Short-lived and ineffective: The Dutch aviation tax of 2008-09

MSc Thesis report

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Abstract

Greenhouse gas emissions from the aviation sector are an important and fast-growing source of emissions worldwide. This is especially concerning taking into account that alternative carbon-zero technologies are far-away from being readily implemented. Therefore, its contribution is likely to grow substantially. A more conventional approach to mitigating GHG emissions is to introduce a carbon tax, with several countries having implemented such a tax in various forms. The Netherlands introduced such a tax in July 2008, but due to the pressure from the industry and other stakeholders, it was abolished one year later. This study investigates the impact of the Dutch aviation tax on the number of departing passengers using counterfactual analysis. Counterfactuals are derived using a fairly recent and attractive method in the impact evaluation literature, called the synthetic control method. Counterfactuals are calculated for each Dutch airport separately, as well as Belgian and German airports close to the border, in order to examine whether these airports have experienced an increase in the passengers due to the introduction of the Dutch aviation tax (i.e. substitution effect). Statistical inference is provided through the use of “placebo tests”, which consists of iteratively applying the synthetic control method to every unit in the donor pool and comparing it to the synthetic control of the treated. The results of this thesis report indicate that the tax did not have a significant effect on the number of departing passenger. Guidance for further research is provided.

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Acknowledgments

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1 Introduction

To achieve the Paris agreement goals of limiting the global temperature increase to well below 2°C, climate policies are needed in all economic sectors. This is especially true for the aviation industry. Although it only accounts for 2% of worldwide global greenhouse gas emissions, it is one of the fastest growing sources (Capoccitti et al., 2010). The main climate impact of aviation is through the burning of jet fuel which results in CO_2 emissions. Other important sources that impacts the Earth's radiative forcing, is the emission of nitrogen oxides (NO_x) and the formation of contrails and cirrus clouds (Lee et al., 2009). Nitrogen oxides' contribution to climate change is through the formation of Ozone (O_3) and the destruction of methane (CH_4), having an overall warming effect (Grewe et al., 2019). Contrails and cirrus clouds trap heat radiating from the Earth's surface. These non-CO_2 impacts have been estimated to be almost as significant as the impact from aviation's CO_2 emissions (Azar & Johansson, 2012).

Despite technology advancements in fuel efficiency in the past centuries, total GHG emissions from aviation have increased due to the rise in demand for air travel. The economic impact of the aviation industry is substantial, as it supports over 65.5 million jobs and contributes 3.6% to the world's gross domestic product (IHLG, 2019). Even though air transport carries only 0.5% of the volume of world trade shipments, it is almost 35% by value, and often carries time-sensitive commodities (ATAG, 2018).

Reducing GHG emissions from air travel is challenging compared to other modes of transportation, given the fact that carbon neutral technologies exist for cars, trains and buses. Market-based instruments are among the most common policy options to tackle emission reductions in aviation. As mentioned in Larsson et al. (2019), some of these policies include jet fuel taxes, distance-based air passenger tax, and quota obligations for biofuels. While fuel taxes are common for other modes of transportation, this is not true for aviation. The 1944 Chicago convention on international civil aviation prohibits taxing fuel on arriving aircrafts (ICAO, 2006). Biofuel mandates and quotas aren't common either. In Europe, most of these policies are still in the proposal phase like in Spain and Sweden (Martínez, 2018; Wetterstrand, 2019). On the other hand, Norway introduced an advanced biofuel mandate of 0,5% on January 1st 2020 (Ministry of Climate and Environment, 2019). In addition, subsidies in the sector are prominent, and many airlines, especially low-cost carriers (LCC) indirectly benefit from these (Gössling et al., 2017; Transport & Environment, 2019). Lastly, distance-based air passenger tax are the most common aviation policy in Europe, as is the case in Austria, Germany, etc. (see table 2). Nevertheless, these policies are only applied at the national level, and so, the effect is partly offset by an increase in demand in air travel in neighboring countries without aviation taxes, as shown by Borbely (2019).

The scientific relevance of this study is two-fold. Firstly, it contributes to the existing literature on the effectiveness of aviation taxes to mitigate GHGs, and secondly, it adds to the literature of the synthetic control method (SCM) by applying it to an aviation tax policy, similarly to Borbely (2019).

The SCM is used in the field of econometrics of program evaluation, which has its roots in epidemiological statistics. In this literature, experiments are often designed to have two separate groups: The treatment and the control group. The former refers to the group that has been treated (i.e. given a new drug, a new type of physiotherapy, etc.) and the later refers to the group that has not received such treatment. The experimental units (people, mice, etc.) are randomly allocated in each group, in order to ensure that if there is any outcome differences, it can be attributed to the treatment, once all confounders are taken into account. This difference is often called the (average) treatment effect. In social sciences however, the analyst has no capacity to manipulate the design of the experiment, which places econometrics within the sphere of nonexperimental statistics (Cerulli, 2015). In such a setting, the treatment effect is often calculated by measuring "counterfactual causality". This concept draws upon the assumption that causality takes the form of a comparison between the outcome of a treated unit and the outcome of the same unit when it is not treated. This last outcome is unobservable[a], and the aim of synthetic control method (SCM) is to estimate this counterfactual outcome (Cerulli, 2015).

This paper will aim to answer the following research question: What are the airport-specific impacts of the Dutch aviation tax on the number of (departing) passengers? More specifically, I will be looking into the following research sub-questions:

- What is the economic rationale behind the tax? (chapter 2)
- What is the context behind the Dutch aviation tax? (chapter 3)

[a] This unobservable outcome answers the question: What would be the outcome of the treated unit be if it would not be treated? This is a counterfactual outcome.

- What is the current state of knowledge with regards to the impact of aviation taxes? (chapter 4)
- What econometric methods are used in the impact assessment of aviation taxes? What are the advantages and disadvantages? (chapter 5)
- What is the synthetic control method and how can it be applied to analyze the impact of the Dutch aviation tax? (chapter 5 & 6)
- What is the average treatment effect (ATE) of the Dutch aviation tax, on the number of departing passengers? (chapter 8)
- What is the effect on neighboring airports? Is there a substitution effect? (chapter 8)

A synthetic control group will be created for each airport in the Netherlands, with the aim to calculate airport-specific treatment effects. In order to estimate potential substitution effects, a synthetic control group will be created for “treated” neighboring airports, similar to Borbely (2019).

This study will start by providing the economic background of the problem (which serves as a justification of the aviation tax policy). Chapter 3 provides an overview on ATs in Europe and context on the Dutch aviation tax. Chapter 4 presents a small literature review on similar studies regarding the impact of aviation taxes that use econometric methods. Chapter 5 compares different methodology that could be applied, and offers an overview of the advantages and disadvantages of each method. Chapter 6 presents the synthetic control method in extensive detail. Chapter 7 presents the data and explains how the analysis will be executed. Chapter 8 presents the results of the study. Chapter 9 discusses and interprets the results, offers some limitations, as well as some ways forward for further work. Finally, chapter 10 provides a conclusion.

2 Economic background

Neoclassical economics is the dominant approach to teaching economics in schools and universities today (Ozanne, 2016). Neoclassical economics attempts to define economic actors as knowledgeable and perfectly rational whose only goal is the maximization of their own welfare (Johnson, 2017). Despite criticism of this approach, the main advantage is that it simplifies economic decisions into optimization problems, which can be analyzed using mathematical and statistical tools. The neoclassical paradigm can be traced back to the works of the Scottish economist, Adam Smith, who in 1776 wrote “The Wealth of Nations”. In this book he introduces, among other concepts, the theory of free market and the so-called “Invisible hand”. A free or competitive market is one in which the forces of supply and demand dictate the equilibrium price of the market. This price is an equilibrium because every quantity supplied to the market is also consumed. The invisible hand refers to how an individual’s self-interested decisions in a free market leads to unintentional benefits for the whole of society (Stiglitz, 1991).

The free or competitive market system has several important implications: Social welfare is maximized by letting the market forces reach the competitive equilibrium, consumers face the lowest possible price, because it equalizes marginal costs, and minimum intervention from the state is needed. Nevertheless, the world economy has changed dramatically compared to the 18th century, and market failures have become increasingly more important. This departure from the “ideal” (as referred to in Perman et al. (2003)) alludes to certain conditions in which the market forces are unable to maximize total welfare, i.e. Adam Smith’s invisible hand theory is not applicable. These conditions are:

- The good is non-excludable and non-rival (public goods)
- The production of a good affects the utility of an economic actor that does not participate in the market (Externalities).
- Increasing returns to scale (Market power).
- Asymmetric information.

These deviations are known in neoclassical economic theory as market failures, and lead to an inefficient allocation of goods or resources (Perman et al., 2003). One of the sub-field of neoclassical economics concerned with environmental issues is called environmental economics, and mostly deals with the first two market failures, which will be explained hereunder.

Public goods satisfy the conditions of non-excludability and non-rivalry. The former refers to the fact that it is either impossible or highly costly to exclude people from consuming the good. In contrast, private goods are excludible because a price is paid to consume the good, and those who are unwilling to pay are excluded. The latter condition is satisfied when one agent's consumption isn't at the expense of another's consumption (Perman et al., 2003). Contrast this with private goods, which due to the limited quantity supplied, are inherently rival. From an economic perspective, the emission abatement resulting from a national aviation tax policy (such as the Dutch aviation tax) can be seen as a public good (Grasso, 2004). The emission abatement from the Dutch aviation tax benefits other countries as well, and there is no way to exclude other countries to benefit from this abatement. Furthermore, the enjoyment or utility other countries receive from the emission abatement has no effect on the enjoyment of the Netherlands from the emission abatement. When the two conditions are met, countries have an economic incentive to free ride. The free rider problem is an important issue in environmental economics, as it hinders effective climate mitigation by giving countries an incentive to not mitigate.

The second main topic of environmental economics is that of externalities. Externalities occur when the production or consumption of a good or service affects the utility or profit of another agent in an unintended way (Perman et al., 2003). If this external effect is negative, it creates an surplus of goods in the market, and supply is higher than demand. This happens because the firm only accounts for private costs, and ignores the external cost borne by the third party. In the case of the aviation industry, every flight causes CO_2 emissions, which affects every member of society by increasing the stock of CO_2 in the atmosphere and enhancing the greenhouse effect. A tax can be levied in order for the firm to internalize the externality. Such a tax is usually called a Pigouvian tax, after English economist Arthur Cecil Pigou. By firms internalizing the externality, the market can return to an equilibrium in which total welfare is maximized.

Figure 1 shows a graphic representation of an externality. The marginal external cost curve represents the marginal value of the externality. This value is also the difference between the social and private marginal cost curves. In the absence of government intervention, firms will produce at the point where the private marginal cost curve and the marginal benefit intersect. At this point, the market is inefficient because supply is higher and price is lower than the optimal level. A Pigouvian tax (represented by τ in figure 1) equal to the marginal external cost curve lead to airlines to sell tickets at the social equilibrium, where welfare is maximized. If the Pigouvian tax is equal to the marginal external cost, it causes the cost curve to shift up and companies will start to produce at the social optimum. This is because airlines will internalize the tax as a cost, which will in turn, increase the price for ticket, and decrease the quantity of tickets sold.

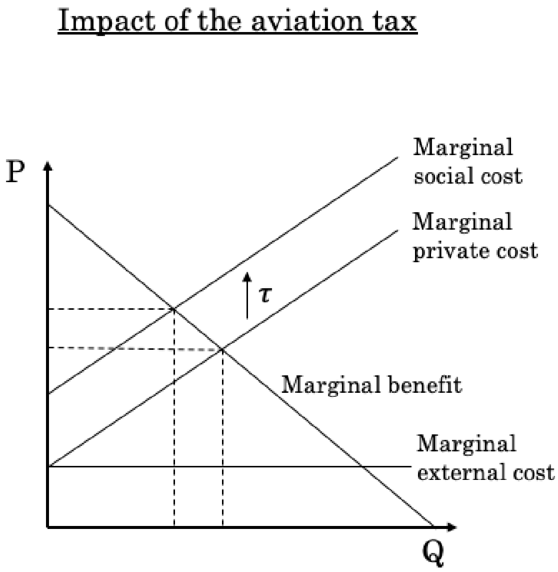


Figure 1: The impact of a Pigouvian tax

The welfare-maximizing equilibrium implies that an optimal level of pollution exists. Although this concept sounds counterintuitive, it refers to the level of pollution that maximizes social welfare (Black et al., 2009). From an economic perspective, some emissions from the aviation industry are permitted as long as it maximizes welfare in society. Another important aspect worth mentioning is the tax incidence. If the tax is passed on to consumers, airfares will rise and demand drops. The magnitude of the effect depends highly on the elasticity of demand, which in turn, depends on the type of passengers and airports (Falk & Hagsten, 2019). The tax incidence depends on the slope of the marginal benefit curve and the marginal cost curves.

3 Overview on aviation taxes.

3.1 Taxes in the Aviation sector.

Aviation is characterized by a lower level of taxation compared to other sectors in the economy (Faber & Huigen, 2018). We can see this, for instance, in the zero-rate value added tax (VAT) on international airline tickets (European Commission, 2020b) exemption on jet fuel taxation (Faber & O'Leary, 2018), and the prohibition of jet fuel taxation on arriving aircrafts, stipulated by the 1944 Chicago convention on international civil aviation (ICAO, 2006). Furthermore, a considerable share of observed growth has been a result of subsidies (Gössling et al., 2017) and deregulation (Hooper, 1998; Wang et al., 2016). This results in a competitive advantage for the airline industry compared to other modes of transportation.

Nonetheless, regulation in the form of air passenger taxes have increased in the last decades (Faber & Huigen, 2018). The UK was the first country in Europe to introduce a distance-based air passenger tax in 1993 (Seely, 2019). France introduced two aviation taxes in 1999, and other countries followed, albeit much later. Furthermore, commercial aviation was included in the EU ETS in 2012, but only accounts for intra-EEA flights. The aim was to apply "full-scope", that is, including all flights with destination in the EEA, but after protests from mainly the US and China, it was decided to apply the reduced-scope (Larsson et al., 2019). The European Union Aviation Allowances (EUAA) are used for the sector and those issued for the period 2013-2020 correspond to 95% of the emissions of 2008-2012. From 2021 onwards, there will be a linear annual reduction in allowances until 2061, where no additional EUAA will be issued (Larsson et al., 2019). Nevertheless, the EU ETS has resulted to only a 2.1% of CO_2 emissions mitigated relative to the global traffic related emissions in 2017, according to Scheelhaase et al. (2018), which has led many to question its efficacy (De Bruyckere & Abbasov, 2016; Efthymiou & Papatheodorou, 2019).

In 2016, ICAO agreed on a resolution for a global market-based measure to address CO_2 emissions from aviation. This resolution is the carbon offsetting and reduction scheme for international aviation (CORSIA), to be introduced in 2021, which would stabilize emissions levels from the aviation industry by requiring airlines to offset the growth of their emissions after the 2020 baseline. Due to the impact of the COVID-19 pandemic on the aviation sector, ICAO (2020) has decided to use 2019's CO_2 emissions as the baseline instead. Depending on the efficacy of CORSIA, the EU will decide whether to apply full-scope in 2024 or not (European Commission, 2020a).

The Netherlands, together with 8 other countries, are calling on the European Commission to come up with a proposal for a European aviation tax (Government of the Netherlands, 2019). An EU-level aviation tax hasn't happened yet, and thus, only national tax policies exist.

3.2 Aviation taxes in Europe.

Figure 2 shows the 8 European countries that currently implement an aviation tax. Switzerland has plans to introduce an aviation tax in the future, and three countries (Ireland, the Netherlands and Denmark) had an aviation tax but have been repealed. On the 1st of January 2021, however, the Netherlands has introduced a new aviation tax. Many of these taxes are levied per passenger, and function as a Pigouvian tax. This is because the tax approximates the private marginal cost to the social marginal cost, and so internalizing the externality or part thereof. If passed onto consumers, this should increase airfares and decrease demand.

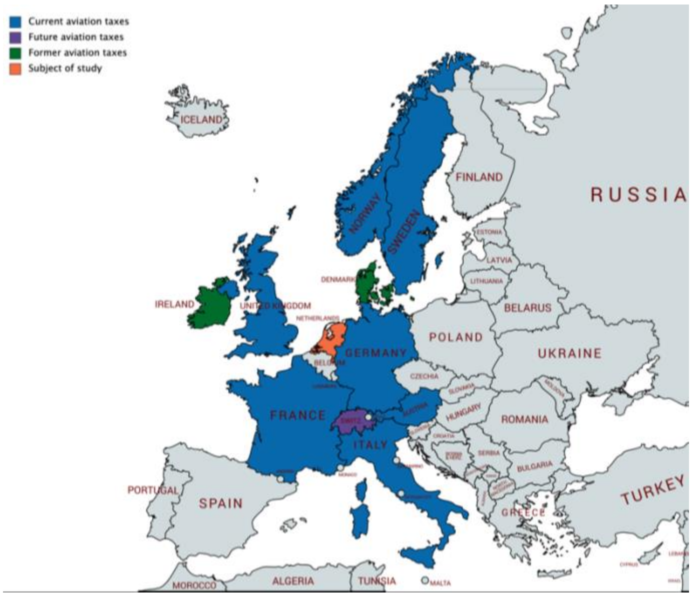


Figure 2: Aviation taxes in Europe

Table 1 Aviation taxes in Europe.

