_avg_speed_device,
         weights = n,
        contrasts = list( vehicle = "contr.Sum", speed_limit = "contr.Sum",
            month = "contr.Sum", week  = "contr.Sum", time = "contr.Sum"))
```

Listing 3.5. Average speed measuring device model

The covariates were the same as in the speed camera model and so were the weights. Also just as in speed camera model we compared every level to the overall mean of means (contr.Sum function in R programming language), which is visible in Listing 3.5.

In Lisiting 3.5 we also see our speed camera model equation where the radar*vehicle term symbolizes the cross between radar and vehicle. This is the same as radar + vehicle + interaction of vehicle and radar. In the model summary Table 3.11 we see coefficients and in parentheses standard errors, for the default and robust version. Also in Table 3.11 $*$ symbolizes $p < 0.1$, $**$ symbolizes $p < 0.05$ and $***$ symbolizes $p < 0.01$.

Table 3.10. Average speed measuring device model - collinearity

Variable	GVIF	Df	GVIF$^{1/(2*Df)}$
radar	2.80	1.00	1.67
vehicle	74.87	3.00	2.05
speed_limit	190.10	7.00	1.45
month	1.21	4.00	1.02
day_week	1.17	1.00	1.08
time	1.08	23.00	1.00
radar:vehicle	3.35	3.00	1.22

Source: Own elaboration based on Canard and GDDKiA data.

We tested whether or not the variables are collinear. We interpreted the GVIF$^{1/(2*Df)}$ estimate because the variables are categorical. As we can see from Table 3.10 that the variables are not collinear.

Next we conducted the Breusch-Pagan test to see whether or not the variance of the residuals is constant. After conducting this test we had to reject the null hypothesis of homoskedasticity and assume heteroskedasticity. Next using clustered covariance matrices with HC1 estimation we assesed robust standard errors. We clustered observations by city and obtained robust standard errors that are visible in Table 3.11. From Table 3.11 we see that the standard errors are now larger than before and also the significance for given variable levels has changed. From Table 3.11 we can observe that in the presence of average speed measuring devices the estimated average decrease of speed is 3,71 km/h. This estimate is statistically significant for the default version, but after calculating robust standard errors, we notice that average speed measuring devices become not significant statistically. We can also observe that average speed measuring devices have a different impact on vehicle types, so we calculated marginal effects

Table 3.11. Average speed measuring device model – estimation results

	Dependent variable:	
	speed	
	default se	robust se
	(1)	(2)
Constant	88.53*** (0.32)	88.53*** (1.85)
radaravg speed device	−3.71*** (0.61)	−3.71 (2.34)
vehicle Truck	1.59*** (0.51)	1.59** (0.75)
vehicle Truck with trailer	−3.54*** (0.50)	−3.54*** (0.80)
vehicle Van	−2.25*** (0.50)	−2.25 (2.55)
speed_limit 50	−12.67*** (0.41)	−12.67*** (1.84)
speed_limit 60	−7.06*** (1.39)	−7.06*** (2.14)
speed_limit 70	−13.60*** (0.80)	−13.60*** (2.81)
speed_limit 80	−4.56*** (0.71)	−4.56 (2.92)
speed_limit 90	−16.56*** (0.55)	−16.56** (7.41)
speed_limit 100	−1.55*** (0.42)	−1.55 (1.96)
speed_limit 120	16.65*** (0.42)	16.65*** (2.09)
month 5	0.70*** (0.16)	0.70 (0.66)
month 6	−0.01 (0.09)	−0.01 (0.52)
month 9	0.28** (0.12)	0.28 (0.55)
month 10	0.74*** (0.16)	0.74 (0.52)
day_week 2	−0.15** (0.06)	−0.15 (0.27)
hour 0	−0.64 (0.44)	−0.64 (0.56)
hour 1	−1.05** (0.47)	−1.05* (0.60)
hour 2	−1.29*** (0.48)	−1.29* (0.66)
hour 3	−1.25*** (0.46)	−1.25 (0.85)
hour 4	−0.67* (0.41)	−0.67 (0.87)
hour 5	−0.79** (0.32)	−0.79 (0.93)
hour 6	−0.94*** (0.24)	−0.94 (0.76)
hour 7	0.35* (0.21)	0.35 (0.39)
hour 8	0.52** (0.21)	0.52*** (0.07)
hour 9	0.70*** (0.22)	0.70* (0.42)
hour 10	0.90*** (0.23)	0.90** (0.41)
hour 11	1.12*** (0.23)	1.12** (0.53)
hour 12	0.71*** (0.23)	0.71 (0.46)
hour 13	0.90*** (0.22)	0.90** (0.39)
hour 14	0.90*** (0.22)	0.90* (0.49)
hour 15	0.58*** (0.21)	0.58** (0.29)
hour 16	−5.64*** (0.20)	−5.64 (4.51)
hour 17	−1.30*** (0.21)	−1.30 (1.53)
hour 18	1.89*** (0.23)	1.89** (0.75)
hour 19	2.84*** (0.25)	2.84*** (0.99)
hour 20	2.17*** (0.28)	2.17*** (0.73)
hour 21	0.29 (0.31)	0.29 (0.56)
hour 22	−0.10 (0.35)	−0.10 (0.26)
radaravg speed device:vehicle Truck	−3.46*** (1.02)	−3.46** (1.41)
radaravg speed device:vehicle Truck with trailer	2.41*** (0.84)	2.41** (0.96)
radaravg speed device:vehicle Van	4.21*** (0.99)	4.21 (2.78)
Observations	172,211	172,211
R^2	0.44	0.44
Note:		*p<0.1; **p<0.05; ***p<0.01

Source: Own elaboration based on Canard and GDDKiA data.