Country	Name	Year	Destination bands/ area applied to/ airport applied to	Current tax rate
Austria	Air Transport Levy	2011	GCD[a] <350 km (very short flights) GDC >350 km (short-medium-long flights)	30€ pp 12€ pp
France	Civil aviation tax	1999	Short flight→ EEA, Switzerland & Overseas France. Long flight → Any other destination Any destination	4,63€ pp 8,32€ pp 1,37€/ton of freight
	Solidarity tax	2005	EEA, Switzerland & Overseas France Any other destination EEA, Switzerland & Overseas France Any other destination	20,27€/Business or First class passenger 2,63€/Economy class passenger 63,07€/Business or First class passenger 7,51 € Economy class passenger
	Airport tax[b]	1999	Class 1: Aerodromes that exceed 20M TUs Class 2: between 5M-20M TUs Class 3: between 5K-5M TUs	4,3€-10,8€/ TU[c] 3,5€-9,5€/TU 2,6€-14€/TU
	Air transport noise pollution tax[d]	2005	Class 1: Paris (Charle de Gaulle, Orly, Le Bourget) & Nantes Atlantique Class 2: Tolouse-Blagnac Class 3: Other aerodromes	20€-40€/flight[e] 10€-20€/flight 0€-10€/flight
Germany	Air passenger tax	2011	Cat. 1: Europe, Russia, Turkey, Morocco & Algeria. Cat. 2: Central Asia, MENA & Sahel region Cat. 3: Other	12,9€ pp 32,67€ pp 58,82€ pp
Italy[f]	Embarkation tax	2012	Domestic EU & EEA Non-EEA	6,57€ pp 12,69€ pp 18,14€ pp
	City council tax	2012	All other airport	6,50€ pp

[a] GDC stands for great circle distance (GCD).

[b] The French airport tax is paid by public air carriers and the rate depends on the airport

[c] A traffic unit is equal to one passenger or 100 kg of freight or mail.

[d] The precise tax rate is calculated by the following equation: the decimal log of the Maximum takeoff weight (MTOW) of the aircraft **x** the coefficient of variation (depends on aircraft's acoustic group and take-off time) **x** aerodrome rate (Ministère de la transition écologique, 2020b).

[e] Due to the complexity of the tax rate, only the most important element of the tax rate equation is shown. This is also how the ministry of ecologic transition displays the tax on their website.

[f] Tax rates of both the embarkation and the city council tax may be outdated, due to lack of information.

			All airports in Rome	7,50€ pp
	Luxury tax[g]	2011	GDC<100 km GDC>100 km, GDC<1500 km GDC>1500km	10€ pp 100€ pp 200€ pp
The Netherlands	Dutch aviation tax	2021	Outside the Netherlands	7,845€ pp
Norway	Air passenger tax	2017	Within Europe Outside Europe	76,6 NOK pp 204 NOK pp
Sweden	Tax on air travel	2018	Appendix 1 countries Appendix 2 countries Other	62 SEK pp 260 SEK pp 416 SEK pp
United Kingdom	Air passenger duty	1994	Band A countries Band B countries	13£-78£ pp [h] 80£-528£ pp

Source: (Agenzia entrate, n.d.; buzer.de, 2020; CE Delft, 2019; FCC Aviation, 2020; gov.uk, 2020; Ministère de la transition écologique, 2020a; Rijksoverheid, 2021; Skatteverket, 2020; The Norwegian tax administration, 2020)

3.3 The Dutch aviation tax.

The Netherlands implemented a ticket tax on the 1st of July 2008, as part of the national tax plan. The tax falls onto every passenger that leaves from one of the Dutch airports, and the rate depends on the destination. The tax was one of the instrument for "greening" the tax system, by transferring some of the tax revenue from labor and profits, to environmental pollution (Gordijn & Kolkman, 2011).

3.3.1 Prior to the tax

Resistance prior and during the implementation of the ticket tax was significant. Many stakeholders in the aviation sector, such as airlines, airports and tour operators, questioned the motives of the tax, as the tax revenue wasn't allocated to solving environmental issues but rather was just an extra source of revenue. Furthermore, many highlighted that the ticket tax wouldn't have the desired effect, since many Dutch passengers will use airports in neighboring countries instead (Gordijn & Kolkman, 2011)

Prior to implementation, a report was commissioned by the central government to the ministry of finance, the ministry of transport and water management, and the ministry of housing, spatial planning and the environment. The aim of the report is to determine the potential impact of several tax schemes on the Dutch aviation sector, and provide policy advise on which tax scheme to use. The government was also considering how much

[g] The luxury tax is levied on private aircrafts only.

[h] The actual rate depends on the class of travel.

they should charge for the low and high tax rates. The airport catchment area and competition model (ACCM) is used to assess different tax schemes. The different tax schemes differ on the basis of whether the tax is paid per passenger or per flight, relationship between the two tax rates[a] (2:3, 1:3 and 1:4), the inclusion of transfer passengers and/or freight, and applying different tax rates based on the carbon efficiency of the aircraft. The results of the model show that by 2011, after the tax has been fully passed through, passenger transport at Dutch airports will be between 7% and 30% lower, compared to the case without the tax. These percentages are based on the expected 4% yearly growth of the aviation sector (Significance & SEO Economic Research, 2007). The expected reduction in passenger transport due to the introduction of the tax will lead to a similar expected reduction in emissions of relevant substances of the Air quality decree, namely nitrogen oxides (NO_x), sulfur dioxide (SO_2), carbon monoxide (CO), particulate matter (PM_{10}), carbon dioxide (CO_2) and VOCs (Tweede Kamer, 2008).

3.3.2 Implementation and issues.

It was decided that the tax would be levied per passenger, not including transfer passengers (which would have significantly impacted Schiphol's competitiveness in international markets), nor freight. Moreover, taxing on the basis of carbon efficiency of the aircraft is excluded. Flight crew is also excluded. The tax is 45€ per passenger, and a lower tariff (11,25€) is applied for destinations in member states of the EU and destinations within 2500km from the departure airport. Therefore, the relationship between the two tax rates is 1:4 (Tweede Kamer, 2008).

The tax is imposed on the operator of the airport for which the passenger departs. This makes the collection of the tax simpler, as the number of those who bear the tax burden is smaller. Aircrafts with a starting weight smaller than 8616 kg are excluded from paying the tax, as well as small airports, whose runway does not exceed 1800 meters (Tweede Kamer, 2008).

Several stakeholders like the Schiphol group, the board of airline representatives in the Netherlands (BARIN), ANVR, and Ryanair filed lawsuits against the Dutch state, charging that the tax was violating agreements established in the treaty of Chicago and EU community law. The lawsuit mainly focused on article 15 of the treaty of Chicago. The

[a] This means that the high tax rate is 1.5, 3 and 4 times higher than the lower tax rate, respectively.

plaintiffs argue that under article 15, fees or charges (except those related to airport costs and traffic control) are prohibited, while the Dutch state's interpretation of the article, is that fees or charges are prohibited when it discriminates against airlines from countries with different tax systems. The judge agreed with the Dutch state (Gordijn & Kolkman, 2011).

The regulation still needed some adjustment, since the sector called attention to some issues, and a new decree passed after the introduction of the tax. Firstly, the sector argued that the international reservation system couldn't cope with the application of different rates for the same country. This was the case for countries like Turkey and Morocco. Secondly, the high rate of 45€ applied to outermost regions of the EU (namely Canary islands, Madeira and the Azores), while other regions at comparable distances had the low rate of 11,25€ (Overheid, 2008).

In views of these issues, an amendment to the environmental taxes act (Wet Belastingen op Mileugrondslag) was introduced, in which it was further specified what regions are included in the low tax rate. Concretely, the low rate applies as the final destination of the passenger (Overheid, 2008):

- Is located in a member state of the EU, including in the outermost regions within a flight distance of not more than 3500km from the departure airport.
- Is located outside the EU, at a flight distance of not more than 2500km, including destinations within a flight distance of not more than 3500km in countries intersected by the 2500km border (namely Algeria, Libya, Morocco, the Russian federation, and Turkey).

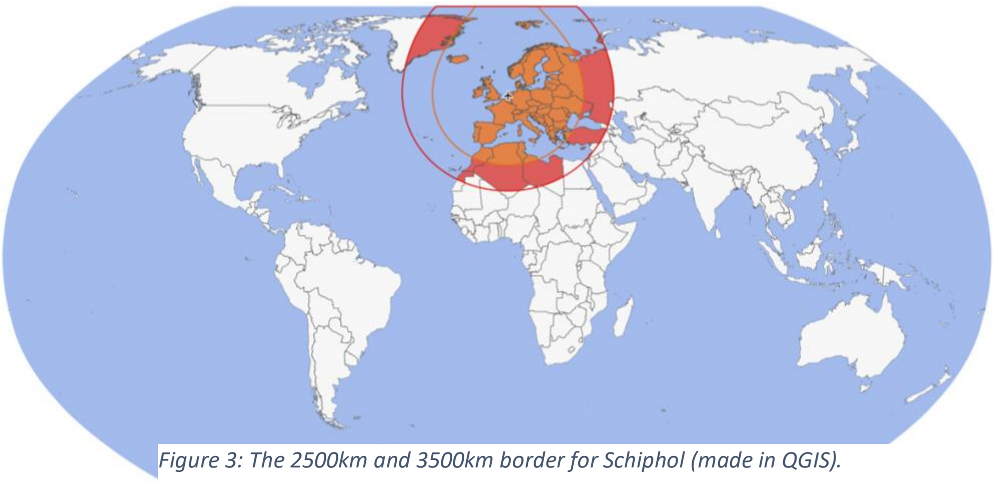


Figure 3: The 2500km and 3500km border for Schiphol (made in QGIS).

Figure 3 shows the 2500km and the 3500km border for Schiphol. All the flights to destinations within the outer border that are in the orange or red area are subject to the low tax rate.

A second issue addressed in the amendment concerns the definition of flight crew. The concept of flight crew for airport charges also include personnel who are transported to another airport to relieve the flight crew of another aircraft, while the definition of flight crew in the law does not include this. In order to facilitate reporting, the amendment includes changing the definition of flight crew to match that of the airport (Overheid, 2008).

3.3.3 Abolition of the air passenger tax

Many airlines were reporting fewer passengers and Schiphol reported and immediate decrease after the introduction of the tax. The reputation of the aviation tax was further affected because it was heavily reported in the news. In February 2009 many employees from the sector protested in the Hague in hopes to change or abolish the policy (Gordijn & Kolkman, 2011).

The tax was abolished in two steps: Firstly, the tax rate was set to zero as of July 1st 2009, as part of a package of measures aimed at lessening the impact of the economic crisis. Secondly, it was finally abolished on January 1st 2010. One of the reasons that helped the government decide to abolish the air passenger tax was the future inclusion of aviation in the EU ECTS (Gordijn & Kolkman, 2011)

4 Literature review

This chapter provides a literature review on studies that use econometric methods to analyze different aspects in the aviation sector. The aim of the literature review is to explain the current state of knowledge in the application of econometric methods within the context of the aviation sector, as well as presenting some of the methods used. Table 2 provides a summary with the main aspects of the studies. The order of the table is based on similarities to the current study. The literature review focuses on three of these studies (Borbely, 2019; Falk & Hagsten, 2019; Markham et al., 2018).These studies analyze the introduction of an aviation tax.

4.1 Borbely (2019): A case study on Germany's aviation tax using the synthetic control approach

The author analyses the impact of the German departure tax on the number of departing passengers, using the synthetic control method. This method was first used by Abadie & Gardeazabal (2003) and it involves the construction of a weighted-average group of control units, to which the treated unit is compared (See chapter 6). The treated group includes 21 German airports and 13 neighboring airports. Two control groups are made, one consisting of a large group of European airports without a change in AT during the selected period, and the second control group is a subsample of this, consisting of only airports in countries surrounding Germany. The control group is chosen based on the best synthetic control fit.

The covariates used in the analysis are: purchasing power per capita in euros at the NUTS2 regional level, lagged passenger number and flight ticket price inflation at the country level. First differences are used to control for airport fixed effects. The time span of the data is from 2003 to 2015 (Borbely, 2019)

Table 2: Studies on the econometric analysis of impacts and other aspects in the aviation sector.

Authors	Aim	Region	Dependent variable	Independent variables (covariates)	Methods	Results
Borbely (2019)	Evaluating the impact of the German aviation tax on German and neighboring airports.	Germany	Number of passengers	Purchasing power per capita, lagged number of passengers, flight ticket price inflation	Synthetic control method	Hub airports have seen a small increase in passengers, while regional airports (with high percentage of LCC) have (mostly) seen a decrease in passengers. Most bordering airports have seen an increase in passengers (spillover effect).
Falk & Hagsten (2019)	Determine the short-run impact of the flight departure tax on the number of air passengers.	Austria & Germany	Number of passengers	Lagged number of passengers, airline ticket prices, accommodation prices & GDP per capita	Dynamic panel difference-in-differences (DID)	The flight departure tax leads to a decline in the number of passengers by 9% in the year of introduction and 5% in the subsequent year. The reduction happens mainly in airports with a higher share of LCC. There is no increase in demand in bordering airports.
Markham et al. (2018)	Determine the impact of the "Clean Energy Future" policy, which lead to the introduction of a carbon tax.	Australia	Revenue passenger kilometer (RPKs)	GDP per capita, fuel price, price of air transport labor, and several dummies (World exposition Brisbane, Airline price war 1991, carbon price period, etc.)	TS regression	The study found no evidence to support the hypothesis that the introduction of the $23AUD-$24,15AUD per ton of CO_2-eq. carbon price is associated with a reduction in domestic air travel.
Seetaram et al. (2014)	Analyzing the impact of the Air passenger duty (APD) on UK outbound tourism demand for 10 destinations.	UK	Aggregate tourist flows	Real aggregate income, relative price, travel tax, seasonal and one-off event dummies	Autoregressive distributed lag (ADL) model	The tax has a negative effect on 5 out of 10 destinations. Overall, the effect of the APD has been limited.
González & Hosoda (2016)	Determine the impact of the 30% reduction in jet fuel tax in 2011.	Japan	Monthly jet fuel consumption	Not specified	Bayesian structural time-series model	The study finds evidence to support the claim that a significant reduction in CO_2 emissions could have been achieved if the reduction in jet fuel tax wouldn't have taken place.
Sobieralski & Hubbard (2020)	Analysis of Georgia's jet fuel tax cut and its impact on air traffic, employment and emissions.	USA	Flights and employment	Dummy for treated airports, a time dummy, interaction term between the last two and a set of covariates	Difference-in-differences	Only small increases were captured. A 0.2% increase in air traffic, No significant change in employment, and a >1% increase in GHGs such as CO_2, CH_4 and N_2O.

Fukui & Miyoshi (2017)	To estimate how effective fuel tax could be as a tool to abate emissions from the aviation industry.	USA	Annual jet fuel consumption per carrier	Average inflation-adjusted after-tax price of jet fuel per gallon, 9-11 attack dummy, unemployment rate, total miles flown per carrier, industry average miles flown per gallon	OLS and Quantile regression for a static and distributed lag model.	The authors find a small, almost negligible reductions in CO_2 emissions, especially in the long-run.
Beltran et al. (2018)	Analyzing cointegration among demand variables for air travel, and constructing an ECM for the demand for tourism, and estimating the consequences of a potential carbon tax.	Mexico	Tourism expenditure & arrivals	Income per capita, relative tourism price index & price index at the alternative destination &	Panel cointegration tests (Engle & Granger, and Johansen) FMOLS and Dynamic OLS to estimate an ECM	There is evidence for cointegration among the variables. Moreover, the higher the carbon tax on aviation, the higher the reduction in demand for air travel to Mexico. These changes are likely to be small, since tourists will adjust their spending on local consumption and/or length of the trip .
Morlotti et al. (2017)	Price elasticities of easy-jet flights from Schiphol to other destinations.	Europe	Demand	Price, eligible alternatives, LC dominance, departure hour, departure day, reservation day, month	OLS and 2SLS (IV method)	Price elasticity decreases when the booking date approaches the flight date, suggesting that business travelers are more inelastic, knowing that they tend to book their flights later. Elasticities also change depending on the booking day, flight day and time, route, and season.
(Mumbower et al., 2014)	Price elasticities on Jet blue flights on four routes within the US using disaggregate data.	USA	Number of bookings	Predicted price (from first stage of 2SLS), dummy when Virgin America were offering promotional sales, dummies for bookings made around labor day, dummies for time of departure, dummies indicating the number of days between booking and flight, dummies for day of the week of departure, dummies for day of the week of booking, dummies for each route and two IVs.	OLS and 2SLS (IV method)	The results show that customers with flights early in the morning are the least price sensitive and those departing late in the afternoon, are the most price sensitive. Moreover, customers booking on the weekend are more price sensitive, as well as those booking many days in advance, since it is likelier that these customers are leisure passengers. Jet Blue customers are more price sensitive during Virgin America's promotional sale.
(Mohammadian et al., 2019)	Determine relevant variables for airline capacity decisions.	Australia	Number of flights, average aircraft size, load factor and available seats.	Total passengers, jet fuel price, products of population for each city pair, product of employment rate for each city pair, HHI index, number of LCC for each route, and dummies for each route.	2SLS (IV method)	A higher demand for flights resulted in increased flight frequency rather than increased aircraft size or load factor. Load factor is only significant for high demand short-haul flights. In long-haul flights, flight frequency and aircraft size are significant.
Carmona-Benítez et al. (2017)	Determine variables that explain air travel demand, forecast demand on state level, and determine in which state an airline airport hub (AAH) can be established and when.	Mexico	Number of passengers	Lagged number of passengers, Indicator of economic activity, national consumer price index, total number of flights and hotel occupancy index.	Arellano-Bover method to estimate an Econometric dynamic model and Hold-Winters method to forecast.	A table is provided in the study showing forecasts for travel demand per state. Mexico city, Quintana Roo and Baja California are all candidates for becoming airline airport hubs (AAH)

Eleven out of thirteen neighboring airports show an increase in the number of passengers compared to their counterfactual. This result suggests a substitution effect, meaning that after the introduction of the tax, an increased number of passengers used bordering airports, instead of German airports. The increase in departing passengers in neighboring airport is as high as 75% in Eindhoven, and as low as -19% in Prague. The results also show that four out of five German hub airports have seen an increase in departing passengers compared to their counterfactual, while most regional and low-cost airports have seen a decrease. Berlin-Tegel and Munich had the highest increase in departing passengers compared to their counterfactual (15% and 13%, respectively). The regional airport most impacted by the tax is Münster-Osnabrück airport, with a decrease of 37% with respect to its counterfactual.

These findings are consistent with the theory that, business passengers mostly use hub airports, and are less price sensitive compared to leisure passengers that mostly use regional and low-cost airports (Brons et al., 2002; Morlotti et al., 2017). An alternative explanation is that hub airports have a larger share of transfer passengers (who are exempt from the tax) than regional airports, meaning that the eventual impact of the aviation tax will be smaller. The estimates indicate that the German AT has significantly reduced passenger numbers, nevertheless, the aggregate effect on all the airports has not been determined. The effect has been larger for LCC, since these airlines serve mostly regional airports.

4.2 Falk & Hagsten (2019): Short-run impact of the flight departure tax on air travel.

The authors analyze the impact of the German and Austrian aviation tax on the number of passengers using a Difference-in-differences (DID) approach. The control group consists of 265 European airports without an aviation tax, 12 of which are within 150km of a tax-affected airport. The treatment group consists of 33 airports located in Germany and Austria. Airports mainly served by LCC are estimated separately.

The main model specification is:

$$
\begin{aligned}
\ln Y_{ict} &= \alpha_i + \rho \ln Y_{ict-1} + \lambda_t \\
&+ \sum_{j=0}^{s} \beta_j Treatedairports_{it-j} + \sum_{j=0}^{s} \theta_j\, neighbours_{it-j} \\
&+ \alpha_1 \ln Airfare_{ct} + \alpha_2 \ln Paccommodation_{ct} + \alpha_3 \ln GDPpc_{ct} + \varepsilon_{ict}
\end{aligned}
\tag{4.1}
$$

Where i denotes airport, c country and t year. The subscript j refers to number of lags of the variable in the model, with a minimum of 0 and a maximum of s lags. The treatment variable, $Treatedairports_{it-j}$ is a dummy that becomes 1 only if the airport is located in Germany or Austria and the time period is 2010 or later. The time effects λ_t, controls for macroeconomic factors that are common to all airports, and include time dummies. The unobserved time-invariant heterogeneity is represented by α_i . A dummy variable is included to account for terror attacks in the year of the event and delayed reactions. The control variables are ticket prices, accommodation prices and GDP per capita.

The authors present a model specification without the lagged-dependent variable, but do not report the results. A total of six models are reported: two different model specifications with three different samples. One model includes the dummy variable $neighbours_{it-j}$, while the second model doesn't include the dummy variable and excludes neighboring airports from the sample. Both models are run three times: with low-cost airports only, with regular airports only, and with the total sample.

All models are estimated using the dynamic quasi-maximum likelihood method with robust standard errors by Hsiao et al. (2002). The result of the analysis show a reduction in the number of passengers by 9 % in the year of the introduction and a reduction of 5% in the subsequent year. The analysis also shows that this reduction comes almost exclusively from airports mainly served by LCC.

Falk & Hagsten (2019) find no increase in passenger number in neighboring airports, and thus no evidence for a substitution effect. This result contrasts with the findings from Borbely (2019), who does find evidence of a strong substitution effect.

4.3 Markham et al. (2018): Does carbon pricing reduce air travel? Evidence from the Australian "Clean energy future" policy, July 2012 to June 2014.

The authors analyze the impact of the carbon price in the aviation industry levied on domestic flights in Australia between July 2012 and June 2014. The carbon price was part of a broader set of measures named the "Clean energy future" (CEF) policy. The measure levied a carbon tax of $23 AUD per ton of CO_2-eq., during its first year, and $24.15 AUD during the second.

The model specification is:

$$\Delta \ln RPK_t = c + \beta_1 t + \boldsymbol{\beta_2} \Delta \ln \boldsymbol{GDP_t} + \boldsymbol{\beta_3} \Delta \ln \boldsymbol{FUEL_t} + \boldsymbol{\beta_4} \Delta \ln \boldsymbol{LABOUR_t} + \boldsymbol{\beta_i} \boldsymbol{DUMMIES} + \varepsilon_t \quad (4.2)$$

The time series model has per capita revenue passenger kilometer (RPK) as dependent variable. RPK is defined as a kilometer of domestic air travel by a paying passenger. The first two variable are a constant c and the time trend t. The independent variables GDP, fuel price, and labor costs all have included a first and second lag. The vector $DUMMIES$ is a set of dummy variables that takes into account several one-time events that have had an effect on the demand for air travel, as well as dummies for each quarter, and, most importantly, a dummy for the carbon price, which is 1 during the carbon price period, and 0 otherwise. The coefficient of this variable represents the effect of the carbon price.

All the one-time event dummies enter the model with a first and second lag in order to capture any delayed reaction on the demand. First differences were taken since the outcome variable displayed evidence of a unit root. Two different transfer function were used, one assuming a step-change in per capita RPKs and the other assuming a change in the growth rate of per capita RPKs. For each transfer function, two models are estimated for each transfer function, including and excluding the capacity variable as a covariate. The capacity variable measures the total available seats, and may present endogeneity problems due to simultaneity (available seats may be affected by per capita RPKs or vice versa). This makes a total of four models being estimated.

Before constructing the model, the authors already highlighted two reasons why the carbon tax can be ineffective or have a reduced effect. Firstly, the carbon tax might not have been passed onto consumers. Major airlines claim to have passed the cost to consumers in the form of higher prices, however, doubts were raised when these airlines didn't reduce prices after the abolition of the tax. Secondly, the CEF included a set of measures that increased household income for low- and middle-income families. This increase in income can lead to an increase in demand for air travel during the CEF period.

The results show no evidence to support the claim that the introduction of the carbon tax is associated with a reduction in domestic air travel. This result contrast with those of Borbely (2019) and Falk & Hagsten (2019). The authors highlight two reasons to explain why the carbon tax had no effect on domestic air travel: the dependency of the industry on a single fuel source, and the so-called “capacity wars” were the competition between the two main airlines (Qantas and Virgin) resulted in irrational pricing.

4.4 Review discussion

From the table and the review, I conclude that most studies do find a negative impact on demand after the introduction of a tax. Six out of the 12 studies presented in table 3, analyze the impact of the introduction of a tax or an increase in the current tax rate. Out of these six studies, four find evidence for a decrease in demand due to the tax, one study finds no evidence, and one study finds limited evidence (really small, almost negligible impact). Two studies analyze the impact of a reduction in the tax rate. Both find evidence to support the claim that the reduction in the tax rate has led to an increase in demand, although the impact found by Sobieralski & Hubbard (2020) is almost negligible. The remaining four studies analyze other aspects of the aviation industry, such as price elasticities (Morlotti et al., 2017; Mumbower et al., 2014), airline capacity decisions (Mohammadian et al., 2019), and modelling and forecasting demand (Carmona-Benítez et al., 2017).

It seems that most aviation taxes are passed down to consumers, which translates into higher prices and lower demand. Nevertheless, it is important to mention that air passenger taxes are less efficient than a tax on jet fuel (Mayor & Tol, 2007) and much higher rates need to be levied to have substantial emission reductions (Larsson et al., 2019). The fact that many studies found that aviation taxes have a negligible or no effect on reducing demand raises the question whether air passenger taxes will be a sizeable contributor in substantially reducing GHGs from the aviation sector.

5 Methods

5.1 Methodology discussion

The literature review provided a broad overview of the different econometric methods used in the assessment of impacts on the aviation sector. Nine out of the twelve studies in this review analyze panel data, while the rest of the studies analyzes time series data. Panel data is considered more efficient for econometric estimates, since it normally offers more observations and sample variability (Hsiao, 2007).

The main methods used to assess the impact of a tax in the studies presented in this review are the Synthetic control method (SCM), Difference-in-Differences (DID), (autoregressive) distributed lag (DL) model and time series regression.

The SCM consists of the construction of a weighted combination of groups used as controls, to which the treatment group is compared. The resulting synthetic control approximates the counterfactual outcome, i.e. how the treated unit would have behaved in absence of the treatment (Abadie et al., 2010). For the difference-in-differences approach (DID) the simplest version is one in which an observed group is exposed to the treatment in period one but not in period zero, and a control group that has not been exposed to the treatment in any period (Imbens & Wooldridge, 2009). The treatment effect can be calculated by taking the difference in the treatment group's outcome and the control group's outcome in period one (after the treatment), and subtracting the difference in the treatment group's outcome and the control group's outcome in period 0 (before the treatment). The treatment effect in DID can be expressed as follows (Cerulli, 2015):

$$\hat{\alpha}_{DiD} = \left(\bar{Y}_{i1}^{T} - \bar{Y}_{i1}^{C}\right) - \left(\bar{Y}_{i0}^{T} - \bar{Y}_{i0}^{C}\right) \tag{5.1}$$

Where we have that:

$\bar{Y}_{i1}^{T}$ = average of Y[a] on treated at $t = 1$

$\bar{Y}_{i1}^{C}$ = average of Y on untreated at $t = 1$

$\bar{Y}_{i0}^{T}$ = average of Y on treated at $t = 0$

$\bar{Y}_{i0}^{C}$ = average of Y on untreated at $t = 0$

---

[a] Y is the outcome of interest.

We can use a simple regression equation to estimate the treatment effect (adapted from Angrist & Pischke, 2008):

$$Y_{it} = \alpha_i + \beta_1 X_i + \beta_2 d_t + \beta_3 (X_i * d_t) + \varepsilon_{it} \qquad (5.2)$$

Where X_i is a dummy variable equal to 1 for a treated unit, d_t is a dummy variable equal to 1 when $t = 1$ (post-treatment period) and $(X_i * d_t)$ is an interaction term whose coefficient represents the treatment effect. This simple model can be expanded upon, by increasing the number of pre- and/or post-treatment periods, increasing the number of control units, and adding covariates in the regression equation (Angrist & Pischke, 2008)

The remaining two methods are relatively standard approaches for establishing causality. Time series regression uses time series data to identify variables that help explain the variation in the variable of interest. In the case of Markham et al. (2018), RPKs per capita are used as a dependent variable, and a dummy variable $CARBONPRICE_t$ is included that is equal to 1 during the period the tax was levied. If the dummy variable's coefficient is negative and significant, it would suggest that total air travel decreased due to the tax, ceteris paribus. The distributed lag model is a dynamic panel data model that uses current and lagged values of explanatory variables (Verbeek, 2017), which is one of the methods used by Fukui & Miyoshi (2017). An autoregressive distributed lag model is one in which a lagged dependent variable is added as a regressor, as is the case for Seetaram et al. (2014).

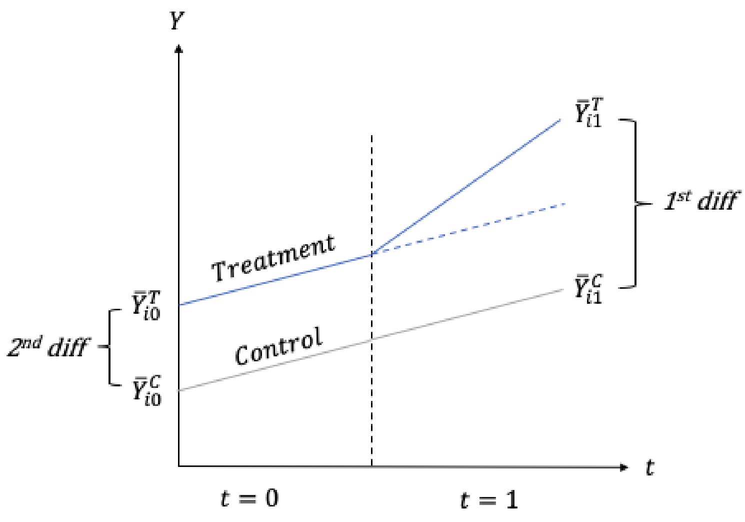


Figure 4: Graphical representation of DID

Out of the four methods, time series regression is the least suited for this study, since the use of time series data would not allow to capture differences in airports (cross-sectional units). Panel (autoregressive) DL models could in theory determine airport-specific impacts, but are hardly ever applied in quasi-experimental research. This is because traditional regression techniques require large samples and many observed instances of the intervention, and thus, are sometimes inappropriate to estimate the effects of uncommon events such as policy interventions (Abadie, 2020). Traditional regression techniques are more often used in studies that determine price elasticities that are then used to determine the impact of a potential carbon tax (Davis & Kilian, 2009; Fukui & Miyoshi, 2017; Y. D. Kim et al., 2011).

The two remaining methods are often used in impact assessment studies, but both present advantages and disadvantages. Firstly, the main advantage of the SCM is that it doesn't rely on the parallel trend assumption (Billmeier & Nannicini, 2013) that is needed for DID estimators to be unbiased (O'Neill et al., 2016). This assumption requires that, in the absence of the treatment, the average outcomes for the control and treatment group would have followed parallel trends, conditional on the covariates (Abadie, 2005). The requirement of this assumption can be easily examined in figure 4, because in the absence of parallel trends, the estimate for the treatment effect would be biased. As a result, the SCM can deal with endogeneity from omitted variable bias by accounting for the presence of time-varying unobservable confounding factors[b] while DID only accounts for time-invariant unobservable confounding factors (Billmeier & Nannicini, 2013).

According to (O'Neill et al., 2016), when the parallel trend assumption does not hold, the DID estimator yields a biased estimate for the treatment effect, and thus, other methods such as the SCM that does not rely on this assumption, provides a more efficient estimate for the treatment effect. Moreover, as mentioned by Borbely (2019), the parallel trend assumption is difficult to validate, because there is a high variety in passenger trends among European airports due to a myriad of factors and conditions. Even though in the context of aviation, the parallel trends assumption is difficult to validate. Nevertheless, many extensions to the DID model has been developed to allow for time-varying confounding factors, mostly combining DID with matching techniques (Basu & Small, 2020).

Nevertheless, the SCM does have some drawbacks. Large idiosyncratic shocks to the outcome variable that are not captured by the covariates can lead to biased estimates

[b] Confounding factors are those variables that have an effect on the dependent variable, as well as on the assignment of the treatment. An example of a confounding factor in the context of this study, if the government of the Netherlands introduced a significant universal basic income (UBI) program during the pre-intervention period, this could affect demand for flights, and the assignment of the treatment (since only Dutch citizens would receive this).

(Abadie et al., 2015). Furthermore, biases may arise if the pre-treatment fit is poor (Abadie, 2020).

Due to the context of the analysis, I consider the SCM to be a better fit to assess the impact of the Dutch aviation tax. Therefore, this method will be used for the study.

5.2 Discussion of the variables.

5.2.1 Dependent variable selection.

Many studies presented in this literature review analyze the impact on the demand for flights, and different dependent variables are presented. Sobieralski & Hubbard (2020) use the number of flights as a dependent variable, which might be an inaccurate measure for demand since the choice of the number of flights is a long-term supply-side decision made by airlines (Mohammadian et al., 2019). It might be an especially inappropriate dependent variable because of the relatively short duration of the Dutch aviation tax. The number of flights may be useful to analyze the climate impact of an aviation tax, since most market-based instruments (if passed onto consumers) result in a reduction in the number of flights (Larsson et al., 2019).