using code present in Lisiting 3.6. The result of Table 3.6 can be seen in Table 3.9. From Table 3.12 we notice that speed cameras have different effects on different vehicle types.

```
margins(avg_speed_device_model,
                     variables = "radar",
                     vcov = vcovCL(m3_opp, cluster = ~city),
                     at = list(vehicle = c("Truck","Truck with trailer","
                        Van","Car")))
```

Listing 3.6. Average speed measuring device - marginal effects code

In Table 3.12 we see that cars and trucks are mostly affected by average speed measuring devices. On the contrary trucks and vans speeds on average were barely influenced in the presence of average speed measuring devices.

Table 3.12. Average speed measuring device model - marginal effects

factor	vehicle	AME	SE	z	p	lower	upper
radaravg speed device	Truck	-7.17	2.51	-2.85	0.00	-12.10	-2.24
radaravg speed device	Truck with trailer	-1.30	2.39	-0.54	0.59	-5.99	3.38
radaravg speed device	Van	0.50	4.18	0.12	0.90	-7.69	8.70
radaravg speed device	Car	-6.87	2.25	-3.05	0.00	-11.28	-2.46

Source: Own elaboration based on Canard and GDDKiA data.

The reason behind average speed measuring devices having a worse effect on lowering the speed on Polish roads might be that Polish drivers are not used to this type of velocity surveillance system.

Conclusions

The goal of this thesis was to measure the effectiveness of automatic traffic supervision. In order to do calculate this effect extensive amount of work regarding data preparation was done. All of the data preparation and modelling work was conducted in R programming language.

The Canard data source had a consistent share of vehicles before and after introducing automatic traffic supervision. The GDDKiA data source had many observations because the data was collected every day. One of the key points was unifying vehicle types and filtering out other and two-wheeled vehicles due to incompatibility. Also, it was important to filter out Złota city due to inconsistencies across months.

From the visual inspection of the effect of introducing automatic traffic supervision we can notice that the average and median speed decreased after implementing both types of devices. The disadvantage of simply comparing before and after speed measurement system is that we do not control for time trends. Due to this fact a different approach had to be carried out.

We calculated the effect of speed cameras and average speed measuring device using the difference in difference estimator. When choosing the control group,it was crucial to pick cities most similar and cities where time trends were consistent. From our estimations we obtained results where the effect of speed cameras caused an average decrease of 12.75 km/h (SE 1.06). This shows that speed cameras fulfill their function of lowering the mean velocity on Polish roads. Additionally this influence was statistically significant with default and robust standard errors. We would also like to note that speed cameras caused a decrease of average velocity for all vehicle types.

On the other hand the effect of average speed measuring device was an average decrease of 3.71 km/h (SE 2.34), which was statistically significant under default standard errors but not under robust standard errors. Also this device did not cause a decrease of average velocity for all vehicle types.

From our analysis we can conclude that speed cameras have a positive effect of decreasing the average speed on polish roads, unfortunately under robust standard errors we cannot say the same about average speed measuring devices. This is a good indicator for the Police Polish to choose speed cameras as a method of lowering average speed. We can be confident that after implementing speed cameras to locations with a high number of speeding violations the mean velocity would decrease leading most likely to a decline in road fatalities.

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List of Tables

List of Figures

List of software scripts