The most common dependent variable used is the number of (departing) passengers, as this is the most widely available. The problem[a], however, is that passengers may react to a distance-based aviation tax by choosing a closer destination. This can be especially problematic for the Dutch aviation tax, which has a substantial difference between the two tax rates, compared to other aviation taxes in Europe. Furthermore, passengers may also react by choosing destinations even further away, since relative prices are more important than absolute prices in decision making (Mayor & Tol, 2010). The dependent variable used by Markham et al. (2018) is revenue per passenger kilometer (RPKs) per capita, which would take into account this substitution effect as it incorporates the distance of flights. Nevertheless, RPKs data for European airports are not available, so the number of (departing) passengers will be used as a dependent variable for this study.

5.2.2 Independent or predictor variables selection.

[a] This may only be concerning for Schiphol, which may be the only airport in the Netherlands that offers flights to destination that are >3500km.

The studies presented in the literature review use various independent variables to analyze different aspects of the aviation sector. For the studies focusing on aviation taxes, some of the most common variables used are: a measure for income or economic output, airline ticket prices, fuel price, a measure for population or population density, unemployment price differences between origin-destination (O-D) and one-time event dummies.

The choice of variables can vary slightly depending on the methods used as well as the context of the study. For example, In regression based methods such as DID and time-series regression, the use of dummy variables are relevant. Not only for the estimate of the treatment effect (Angrist & Pischke, 2008) (as is the case in DID, which needs both dummy and interaction variables), but also for additional independent variables, such as time dummies in DID and event dummies in time-series regression, as is the case in Markham et al. (2018). The SCM does not use dummy variables, since it assumes no differences in intercepts between the treated unit and its counterfactual (Doudchenko & Imbens, 2016).

For the choice of dependent variables for this study, it is important to look into variables that affect demand and supply of air travel, since an aviation tax can have an effect on both (CE Delft, 2019). If airlines pass the tax on consumers, prices are expected to rise, and demand falls. Furthermore, airlines may decide that some routes become unprofitable with a tax, resulting in the withdrawal of some routes.

Many studies use some measure of income or economic output as an independent variable. This is because demand for air transport is partially determined by the spending capacities of customers (Brons et al., 2001; Valdes, 2015). Measures like purchasing power per capita (Borbely, 2019), real aggregate income (Seetaram et al., 2014), income per capita (Sobieralski & Hubbard, 2020) or GDP per capita (Falk & Hagsten, 2019; Markham et al., 2018), all try to measure the ability of potential customers to pay for air travel. Because of the fact it is such a vital factor in determining demand, a measure of income is a key variable for the analysis at hand.

Another relevant measure is one that takes into account inflation or prices changes over time, as this has a significant effect on air travel demand (Morlotti et al., 2017). Borbely

(2019) uses flight ticket price inflation per country to account for this effect. Falk & Hagsten (2019) on the other hand, use airline ticket prices as an independent variable.

Operating costs may affect the demand, albeit via changes in airline tickets. Two relevant variables here are fuel price and labor costs, since these are the two biggest operating expenses for airlines (Markham et al., 2018).

Two economic variables that may be important in the analysis are unemployment rate and sectoral shares. One would expect that a low unemployment rate would have a positive effect on the economy and therefore on overall air travel demand. However, even though multicollinearity is not a problem in the synthetic control method, the effect that unemployment has on the number of passengers is probably similar to the effect a measure of income or economic output has. Therefore, unemployment will not be considered in this study. Furthermore, sectoral shares may also be important, since a higher share of the population working in industry would likely lead to more air travel demand. Nevertheless, the local population is not the only one that makes use of airports, therefore it's likely that the this variable would have a small effect on passenger numbers, and thus is excluded.

Moreover, one-time event dummies, and airline labor costs are excluded, the former because the synthetic control method doesn't use dummy variables, and the latter because data on labor costs for airlines is not available in the EU.

To conclude, the final variables chosen are a measure for economic output, a measure for airline ticket price changes, and a measure for fuel price. For further detail on the variables and sources, see chapter 7.

6 Synthetic control method

This chapter will introduce the synthetic control method. Firstly, an intuitive description will be given, followed by a more technical one, which forms the basis of the theoretical framework of this thesis. Lastly, the SCM will be compared to a regression-based approach to construct counterfactuals, to better understand the differences between the current method and standard regression analysis.

6.1 Intuitive description

Consider a setting in which one aggregate unit, such as a municipality, state or country is exposed to an intervention, while other aggregate units are not. In the program evaluation literature in economics, the terms “treated” and “untreated” are often used to refer to units that are exposed and not exposed to an intervention, respectively (Abadie, 2020). The aim, therefore, is to correctly estimate the effect of such an intervention, on the outcome of interest, i.e. the causal relationship of the intervention. In the natural sciences, the gold standard of such an experimental design is the randomized control trial (RCT), which consists of randomly allocating experimental units into the treatment and control group. Treatment randomization reduces selection biases (Hariton & Locascio, 2018). When the experimental units consists of aggregate units such as states or countries, randomizing the intervention is often unfeasible. Alternative methods are used instead, in order to still be able to assess the impact of a certain intervention.

The treatment group or unit is often compared directly to a non-treated group or unit. This is the case in Card & Krueger (1993) who study the effect of the 1992 New Jersey’s minimum wage increase on employment rates in fast food restaurants, by comparing it to employment rates in Pennsylvania, a US state that didn’t have a minimum wage increase. The authors use a difference-in-differences (DID) approach which is one of the most popular tools in applied economics. It is well-known however, that the DID estimator is based on strong identifying assumptions. Of course, Card & Krueger (1993) test the validity of the Pennsylvania control group and try to minimize biases as much as possible. The DID approach is an example of how scientists use alternative methods to try to mimic a controlled experimental design.

The synthetic control method (SCM) is a fairly recent method in the program evaluation literature, and one of the most important innovations in this literature in the last 15 years, according to Athey & Imbens (2017). The core idea of the SCM is to use the evolution of the (treated) variable of interest, and compare it to a synthetic control unit, which represents the evolution of the variable of interest in the case that it wouldn't have been treated. The latter is often called the counterfactual, and the difference between the two is the treatment effect. The main obstacle, of course, is to estimate this counterfactual.

The SCM estimates the counterfactual, by taking a weighted average of control units that best resembles the outcome of interest during the pre-intervention periods. The weights are chosen so that the pre-intervention characteristics of the counterfactual best resembles the characteristics of the actual data. These characteristics are often called predictor variables of the outcome of interest and play an important role in the SCM. The idea here is that covariates significantly affect the evolution of the outcome of interest, and therefore, if we choose a weighted combination of untreated units, by means of minimizing the difference in covariates between the treated and untreated units, we essentially construct the evolution of the outcome of interest of the treated unit in the absence of the treatment. In other words, the resulting synthetic control provides a weighted average of untreated units chosen to reproduce characteristics of the treated unit before the intervention (Abadie & Cattaneo, 2018).

This can be made more clear by means of an example: Abadie & Gardeazabal (2003) first used the method by applying it to estimate the economic impact of terrorism in the Basque country. In the study, the surge of terrorism in the mid 1970s is considered as the intervention. The authors compared the evolution of GDP per capita in the Basque country, with a weighted average GDP per capita of other Spanish regions. The latter represents the "synthetic" Basque country, or counterfactual, i.e. how the Basque country's GDP per capita would have evolved int the absence of terrorism. The weights are chosen so that the predictor variables of the counterfactual best resembles the predictors of the Basque country. The predictors used in the analysis are different variables for human capital, investment rate, population density, and industrial-sector shares as a percentage of total production (Abadie et al., 2011).

The SCM is based on the idea that a combination of units provides a better comparison for the unit exposed to the treatment than any single unit alone (Abadie et al., 2010). It essentially uses a data-driven procedure to create a comparison unit (Abadie & Cattaneo, 2018).

The SCM has been used in a wide range of academic fields, and some of the applications include the impact of antitobacco policies (Abadie et al., 2010), the economic impact of natural disasters (Coffman & Noy, 2012), the effect of universal coverage on health outcomes (Courtemanche & Zapata, 2014), the impact of the German reunification (Abadie et al., 2015), the effect of organized crime (Pinotti, 2015), the spatial effect of nuclear power plants (Ando, 2015), the effect of tourism taxation (Biagi et al., 2017), the economic cost of revolution (Hasancebi, 2020), and the effect of face mask mandates on the spread of COVID-19 (Mitze et al., 2020).

6.2 The model.

This section provides a more theoretical background on the synthetic control model, and thus, will explain how exactly the synthetic control is derived.

6.2.1 Model setup

Consider the following setting. We gather data on $J+1$ units, where $j=1$ is the treated, or exposed unit, and $j=2,3,\dots,J+1$ are the untreated or unexposed units. The untreated units are often called the "donor pool" because the synthetic control often only selects a few untreated units from the available controls. There is a total of T periods, where $t>T_0$ refer to the post-intervention periods, while $t\leq T_0$ refer to the pre-intervention periods (Abadie, 2020). Furthermore, for each j unit, we observe k predictors $X_{1j},\dots,X_{kj}$. Let $\boldsymbol{x_1}$ be a $k\times 1$ vector of pre-intervention predictors for the treated unit ($j=1$). On the same note, let $\boldsymbol{X}_0$ be a $k\times J$ matrix of pre-intervention predictors, but for the untreated units (Abadie & Cattaneo, 2018). The SCM uses two kind of predictors: r covariates, and m so called "linear combinations"[a] of the outcome of interest in the pre-treatment period, such that $k=r+m$ (Kaul et al., 2017). For $j=1$ and $t>T_0$, we define y_{1t}^{I} as the outcome of interest (the dependent variable) under the intervention, and y_{jt}^{N} as the outcome without the

[a] Most of the literature calls m "linear combination" of values in the pre-treatment outcome of interest, $\boldsymbol{U_0}$ (Becker et al., 2017; Firpo & Possebom, 2018; Kim et al., 2020). Nevertheless, m can be lagged values of $\boldsymbol{U_0}$, as used in Stearns (2015), all pre-treatment values of $\boldsymbol{U_0}$, as is the case in Liu (2015) and Kreif et al. (2016) or even arbitrary post-treatment values of the outcome of interest ($\boldsymbol{Y_0}$) as used in Billmeier & Nannicini (2013), who use T_0+5 and T_0+10.

intervention for each unit j and time period t. The effect of the intervention for the treated unit in period t is:

$$\tau_{1t} = y_{1t}^I - y_{1t}^N \tag{6.1}$$

Because y_{1t}^I is already known, the challenge here is to estimate y_{1t}^N. Notice that equation (6.1) allows for the effect of the intervention to change over time. This is useful because the effect may be delayed in time. The synthetic control has a $J \times 1$ vector of weights $\boldsymbol{w} = (w_2, w_3 \ \dots, w_{J+1})'$. The synthetic control estimators of Y_{1t}^N and τ_{1t} are:

$$\hat{y}_{1t}^N = \sum_{j=2}^{J+1} w_j y_{jt} \tag{6.2}$$

$$\hat{\tau}_{1t} = y_{1t} - \hat{y}_{1t}^N \tag{6.3}$$

The resulting synthetic control is a weighted average of the units in the donor pool (Abadie, 2020).

6.2.2 The optimization problem

This section describes how equation (6.2) is estimated. The starting point is how the donor weights $w_2, w_3 \ \dots, w_{J+1}$ are chosen. Abadie & Gardeazabal (2003) and Abadie et al. (2010) propose to choose the weights so that the resulting synthetic control best resembles the pre-intervention period values of the treated unit's predictors. Given a set of non-negative constants $v_1, \dots, v_k$, the weight vector $\boldsymbol{w}^* = (w_2^*, \dots, w_{J+1}^*)'$ is chosen so that the Euclidean norm[b] of $(\boldsymbol{x_1} - \boldsymbol{X_0 w})$ is minimized. The minimization problem looks as follows:

$$\min_{\boldsymbol{w}} \|\boldsymbol{x_1} - \boldsymbol{X}_0 \boldsymbol{w}\| = \left(\sum_{h=1}^{k} v_h \left(x_{h1} - \ w_2 x_{h2} - \dots - w_{J+1} x_{hJ+1} \right)^2 \right)^{1/2} \tag{6.4}$$

$$\textit{subject to } w_j \geq 0 \textit{ and } \sum\nolimits_{j=2}^{J+1} w_j = 1$$

The resulting estimated treatment effect is:

$$\hat{\tau}_{1t} = y_{1t} - \sum_{j=2}^{J+1} w_j^* y_{jt} \tag{6.5}$$

[b] Recall that the Euclidean norm of a matrix or vector is a function on the coordinate space $\mathbb{R}^n$, which is the square root of the sum of the squares of the elements of the matrix or vector (Szabo, 2015).

Alternatively, equation (6.4) can also be expressed in matrix form[c] (Abadie & Cattaneo, 2018):

$$\min_{\boldsymbol{w}} \|\boldsymbol{x_1} - \boldsymbol{X}_0\boldsymbol{w}\| = \sqrt{(\boldsymbol{x_1} - \boldsymbol{X}_0\boldsymbol{w})'\boldsymbol{V}(\boldsymbol{x_1} - \boldsymbol{X}_0\boldsymbol{w})} \quad (6.6)$$

Subject to the same constraints. $\boldsymbol{V}$ is a diagonal $k \times k$ matrix with non-negative constants, and each v_h element in $\boldsymbol{V}$ reflects the relative importance of approximating the values of x_{h1} for predicting y_{1t}^N. The $\boldsymbol{V}$ matrix (or $v_1, \dots, v_k$) also reflects the predictive power of each of the k predictors on y_{1t}^N .The important issue now is how to choose $\boldsymbol{V}$, since there are multiple methods.

Let $\boldsymbol{u_1}$ be a $T_0 \times 1$ vector of the outcome of interest during the pre-intervention period for the treated unit, and $\boldsymbol{U_0}$ be the analogous $T_0 \times J$ matrix for the untreated units. Let $\boldsymbol{z_1}$ and $\boldsymbol{Z_0}$ be a (chosen)[d] subset of $\boldsymbol{u_1}$ and $\boldsymbol{U_0}$, respectively. Abadie & Gardeazabal (2003) and Abadie et al. (2010) choose $\boldsymbol{V}$ to minimize the mean square prediction error (MSPE) of the synthetic control[e]:

$$\arg\min\big(\boldsymbol{z_1} - \boldsymbol{Z_0}\boldsymbol{w}^*(\boldsymbol{V})\big)'\big(\boldsymbol{z_1} - \boldsymbol{Z_0}\boldsymbol{w}^*(\boldsymbol{V})\big) \quad (6.7)$$

MSPE is a metric to measure forecast accuracy, and is the expected squared difference between the fitted and the actual values (Verbeek, 2017). The optimization problems of $\boldsymbol{w}$ and $\boldsymbol{V}$ are not separate, but is rather a bilevel or nested optimization problem[f] (Malo et al., 2020), with an outer (or upper) and inner (or lower) part. Bilevel optimization problems have a second optimization problem as part of their constraints (Dempe, 2002). The entire optimization problem is:

---

[c] For the remainder of this thesis, matrix notation will be prioritized. As is common, bold uppercase denote matrices, bold lowercase denote vectors, and non-bold lowercase denote scalars.

[d] The analyst can choose a subset of the pre-intervention period over which the MSPE is minimized.

[e] Other methods to choose $\boldsymbol{V}$ also exist in the literature, such as an out of sample validation method (Abadie et al., 2015), or a regression-based method (Bohn et al., 2014).

[f] The first application of such a problem was in the context of Stackelberg competition. In economics, further applications followed, such as in principal-agency problems, one-way pollution problems, urban transport problems, etc. (Dempe, 2002).

$$
\arg\min\left(\boldsymbol{z_1} - \boldsymbol{Z_0}\boldsymbol{w}^*(\boldsymbol{V})\right)'\left(\boldsymbol{z_1} - \boldsymbol{Z_0}\boldsymbol{w}^*(\boldsymbol{V})\right)
$$

$$
subject\ to: \begin{cases} v_h \geq 0 \\ \sum_{h=1}^{k} v_h = 1 \\ \boldsymbol{w} \in \arg\min_{\boldsymbol{w}} \|\boldsymbol{x}_1 - \boldsymbol{X}_0\boldsymbol{w}\| = \sqrt{(\boldsymbol{x_1} - \boldsymbol{X_0}\boldsymbol{w})'\boldsymbol{V}(\boldsymbol{x_1} - \boldsymbol{X_0}\boldsymbol{w})} \\ subject\ to: \begin{cases} w_j \geq 0 \\ \sum_{j=2}^{J+1} w_j = 1 \end{cases} \end{cases} \tag{6.8}
$$

For all the possible combinations of $\boldsymbol{V}$, the synthetic control method chooses a vector $\boldsymbol{w}$ that minimizes the inner optimization problem, i.e. the difference in pre-treatment predictor variables between the actual treated unit and the synthetic control[g]. Out of the infinitely large set of $\boldsymbol{w}^*(\boldsymbol{V})$, the method then chooses the weight vector $\boldsymbol{w}^*(\boldsymbol{V}^*)$ that minimizes the outer optimization problem, i.e. that minimize the MSPE of the variable of interest during the pre-intervention period (Abadie et al., 2011). Figure 5 which is an adapted version from Klößner et al. (2018), gives of a good overview of the synthetic control method.

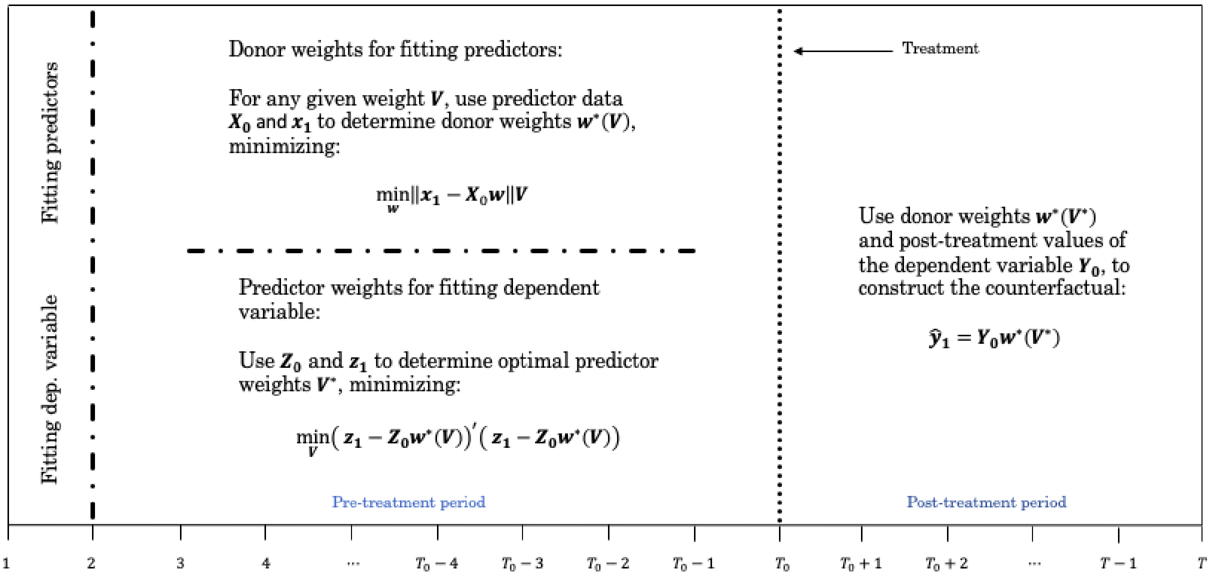


Figure 5: Schematic overview of the synthetic control method using Abadie & Gardeazabal (2003) and Abadie et al. (2010) method of choosing V. Adapted from Fig. 2 in Klößner et al. (2018)

In order to automate this hefty task, the SCM uses optimization algorithms to find the optimal solution $\boldsymbol{w}^*(\boldsymbol{V}^*)$. The synth command in R can use all the optimization algorithms

[g] The inner optimization problem is a constrained quadratic optimization problem. The synth command uses R'kernlab package to solve it.

currently implemented in the optimx function[h], but the default are the BFGS and Nelder-Mead[i] algorithms (Abadie et al., 2011). The synth command will run the optimization problem using both algorithms, and return the result for the best performing method (Abadie et al., 2011).

Depending on the setup of the data, there may be situation in which the objective function contains one or multiple local minima. There is no analytical guarantee that the optimization algorithms may converge to the global minimum. There are some safeguards against this. A non-derivative based algorithm such as Nelder-Mead or SANN can be specified. Furthermore, the argument genoud( ) can be set to true, in order for the synth command to embark in a two-step optimization process. For more information see Abadie et al. (2011).

6.2.3 Properties of the synthetic control estimator

Uniqueness and sparsity are two attractive properties of the synthetic control estimator. Uniqueness refers to the fact that the optimization problem in equation (6.4) returns only one optimal weighting vector $\boldsymbol{w}^*$, instead of multiple solutions. Sparsity refers to having only a few non-zero weights in $\boldsymbol{w}^*$, meaning that only a few units from the donor pool contributes to the synthetic control. These properties may be desirable, since it simplifies the results, but are not guaranteed[j]. In general, if $\boldsymbol{x_1}$ falls outside the convex hull[k] of columns of $\boldsymbol{X}_0$, then $\boldsymbol{w}^*$ is unique and sparse. Sparsity of the weights is common for synthetic control estimators, and is a consequence of the optimization problem (Abadie, 2020).

One of the advantages of the synthetic control method is that, because it bounds the donor weights $\boldsymbol{w}$ to be in the $[0, 1]$ interval, it avoids extrapolation. This is not the case for regression-based estimators, which rely on extrapolation for the construction of the counterfactual. More information on this will proceed in section 6.3.

[h] See Nash & Varadhan (2011) for an overview of the different optimization algorithms.

[i] The main difference between the two is that BFGS is a Quasi-Newton method, while Nelder-Mead is derivative-free (Nash & Varadhan, 2011). For an overview, see (Lam, 2020) for BFGS and (Moraglio & Johnson, 2010) for Nelder-Mead.

[j] Abadie & L'Hour (2019) propose a penalized version of the synthetic control estimator, to restrict the solution to be unique and sparse.

[k] A convex hull is the smallest convex set that contains its data points. See figure 5 for an example of a convex hull.

6.3 Comparison to regression

This section will focus on the differences between the synthetic control estimator and a regression-based estimator followed by a discussion of the implications of (un-)restricting the weights.

6.3.1 Regression-based estimator

Abadie et al. (2015) show that the regression-based estimator for the counterfactual, can be represented as a weighted average of control units, the same way that the synthetic control estimator for the counterfactual does. Secondly, although the weights of the regression-based estimator sum up to one, the weights are unconstrained, and can take negative values, as well as values larger than one. This contrasts with the synthetic control weights, that are bounded in the $[0, 1]$ interval. This has important implications that will be discussed later.

The explanation follows Abadie et al. (2015), albeit, more detailed. Consider the following regression equation:

$$\boldsymbol{Y_0'} = \boldsymbol{X_0'}\widehat{\mathrm{B}} + \widehat{\mathbf{E}}' \tag{6.8}$$

Where $\boldsymbol{Y_0}$ is a $(T - T_0) \times J$ matrix representing the post-intervention outcome of interest for every untreated unit in the donor pool, $\boldsymbol{X}_0$ (as defined in section 6.1) is a $k \times J$ matrix of pre-intervention predictors for the untreated units, $\widehat{\mathbf{B}}$ is $k \times (T - T_0)$ matrix of coefficients and $\widehat{\mathbf{E}}$ is a $(T - T_0) \times J$ matrix of residuals.

$\boldsymbol{Y_0}$ is a panel, while $\boldsymbol{X}_0$ is a cross-section, therefore, (6.8) is essentially set of $(T - T_0)$ stacked regression equations, for every post-intervention period t:

$$\begin{aligned}
\boldsymbol{y'_{0\,T_0+1}} &= \boldsymbol{X'_0}\widehat{\boldsymbol{\beta}}_{\boldsymbol{T_0+1}} + \hat{\boldsymbol{\varepsilon}}'_{\boldsymbol{T_0+1}} \\
\boldsymbol{y'_{0\,T_0+2}} &= \boldsymbol{X'_0}\widehat{\boldsymbol{\beta}}_{\boldsymbol{T_0+2}} + \hat{\boldsymbol{\varepsilon}}'_{\boldsymbol{T_0+2}} \\
&\vdots \\
\boldsymbol{y'_{0\,T_0+(T-T_0)}} &= \boldsymbol{X'_0}\widehat{\boldsymbol{\beta}}_{\boldsymbol{T_0+(T-T_0)}} + \hat{\boldsymbol{\varepsilon}}'_{\boldsymbol{T_0+(T-T_0)}}
\end{aligned} \tag{6.9}$$

The matrix $\widehat{\mathbf{B}}$ therefore, collects the k coefficients for all the $(T - T_0)$ regression equations. The OLS estimator for $\widehat{\mathbf{B}}$ is[l]:

$$\widehat{\mathbf{B}} = (\boldsymbol{X_0X_0'})^{-1}\boldsymbol{X_0Y_0'} \tag{6.10}$$

[l]See Appendix A for the derivation of the OLS estimator.

The regression-based counterfactual for the outcome of the treated unit in the absence of the treatment is $\hat{\mathbf{B}}$ times $\boldsymbol{x}_1$, the $k \times 1$ vector of pre-intervention predictors for the treated unit:

$$\hat{\mathbf{B}}'\boldsymbol{x_1} = ((\boldsymbol{X_0}\boldsymbol{X_0'})^{-1}\boldsymbol{X_0}\boldsymbol{Y_0'})'\boldsymbol{x_1} \tag{6.11}$$

Which results in a $(T - T_0) \times 1$ .Equation (6.11) can be expressed differently if we first define a specific subset of the equation:

$$\boldsymbol{w^{reg}} = \boldsymbol{X_0'}(\boldsymbol{X_0}\boldsymbol{X_0'})^{-1}\boldsymbol{x_1} \tag{6.12}$$

Which is a $J \times 1$ vector. Multiplying $\boldsymbol{w^{reg}}$ by $\boldsymbol{Y_0}$:

$$\boldsymbol{Y_0}\boldsymbol{w^{reg}} = \boldsymbol{Y_0}\boldsymbol{X_0'}(\boldsymbol{X_0}\boldsymbol{X_0'})^{-1}\boldsymbol{x_1} \tag{6.13}$$

Gives us the same result as in equation (6.11): a $(T - T_0) \times 1$ vector, but now expressed as a vector of weights times the outcome of interest, Y_0. Abadie et al. (2015) further show that the sum of the elements in $\boldsymbol{w^{reg}}$ do in fact sum up to one, making the $\boldsymbol{Y_0}\boldsymbol{w^{reg}}$ a weighted average.

Let $\boldsymbol{\iota}$ be a $J \times 1$ vector of ones. Because $\boldsymbol{\iota'}\boldsymbol{w^{reg}}$ is a scalar, it is essentially the sum of the elements in $\boldsymbol{w^{reg}}$. Let $\boldsymbol{X}_0$ and $\boldsymbol{x}_1$ be expanded to $\boldsymbol{\bar{X}_0}$ and $\boldsymbol{\bar{x}_1}$ respectively, with the first row being a row of ones[m]. The $(k+1) \times 1$ coefficient vector resulting from the regression of $\boldsymbol{\iota}$ on $\bar{X}_0$ is equal to $(\bar{X}_0\bar{X}_0')^{-1}\bar{X}_0\iota$, of which the first element is equal to one and the k remaining elements are equal to zero. This is because the resulting regression line is horizontal with an intercept equal to one. Because the first element in $\boldsymbol{\bar{x}_1}$ is equal to one, it implies that $\boldsymbol{\iota'}\boldsymbol{w^{reg}} = \boldsymbol{\iota'}\boldsymbol{X_0'}(\boldsymbol{X_0}\boldsymbol{X_0'})^{-1}\boldsymbol{x_1}$ equals one.

6.3.2 Weights, extrapolation and interpolation.

The weights of the regression-based counterfactual are unbounded, and can therefore take any value outside the $[0,1]$ interval. This implies that the regression-based estimator relies on extrapolation, since the counterfactual can be constructed using values beyond the observation range, and thus, beyond the support of the data. Due to the ability to extrapolate, a regression-based counterfactual is able to guarantee a perfect fit $\boldsymbol{\bar{X}_0}\boldsymbol{w^{reg}} = \boldsymbol{\bar{x}_1}$, even if the elements of $\boldsymbol{\bar{x}_1}$ fall far away the convex hull of $\boldsymbol{\bar{X}_0}$ (Abadie, 2020). Figure 6

[m] It is common in the literature using matrix notation, to add a column or row of ones, in order to allow the regression equation to have an intercept (Verbeek, 2017).

shows an example of a convex hull, using the Basque dataset, available in the "Synth" package in R. In addition, Abadie et al. (2015) provide SC and regression-based weights as means of illustrating the difference between the two (table 3). Notice that the regression weights are sparse, while the SC weights are not

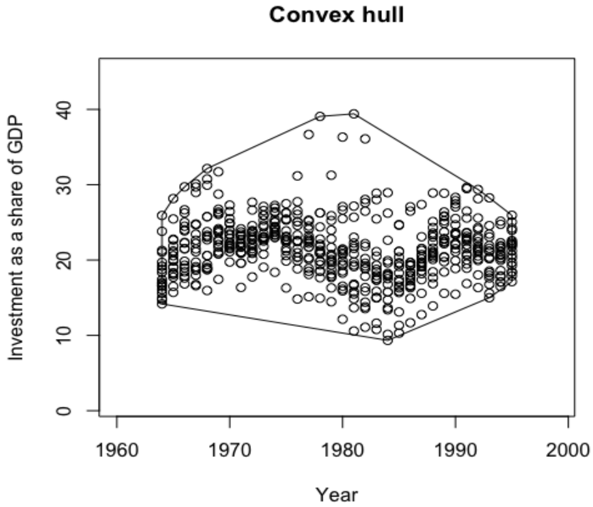


Figure 6: Convex hull of investment rate from the Basque dataset used in Abadie & Gardeazabal (2003).

Relying on extrapolation for the construction of counterfactuals can increase the dependence of the results on the model specification, rather than empirical evidence (King & Zeng, 2007). This can lead to extrapolation biases[n]. Furthermore, because the synthetic control estimator does rely on interpolation for the construction of the counterfactual, i.e. relies on observation within the convex hull, interpolation biases may arise. Nevertheless, Abadie (2020) argues that if the donor pool is restricted to be control units similar to the treated unit, you avoid interpolation biases[o].

Table 3: SC and Regression weights for West Germany (Abadie et al., 2015)

Country	SC weights	Reg weights	Country	SC weights	Reg weights
Australia	0	0.12	**Netherlands**	0.09	0.14
Austria	0.42	0.26	**New Zealand**	0	0.12
Belgium	0	0	**Norway**	0	0.04
Denmark	0	0.08	**Portugal**	0	−0.08
France	0	0.04	**Spain**	0	−0.01
Greece	0	−0.09	**Switzerland**	0.11	0.05
Italy	0	−0.05	**UK**	0	0.06
Japan	0.16	0.19	**USA**	0.22	0.13

Moreover, the regression-based weights for the counterfactual are hardly ever calculated, and thus hidden from the analysis. This contrasts with the weights in the SCM, which are central for the analysis (Abadie et al., 2015). Furthermore, The synthetic control

[n] See King & Zeng (2006) for further discussion on relying on extrapolation to estimate counterfactuals.

[o] Kellogg et al. (2020) Propose an estimator that combines matching and the synthetic control method, in order to trade off extrapolation and interpolation biases

method does in principle, not require post-treatment outcomes in the design of the study, while regression-based estimators do require. This can provide safeguard against specification searches, and can play a similar role to pre-analysis plans in RCTs (Abadie, 2020).

7 Data

This chapter provides a description of the variables, as well as its sources, and the final dataset used for the study. Descriptive statistics are also provided.

7.1 Variable description and data sources.

In section 5.2.2, A discussion of potential variables is given, based on the literature review. Here, a more detailed description is provided, as well as the source of each variable.

For the current study, the outcome or variable of interest is the number of departing passengers. Data is used from the Eurostat "avia_paoa" dataset (Eurostat, 2021b). This dataset reports air passenger transport by main airports in each reporting country. The number of departing passengers is selected, since the Dutch aviation tax is only levied on outgoing traffic. Furthermore, "passengers carried (departures)" is chosen over "passengers on board (departures)" because the former does not include transit passengers (Eurostat, 2021a).

As a predictor variable, a measure of national income/economic output is of great importance for the analysis at hand, since it may have a high covariance with passenger numbers. The most common measure for this is GDP or GDP per capita. Nevertheless, because of the short time span of the Dutch aviation tax (one year), monthly data is more appropriate, but a monthly overall measure of the state of the economy is lacking (Hoven & Schreurs, 2013). Instead, indicators and estimates are often used (Hoven & Schreurs, 2013; Mitchell et al., 2005). For this study, the monthly industrial production index (IPI) will be used (Eurostat, 2021f). The industrial production index is a business cycle indicator which measures monthly changes in the price-adjusted output of industry[a]. It is calculated in the European Union, as well as some EFTA and candidate countries (Eurostat, 2021e). It is used to asses to identify turning points in the economic development at an early stage, as well as assessing the future development of GDP (Eurostat, 2021e). Moreover, the data is seasonally and calendar adjusted, and has 2015

[a] The economic activities it takes into account are mining, quarrying, manufacturing, electricity, gas, steam and air conditioning supply (Eurostat, 2021f).

has its base year (i.e. 2015=100). The data is country-level, so each unit (airport) has the value for the country it is located in.

A second predictor variable is the monthly harmonized index of consumer prices (HICP) for airfares (Eurostat, 2021d). It is an indicator of price stability and changes on a monthly basis. The HICP is subcategorized among various consumer goods and services, of which airfares is chosen for the analysis. The base year is 2015, and data is offered on a country-level, so each airport has the value of the country it is located in.

The last predictor variable used is crude oil import prices per country (Eurostat, 2021c), as a proxy for jet fuel prices. Crude oil prices is a good proxy for petroleum-based products since price volatilities are very similar (Jiang et al., 2018). Because fuel is the main cost faced by airlines, it may also affect the number of passengers. The crude oil import prices are presented in USD per barrel, inflation adjusted, with a base year of 1970.

7.2 Dataset description

The initial dataset from Eurostat results in a total of 345 units (airports) from 30 countries. Nevertheless the final dataset will be smaller since some airports are not appropriate control units to compare to. Appendix B present a list of excluded airports.

Airports located in French overseas territories (5 airports) are dropped, since due to their geographical location, their characteristics may differ significantly from the treated airports. Moreover, various countries either introduced or abolished an aviation tax during the time span of the data, making the airports located in these countries invalid as control units. As explained in Abadie (2020), it is important to eliminate from the donor pool any unit that suffered idiosyncratic shocks to the outcome of interest during the study period, if it would not have affected the outcome of interest of the treated unit(s) in the absence of the treatment. Ireland introduced an Air travel tax of 3€ on the 30th of March, 2009, which was modified on the 28th of February 2011 to 2€ (for flights <300km) and 10€ (for flights >300km) and finally abolished on the 31st of March, 2014 (Irish Tax and Customs, 2016). Moreover, Denmark introduced an Air passenger duty in 2005 with two tax rates, 75 DKK (~10€) and 300 DKK (~40,26€) (Skatteministeriet, 2005), which was halved in 2006 and abolished in 2007 (Krenek & Schratzenstaller, 2016). Finally, Malta introduced a departure tax of 12€ per passenger, and abolished it in 2008 (Krenek &

Schratzenstaller, 2016). This means that all Irish (5), Danish (9) and Maltese (1) airports are dropped.

In addition, all rates for the Air Passenger Duty (APD) in the UK doubled on the 1st of February, 2007 (HM Treasury, 2006), therefore, all 43 UK airports are dropped. Moreover, data import oil prices for 12 countries[b] are lacking, so all 41 airports from these countries are dropped. The 5 Croatian airports are also dropped since passenger number and oil price important are missing. Lastly, 8 airports from various countries are dropped as well, due to some missing data in passenger numbers.

We end up with a long panel data set with a total of 6840 observations: 228 units across 13 countries, and 30 time periods per unit (from January 2007 to June 2009).

7.3 Summary statistics and plots.

Table 4: Summary Statistics

Variable	Mean	Median	Std. Dev.	Min	Max	Nº of obs.
Pax (number of departing passengers; monthly, airport)	162780	35220	358557.8	41	3158385	6840
Industrial output (Ind. Prod. Index, monthly, country)	114.6	114.1	17.66	71.4	149.8	6840
Ticket price (HICP flight ticket price, monthly, country)	84.67	82.89	18.53	56.04	168.25	6840
Jet fuel price proxy (Oil import prices, monthly, country)	76.80	71.83	25.75	38.88	135.91	6840

Table 4 shows summary statistics for the four variables. Notice that the number of observations is the same for all variables, meaning that we have a balanced panel dataset. All three covariates are normalized to a have a base year equal to 100, so all other observations are relative to that base year. As expected, oil import prices has the highest standard deviation out of the three. Also notice that the mean and median differ

[b] These countries are: Bulgaria (2), Cyprus (2), Estonia (1), Hungary (1), Latvia (1), Lithuania (3), Luxembourg (1), Norway (18), Romania (3), Slovakia (2), Slovenia (1) and Switzerland (6) .

significantly for the number of departing passengers, meaning that the resulting distribution won't be normal, as we can see in figure 7.

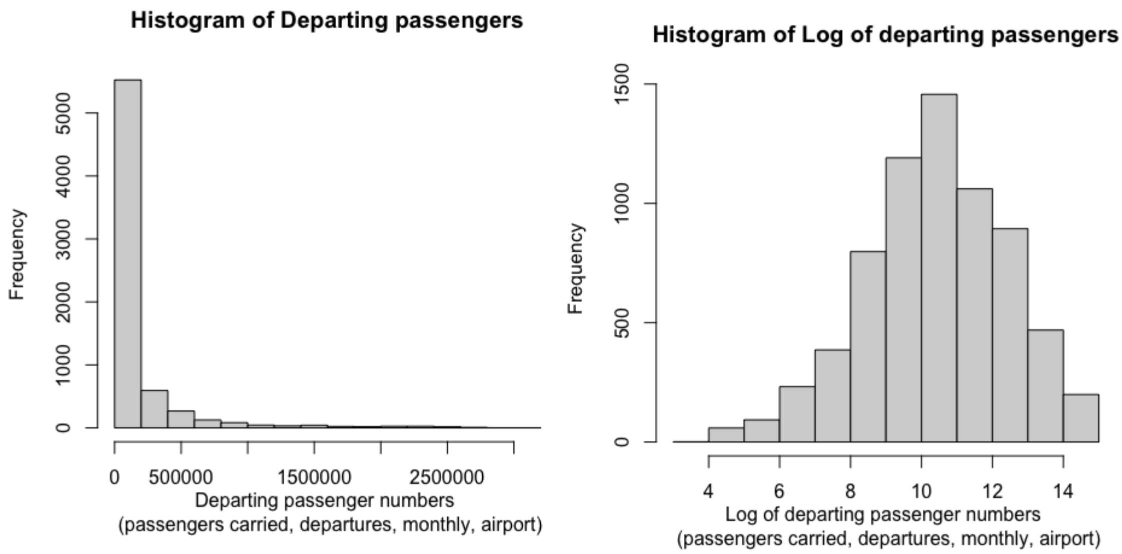


Figure 7:Distribution of Departing passengers and the logarithm of departing passengers

Figure 7 shows the histogram of the number of departing passengers. Because the data set is large, there are many airports with relatively low traffic. There are only 11 airports in the dataset that has more than one million departing passengers for at least one time period. The right side of figure 7 shows the distribution of the logarithm of departing passengers, which follows more closely a normal distribution.

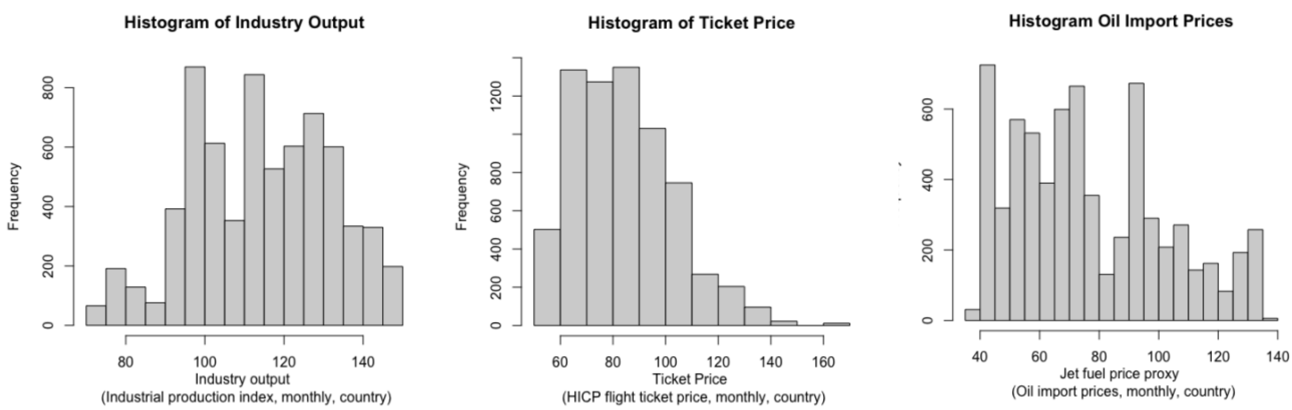


Figure 8: Distribution of industry output, Ticket price and Oil import prices.

Figure 8 shows the distribution of the remaining three variables. Ticket price is the variable that closer resembles a normal distribution, while the remaining two seem to be more randomly distributed.

7.4 Treated units selection

A remaining issue to be discussed is selecting which units will be considered "treated" and thus, which will be considered "untreated". Obviously, all 5 Dutch airports will be considered treated units, since passengers departing from these airports were subject to the aviation tax. In order to attempt to quantify the substitution effect, we need to consider airports in neighboring countries that Dutch passenger may have used to avoid paying the tax.

In Belgium, four airports will be considered as treated. Brussels airport will be considered because it is an important, well-known airport that offers international flights. Charleroi/Brussels South airport is also considered, because LCC airlines use this airport, and thus, price-sensitive passenger may be drawn to it. Although Liège airport is relatively small, its proximity to the Dutch border makes it an interesting case study, especially since it may directly compete with Maastricht-Aachen airport. Lastly, Antwerpen airport will also be considered treated, again, for its proximity.

Table 5: Treated units and convex hull of X_0.

Airport	Pax	Ind. output	Ticket price	Oil imports	In convex hull?
Min & Max of X_0	(172.05, 2472089.61)	(77.6, 143.67)	(59.46, 121.59)	(80.13, 84.19)	–
Amsterdam	1964047.22	106.15	69.72	80.68	✓
Rotterdam/The Hague	43660.11	106.15	69.72	80.68	✓
Eindhoven	63446.38	106.15	69.72	80.68	✓
Groningen	5832.16	106.15	69.72	80.68	✓
Maastricht/Aachen	7235.16	106.15	69.72	80.68	✓
Düsseldorf	735844.83	99.15	71.17	83.91	✓
Weeze	42034.77	99.15	71.17	83.91	✓
Münster/Osnabrück	62475,83	99.15	71.17	83.91	✓
Cologne/Bonn	427962.77	99.15	71.17	83.91	✓
Brussels	740782.33	97.96	61.32	81.83	✓
Charleroi	106910.72	97.96	61.32	81.83	✓
Antwerpen	5901.72	97.96	61.32	81.83	✓
Liege	13685.11	97.96	61.32	81.83	✓

For German airports, I first look into Gordijn & Kolkman (2011)'s study. The authors use a rational choice models, together with surveys, to analyze the effect of the Dutch aviation tax on Dutch airports, but also neighboring airports. The chosen airports in Germany are Düsseldorf, Weeze and Münster/Osnabrück airports. These three will be used in this analysis as well, together with Cologne/Bonn airport, which is an easily accessible airport for the Southern region of the Netherlands.

Table 5 shows all 13 treated units and their mean pre-intervention values for each predictor. Remember from chapter 6 that $\boldsymbol{X_0}$ is the pre-intervention predictors for the untreated units. We see from the table that all treated units satisfy the convex hull condition, meaning that the values in $\boldsymbol{x_1}$ fall within the columns of $\boldsymbol{X_0}$. This often results in having a good pre-treatment fit for the counterfactuals. Nevertheless, the implication of this is that, the optimal solution $\boldsymbol{w}^*(\boldsymbol{V}^*)$ is not unique, and there may in fact be infinitely many solutions[c] (Abadie, 2020). This would normally not be a problem, however, in cases with a high number of treated and untreated units, large interpolation biases may become an issue. This is because the selected optimal solution $\boldsymbol{w}^*(\boldsymbol{V}^*)$ may have positive entries for units that are far away from the treated unit in the space of the predictors, even when an alternative solution exists, based on units with similar predictor values (Abadie, 2020).

There seems to be a trade-off between having a good pre-treatment fit and avoiding interpolation biases. In order to remedy this, beside constructing counterfactuals using the entire donor pool, another set of counterfactuals will be estimated based on a sub-selection of similar control units to the treated unit. The next section will explain this in more depth.

7.5 Data subset based on airport classification.

It important to use also a subset in order to restrict the donor pool to airports that have similar characteristics. It would be reasonable to restrict the comparison units for Amsterdam Schiphol to other hub airports in Europe, that play a similar role within the European aviation network. For instance, if in the construction of a counterfactual for a large hub airport, there is a positive weight for a small regional airport which also happens to be afar, it would be rather difficult to conceptually justify this positive weight.

[c] This is because if both $\boldsymbol{w}_1^*$ and $\boldsymbol{w}_2^*$ are optimal solutions, then any combination $a\boldsymbol{w}_1^* + (1-a)\boldsymbol{w}_2^*$ where $a \in (0,1)$, is also an optimal solution (Abadie, 2020).

Moreover, it is fairly common in the synthetic control literature to restrict to a relatively small donor pool.

Some studies have attempted to offer a classification of airports based on numerous criteria. Most classifications use criteria such as operational capacity, regional location, and/or functional role (Adikariwattage et al., 2012). Table 5 summarizes the literature on airport classification. Although the number of studies is rather low, the table shows different ways of classifying airports.

Table 6: Airport classification based on numerous studies

Author	Region	Criteria/ Method	Classification
(Adikariwattage et al., 2012)	United States	Airport size based on the nº of gates, destination of passengers, and type of passengers.	Results in 16 “types” based on size (small, medium, large and very large), destination (serving majority domestic or international) and type of passenger (majority O-D or transfer). Only 9 out the 16 categories are used.
(Graham, 1998)	Europe	Number of annual passengers	Capital hubs (1), airports serving metropolitan regions (2), airports serving peripheral core cities (3), major regional (4), secondary regional (5), leisure (6) and local airports (7).
(Malighetti et al., 2009)	Europe	Cluster analysis using several variables representing four criteria: traffic, destination, connectivity and typology of service[d].	A total of 8 clusters: world-wide Hub, Hub, secondary gate (serves as intermediate connections), LCC (>75%), No-low cost gate (serves only European market), Regional, Low-cost regional, and local airports.
(European Commission, 2005)	Europe	Based on two other classifications: one from the council of EU, and the other from the committee of the regions.	Four categories, from A to D: Community, national, large regional and small regional airports[e].
(Burghouwt & Hakfoort, 2001)	Europe	Ward’s method of cluster analysis, using three variables: average seat capacity, average number of destinations, and average number of intercontinental destinations	Results forced to 5 clusters: Primary hubs, secondary hubs, medium, small and very small airports.

[d] Three variables for traffic: number of seats available (seats/day), number of daily flights and number of destinations. Three for destination: % of EU destinations, % of domestic destinations and HHI index. Two variables for connectivity: number of times per day the airport works as intermediate connections between two between two airports, and the % of times the airport cannot be bypassed through routes of similar duration. And finally, one variable for typology of service: % of seats offered by low cost carriers (LCC) (Malighetti et al., 2009).

[e] Community airports are those that serve more than 10 million passengers, national airports are those that serve between 5 and 10 million, large regional are those that serve between 1 and 5 million, and small regional are those that serve less than 1 million passengers (European Commission, 2005).

The classification from Malighetti et al. (2009) is chosen as the preferred method to classify airports in the donor pool for this thesis report. Firstly, Malighetti et al. (2009)'s classification uses a data-driven procedure to identify different groups of airports that have similar characteristics. This procedure is called cluster analysis, which is the task of grouping a set of objects such that the objects in the same group are as similar as possible while object outside the group are as dissimilar as possible (Soetewey, 2020). Secondly, out of all the proposed classifications, it is by far the most comprehensive one, as it classifies 467 airports, an uses a total of nine variables to cluster the airports together. Lastly, the publication year is 2009, which is during the time period of the data analyzed in this thesis report. Although airport characteristics changes slowly, a classification made further away in time, might be less accurate due to changes in these characteristics.

The treated airports can be classified into four groups:

1. WW hub airports: All these airports have similar dimensional characteristics, with a high percentage of overseas destinations. These airports also work as a main base for many carriers and have a low presence of low-cost airlines.
2. Hub airports are similar to the previous group, but cater mostly to European routes. These airports are former flag carrier's hub or secondary large-sized hubs.
3. Medium-sized (low-cost) airports represent cluster number 3 and 4 in Malighetti et al. (2009). These are all medium-sized airports, with less-competitive routes, or a high concentration of low-cost carriers. The control group is restricted to units that are relatively closer to the treated units.
4. Regional/local airport are those with a low number of passengers. This groups is much less homogenous than the previous groups. It has low to medium concentration of low-cost carriers. The control group is also restricted to units that are relatively closer to the treated units.

Table 7 shows the final airport classification used for this thesis report. The choice of the control group is based on airport characteristics and also geographical proximity. When the group with similar characteristics is small, we are unable to further decrease the donor pool to restrict units that are nearby. This is because having a large enough donor pool is more important than satisfying the criteria of geographical proximity. As a result, the donor pool for World-wide hub airports still include airports in Spain and Italy, because otherwise the donor pool would have a total of three units.

Table 7: Airport classification and donor pools

Type of airport	Treated unit(s)	Control groups
World-wide hub airport	Amsterdam Schiphol	Paris Charles de Gaulle, Frankfurt main, Madrid-Barajas Adolfo Suarez, Barcelona el prat, Munich airport Roma-Fiumicino.
Hub airport	Brussels, Dusseldorf	Vienna international, Lisbon, Athens, Paris-Orly, Milan-Malpensa, Stockholm Arlanda, Berlin-Tegel, Warsaw, Helsinki, Prague, Hamburg, Stuttgart,
Medium-sized (low-cost) airports	Cologne/Bonn, Charleroi,	Palma de Mallorca, Malaga, Valencia, Toulouse, Nantes, Berlin-Schönefeld, Frankfurt-Hahn, Nice, Bremen, Dortmund, Leipzig, Lyon, Stockholm-Skavsta, Goteburg-Landvetter, Malmo, Roma-Ciampino, Milan-Linate, Torino, Krakow, Bordeaux, Hannover, Nuremberg, Gdansk, Katowice, Salzburg.
Regional/ local airport	Eindhoven, Rotterdam, Groningen/Eelde, Maastricht, Weeze, Munster/Osnabrück, Antwerpen/Deurne, Liege.	Karlovy, Karlstad, Sylt, Laage, Oostende, Stockholm-Vasteras, Lorraine, Erfurt-Weimar, Luebeck-Blanksee, Friederichshaven Linz, Goteborg-Save, Bale-Mulhouse, Graz, Innsbruck, Lille, Karlsruhe, Padeborn, Wroclaw, Strasbourg, Malmo, Dresden, Stockholm-Bromma, Beauvais-Tille.

7.6 Specification searches in SCM.

Abadie et al. (2010) argues that the synthetic control method reduces subjective researcher bias, because the method does not require post-intervention outcomes, which allows the researcher to design the study, without knowing how those decisions affect the results of the study. More often than not, post-intervention outcomes are available, and there is nothing to stop the researcher from running various model specifications and report the one with the most attractive results. This problem concerns with the choice of predictors. Remember from chapter 6 that predictors k is the sum of r covariates and m so-called "linear combination of the outcome of interest". The researcher can still choose which covariates to include or exclude, and in what form will the outcome of interest be used a predictor (mean of pre-intervention values, one lag, multiple lags, etc.). As explained by Cunningham (2021), through repeated iterations on the different specifications, the researcher can potentially reintroduce bias through the endogenous selection of predictors, when engaging in specification searches.

Ferman et al. (2020) try to fill in the gap in the literature by providing some guidance in the choice of predictors. The authors use a total of seven common synthetic control specifications (based on m "linear combination of the outcome of interest"), and run randomization inference test to calculate p-values and quantify the probability of falsely rejecting the null hypothesis. Ferman et al. (2020) suggest to present multiple results using various specifications.

The specifications used by Ferman et al. (2020) are[f]:

1. All pre-treatment outcome values: $X_j = \left[y_{j1}, \dots, y_{jT_0}\right]'$
2. The first three fourths of the pre-treatment outcome values$X_j = \left[y_{j1}, \dots, y_{j\frac{3T_0}{4}}\right]'$.
3. The first half of the pre-treatment outcome values $X_j = \left[y_{j1}, \dots, y_{j\frac{T_0}{2}}\right]'$.
4. Odd pre-treatment outcome values: $X_j = \left[y_{j1},\ y_{j3},\ \dots, y_{j(T_{0-3})},\ y_{j(T_{0-1})}\right]'$.
5. Even pre-treatment outcome values: $X_j = \left[y_{j2},\ y_{j4},\ \dots, y_{j(T_{0-2})},\ y_{jT_0}\right]'$.
6. Pre-treatment outcome mean: $X_j = \left[\frac{\sum_{t=1}^{T_0} y_{jt}}{T_0}\right]'$.
7. Three outcome values (first, middle and last): : $X_j = \left[y_{j1}, y_{j\frac{T_0}{2}}, y_{jT_0}\right]'$

Ferman et al. (2020) also theoretically investigate whether, under certain conditions[g], different specifications lead to asymptotically equivalent SC estimators when $T_0 \to \infty$. Nevertheless, this asymptotic convergence only happens in settings with a very large T_0, beyond most if not all current applications in the literature.

For the current analysis, specification 6 is chosen, since it was used by Abadie & Gardeazabal (2003) and roughly a third of the papers analyzed by Ferman et al. (2020) use this specification[h]. For simplicity I call this specification 1. A second sepcification will

[f] The authors only investigate different specifications for m, assuming no covariates ($r = 0$).

[g] The condition here is that number of predictors goes to infinity when $T_0 \to \infty$. This condition only holds for the first five specifications.

[h] The authors analyze a total of 17 studies published in highly reputable journals in economics. For a list of these journals, the reader is the referred to the original study.

be using the lagged number of passengers (i.e. number of passengers in period $T_0 - 1$) as a predictor variable. This specification was used by Borbely (2019) to capture airport specific trends.

8 Results

The first section provides a small description of the analysis. Section 8.2 shows the results from the synthetic control analysis, and section 8.3 provides MSPE ratios and p-values for the estimated treatment effect.

8.1 Description of the analysis

The analysis was conducted in R version 4.0.3, and figures were produced using the base package (R Core Team, 2020). To construct the counterfactuals using the synthetic control method, The “Synth” package version 1.1.5 is used (Abadie et al., 2011), as well as the package “SCtools” version 0.3.1 (Castanho Silva & DeWitt, 2020) for further analysis in section 8.3. The two most important commands are “dataprep( )” and “synth( )”. The former prepares the data to be an input for the “synth( )” command, which then finds the optimal weights $\boldsymbol{w}^*(\boldsymbol{V}^*)$, to construct the counterfactual. The output of “dataprep( )” are $\boldsymbol{z_1}$, $\boldsymbol{Z_0}$, $\boldsymbol{x_1}$ and $\boldsymbol{X_0}$, which are then used to find the optimal weights. The command “multiple.synth()” is also used and automates the process of applying “synth( )” to each treated unit.

Figure 9: Location of the treated airports and their IATA code

The counterfactuals will be constructed according to the following two specifications:

1. Specification 1: Pre-treatment outcome mean: $X_j = \left[\frac{\sum_{t=1}^{T_0} y_{jt}}{T_0}\right]'$.
2. Specification 2: First lag of pre-treatment outcome: $X_j = \left[y_{j(T_{0-1})}\right]'$

Furthermore, two datasets will be used: the full data and a restricted version explained in section 7.5. This subset is chosen on the basis of airport type and/ or geographical proximity.

8.2 Time-series of treated airports

Before looking into the counterfactuals of each treated airport, it may be interesting to first investigate time series of the treated unit. Figure 10 shows time series for all the treated unit, divided by their type. The time period goes from January 2005 until December 2010, and the grey area represent the time period used in this study. We can

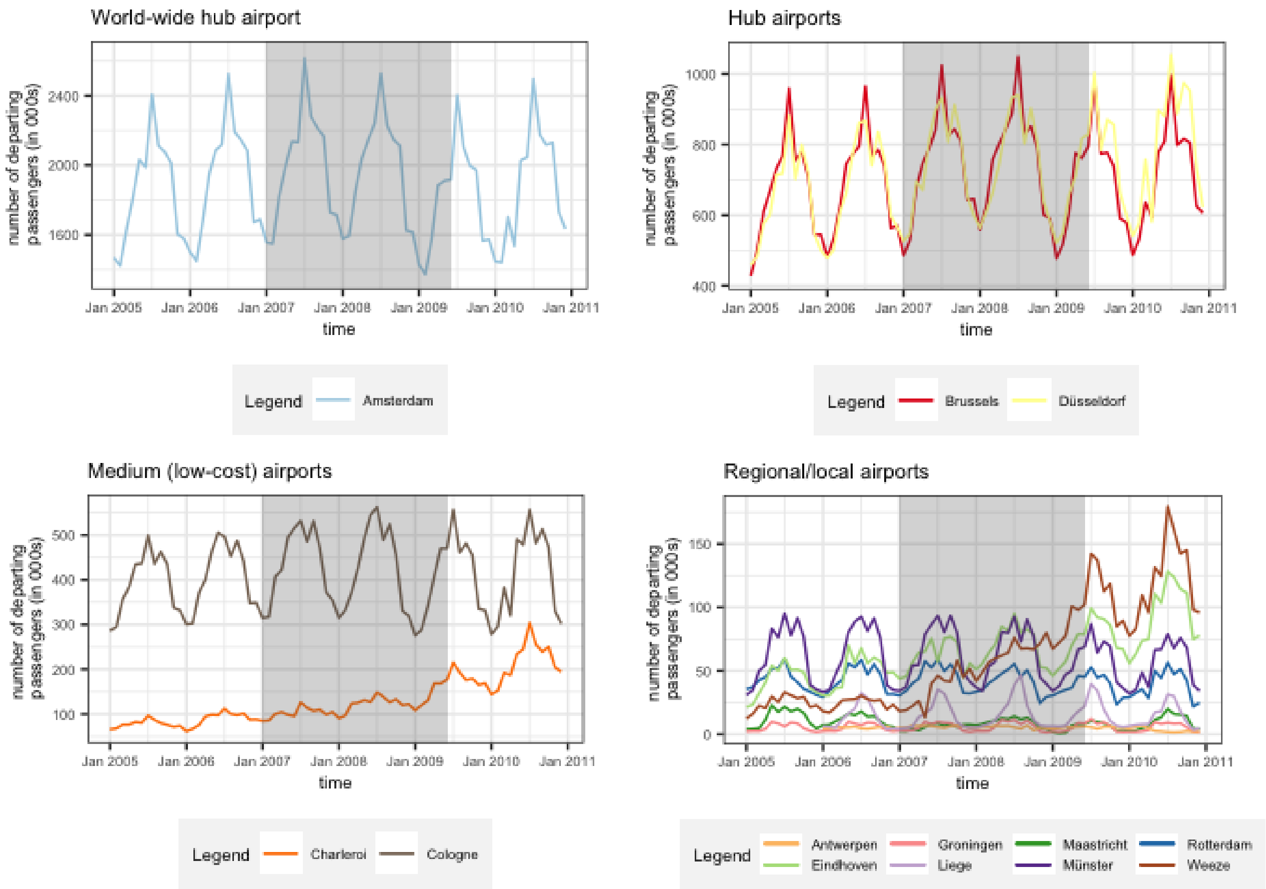


Figure 10: Time series for treated airport, divided by type, made with ggplot2 (Wickham, 2016). Grey area indicates the time period for this analysis.

already see very different trends among these airports. For example airports like Amsterdam Schiphol, Münster and Rotterdam show a downward trend during the studied period, while others show an increasing trend. For the entire time series, there are a some airports like Charleroi, Eindhoven and Weeze, with a clear increasing trend. Nevertheless, several airports show a larger than usual decrease between the summer of 2008 and January 2009, which is usually the month with the lowest number of passengers. This suggests that the financial crisis plus the Dutch aviation tax did have some effect on passenger numbers.

8.3 Results of synthetic control

This section provides the results for both the Dutch airports and neighboring airports

8.3.1 Results for Dutch airports

<u>Amsterdam Schiphol</u>

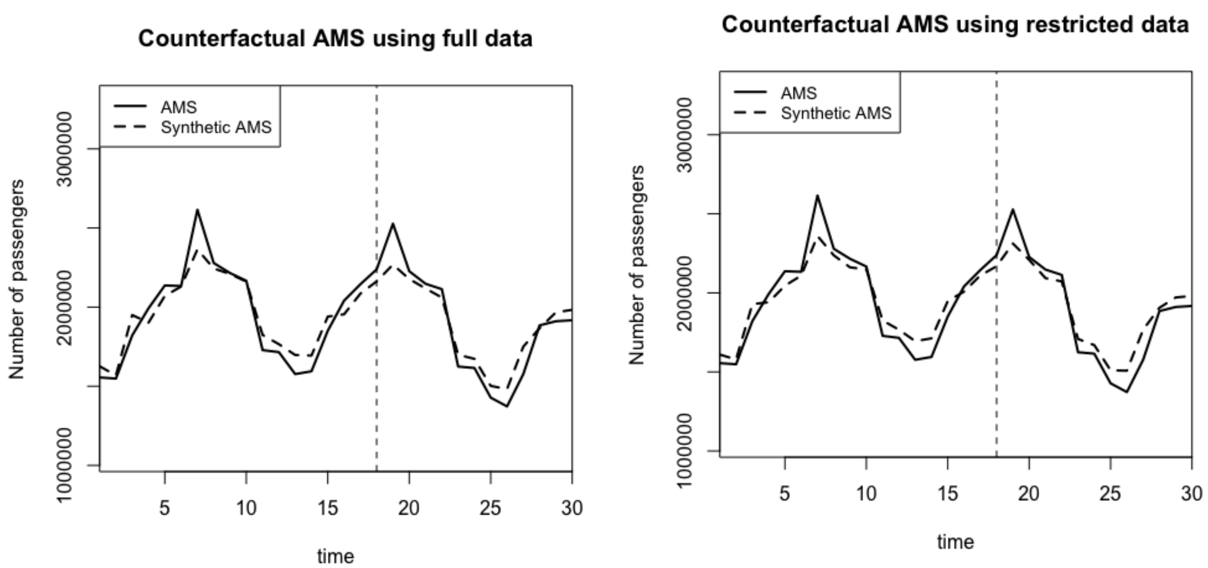


Figure 11: Counterfactuals for Amsterdam Schiphol using full and restricted data

The two plots in figure 11 show the actual and synthetic passenger numbers for Amsterdam Schiphol using the full and restricted data. We see that the chosen control units for the counterfactual are able to match the pre-treatment period quite well. Nevertheless, according the above graphs, the tax seems to have little to no effect on passenger numbers for Schiphol. A limitation of this analysis is that the data includes transfer passengers, to which the tax does not apply to. Schiphol has a sizable share of transfer passengers, meaning that the results may have a downward bias. The share of transfer passengers for Schiphol in 2007 was 41,32% (Schiphol, 2021).

Table 8: Donor weights for Amsterdam Schiphol airport

Specification & Data	Donor weights[a]
Specification 1 full data	Madrid Barajas (.017), Athens (.131), Barcelona el Prat (.002), Frankfurt-Main (.823), Munich (.003)
Specification 1 restricted data	Madrid Barajas (.055), Barcelona-El prat (.043), Frankfurt-Main (.455), Munich (.250), Paris Charles de Gaulle (.144), Roma Fiumicino (.052)

Rotterdam-The Hague airport

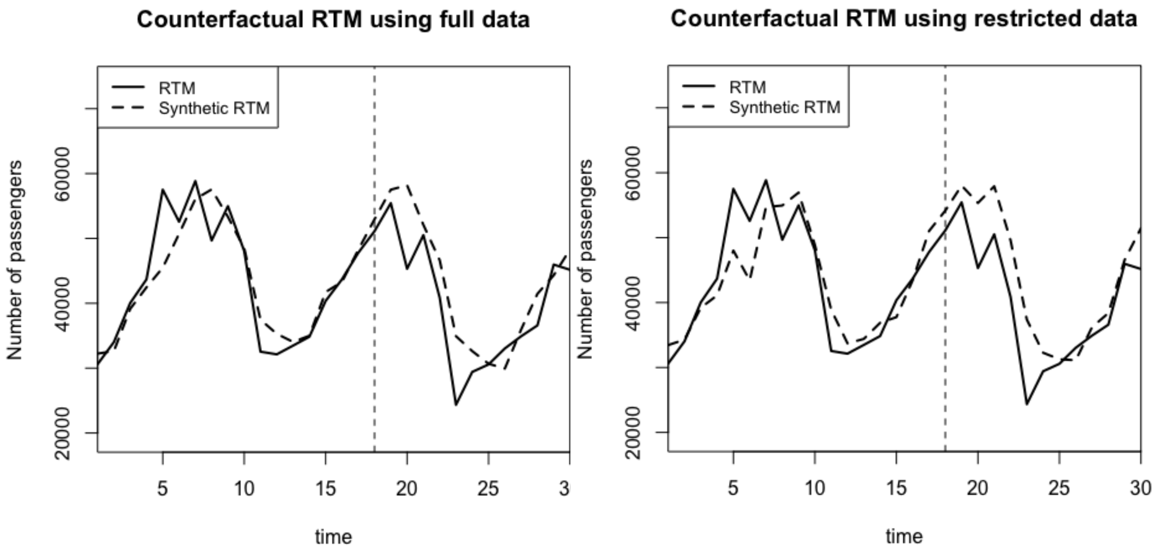


Figure 12: Counterfactuals for Rotterdam-The Hague airport using full and restricted data

Rotterdam-The Hague airport is a small international airport located in the North of Rotterdam. In contrast to Schiphol, Rotterdam airports has a low share of transfer passengers, with flights to destinations to other European cities. The counterfactual is able to match the trajectory quite closely. Nevertheless, according to the current analysis, the tax did not seem to have an effect on passenger numbers in Rotterdam.

[a] Notice that many donor weights throughout the analysis do not sum up to unity. This is because many control units do have a positive weight, albeit very small. Weights that are less than 0.002 are not reported. Weights between 0.002 and 0,005 are reported depending on the total number of already reported weights.

Table 9: Donor weights for Rotterdam-The Hague airport

Specification	Donor weights
Specification 1 full data	Brno-Turany (.004), Karlovy Vary (.729), Ostrava (.008)
Specification 1 restricted data	Dresden (.369), Karlovy Vary(.007), Ostend-Bruges (.370), Wroclaw (.234)

<u>Eindhoven Airport</u>

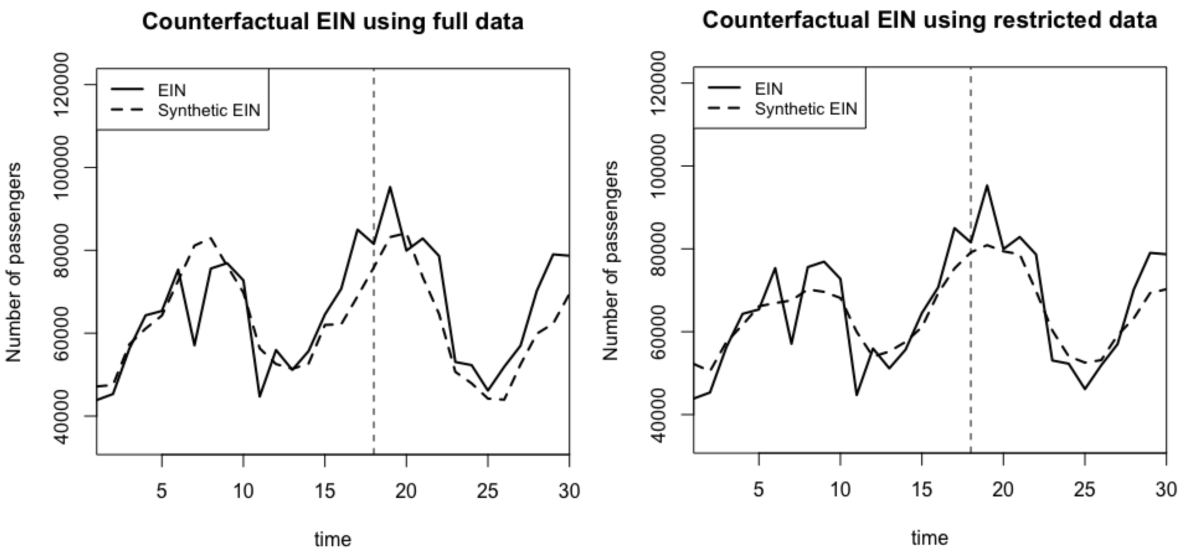


Figure 13: Counterfactuals for Eindhoven airport using full and restricted data

The counterfactuals for Eindhoven airport using the full and restricted data differ more between each other compared to the previous two airports. (As a result we see that the optimal w weights are quite different as well). The high variation from one time period to the next makes it more difficult to match that path well, especially when the donor pool does not contain units with the same variability. According to the analysis, there does not seem to be an effect of the tax on passenger numbers for Eindhoven. The counterfactual using the full data set is almost consistently laying underneath the observed path of passenger numbers. This is counterintuitive, since you would expect at least the counterfactual to lay above, indicating that if the tax would have never been implemented, the number of passengers would be higher.

Table 10: Donor weights for Eindhoven Airport

Specification	Donor weights
Specification 1 full data	Madrid Barajas (.013), Karlovy Vary (.616), Poznan (.053), Prague (.012).
Specification 1 restricted data	Beauvais-Tille (.184), Dresden (.045), Graz (.017), Malmo (.080), Ostend-Bruges (.012), Paderborn (.008), (Stockholm-Bromma (.089), Wroclaw (.494)

<u>Groningen airport</u>

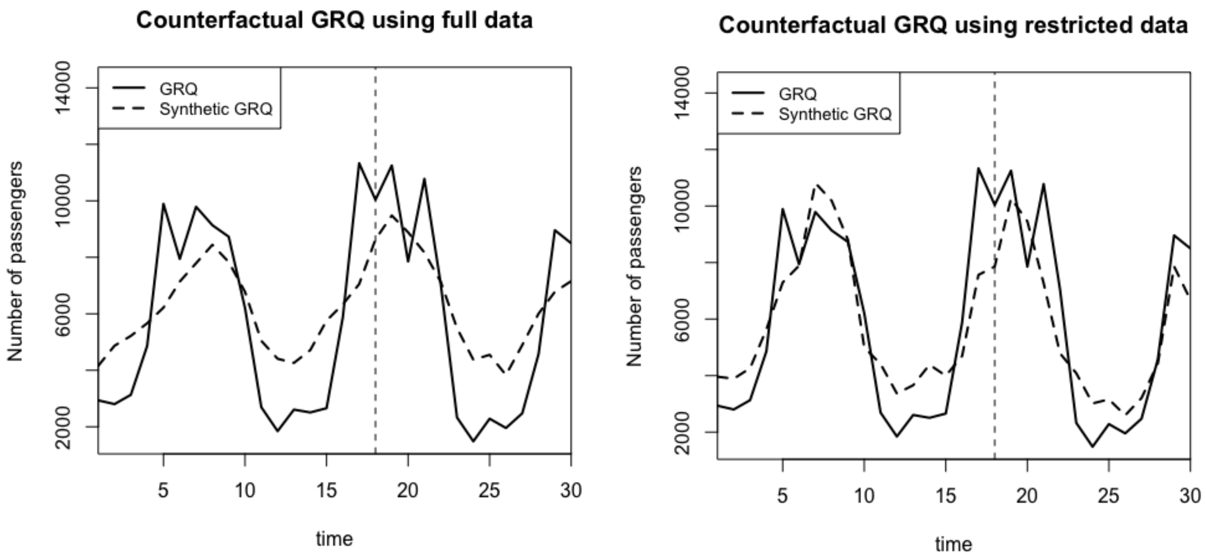


Figure 14: Counterfactuals for Groningen airport using full and restricted data

Groningen Airport seems to be an airport with high seasonality, since the number of passengers increases drastically in the summer season. The counterfactual using restricted data seems to better capture this seasonality. According to the result, the Dutch aviation tax did not seem to affect the number of departing passengers in Groningen airport.

Table 11: Donor weights for Groningen-Eelde airport

Specification	Donor weights
Specification 1 full data	Charlons Vatry (.012), Foggia (.038), Karlovy Vary (.714), Kastelorizo (.051), Poznan (.005), Skiros (.004), Syros (.099)
Specification 1 restricted data	Karlovy Vary (.258), Karlstad (.162), Ostend-Bruges (.567), Stockholm-Vasteras (.006)

<u>Maastricht-Aachen airport</u>

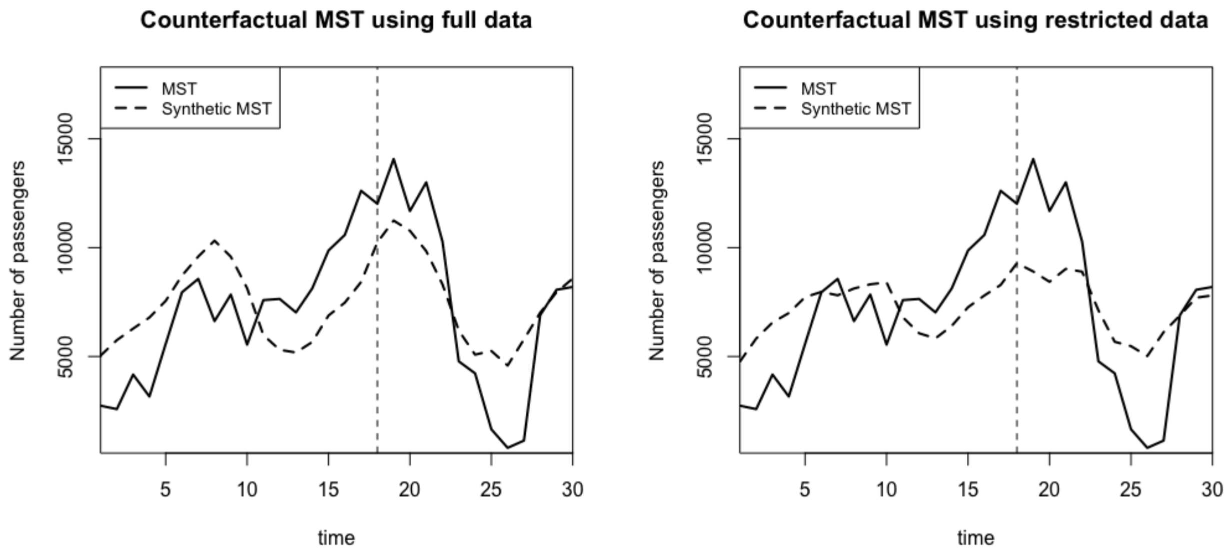


Figure 15: Counterfactuals for Maastricht-Aachen airport using full and restricted data

Maastricht-Aachen airport is located in the south of the Netherlands, close to the German and Belgian border. The airport also serves to the German city of Aachen, providing a shuttle bus service to the city. Unfortunately the counterfactual is unable to closely match the pre-treatment period. This is especially unfortunate taking into account the large unusual drop in departing passengers during the post-intervention period. This will be explained further in the discussion chapter.

Table 12: Donor weights for Maastricht-Aachen airport

Specification	Donor weights
Specification 1 full data	Brno (.002), Erfurt-Weimar (.002), Karlovy Vary (.705), Kastelorizo (.032), Poznan (.004), Syros (.121)
Specification 1 restricted data	Goteborg-Save (.062), Karlovy Vary (.648), Karlstad (.144), Malmo (.012), Stockholm-Bromma (.012), Strabourg(.121)

8.3.2 Results for neighboring airports (substitution effect).

This section provides the result for the remaining 8 airports. We expect these airports to have a higher number of departing passengers compared to their counterfactual, meaning that we expect the actual time path to lay above their synthetic version.

<u>Dusseldorf airport</u>

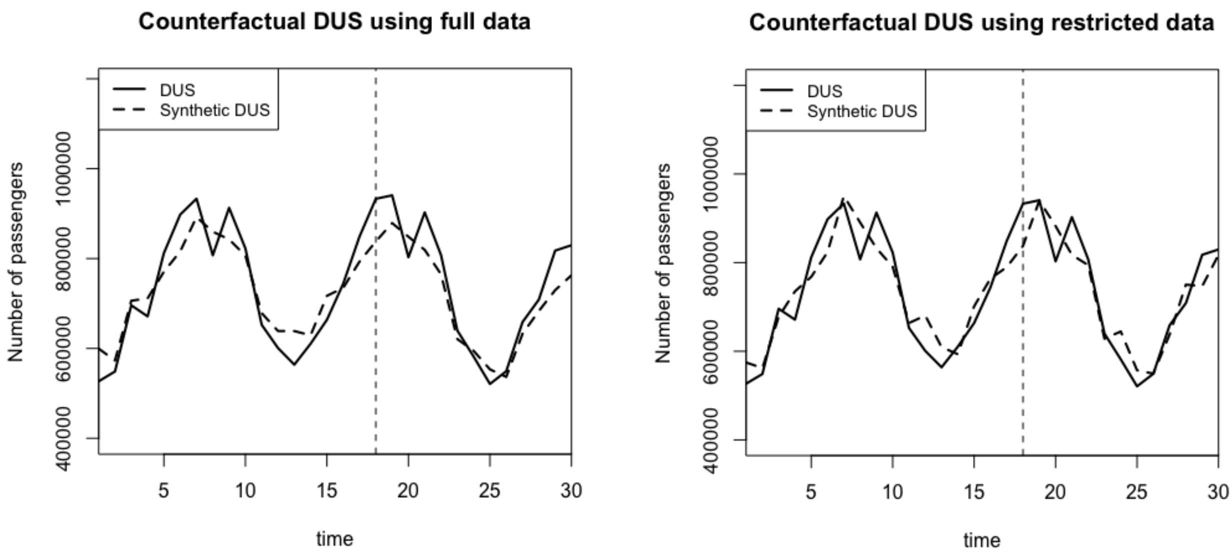


Figure 16: Counterfactuals for Düsseldorf airport using full and restricted data

Dusseldorf airport is a large international airport located around 50km from the Dutch border. Even though its position is not as advantageous, it provides multiple long haul flights, meaning that it could potentially compete against Amsterdam Schiphol. The high tax rate of 45€ makes Dusseldorf airport an attractive option for Dutch passengers. Therefore, it is interesting to investigate whether there was an increase in passenger numbers during the post-treatment period. Figure 16 shows the counterfactuals for Dusseldorf airport using specification 1 and the full and restricted data. The counterfactual is able to match the pre-treatment period relatively well. According to the results however, there does not seem to be an effect of the Dutch aviation tax on the number of departing passengers in Dusseldorf. Table 13 shows the donor weights for the two counterfactuals, and the weights are much more sparse than weights for other units.

Table 13: Donor weights for Dusseldorf airport

Specification	Donor weights
Specification 1 full data	Madrid-Barajas (.006), Athens airport (.004), Barcelona-el Prat (.007), Berlin-Schönefeld (.005), Berlin-Tegel (.008), Frankfurt-Main (.206), Munich (.021), Paris-Orly (.006), Prague (.010), Roma-Fiumicino (.006), Stuttgart (.007), Warsaw (.363).
Specification 1 restricted data	Athens (.439), Berlin-Tegel (.288), Lisboa (.007), Paris-Orly (.229), Prague (.006), Stuttgart (.007), Warsaw (.006)

<u>Weeze-Niederrhein airport</u>

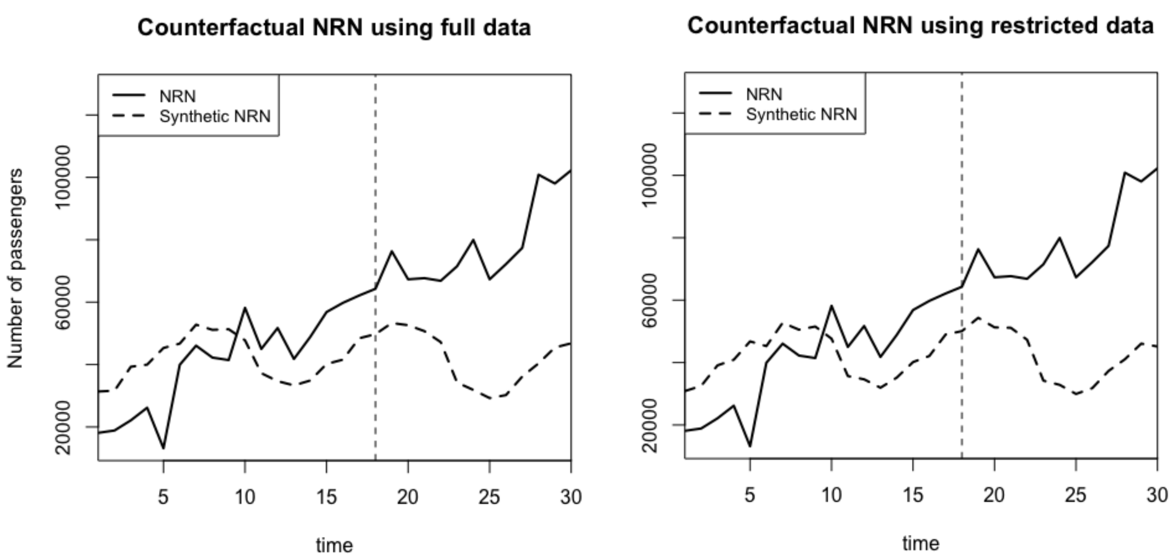


Figure 17: Counterfactuals for Weeze-Niederrhein airport using full and restricted data

Weeze airport is a small airport located very close to the Dutch border and close to the Dutch cities of Nijmegen and Eindhoven. It's a base for Ryanair, who offer many low-cost flights to various destinations. This airport is the perfect case study to investigate a substitution effect, because of its proximity to the Netherlands and because flights are provided mainly by low-cost airlines, and target the most price-sensitive passengers. Even though the pre-treatment fit is poor, the Dutch aviation tax does seem to have an effect on the number of departing passengers in Weeze airport. Further discussion is provided in the next chapter. The donor weights are also more sparse compared to the weights for the Dutch airports.

Table 14: Donor Weights for Weeze-Niederrhein airport

Specification	Donor weights
Specification 1 full data	Berlin-Tegel (.005), Erfurt-Weimar (.135), Frankfurt-Main (.005), Friedrichshafen (.043), Karlsruhe (.014), Laage (.244), Luebeck (.053), Paderborn (.009), Saarbrücken (.115), Sylt (.315).
Specification 1 restricted data	Beauvais-Tille (.098), Dresden (.146), Erfurt-Weimar(.080), Friedrichshafen (.094), Karlsruhe (.112), Laage(.074), Luebeck (.091), Paderborn (.120), Strasbourg (.038), Sylt (.072)

<u>Münster-Osnabrück airport</u>

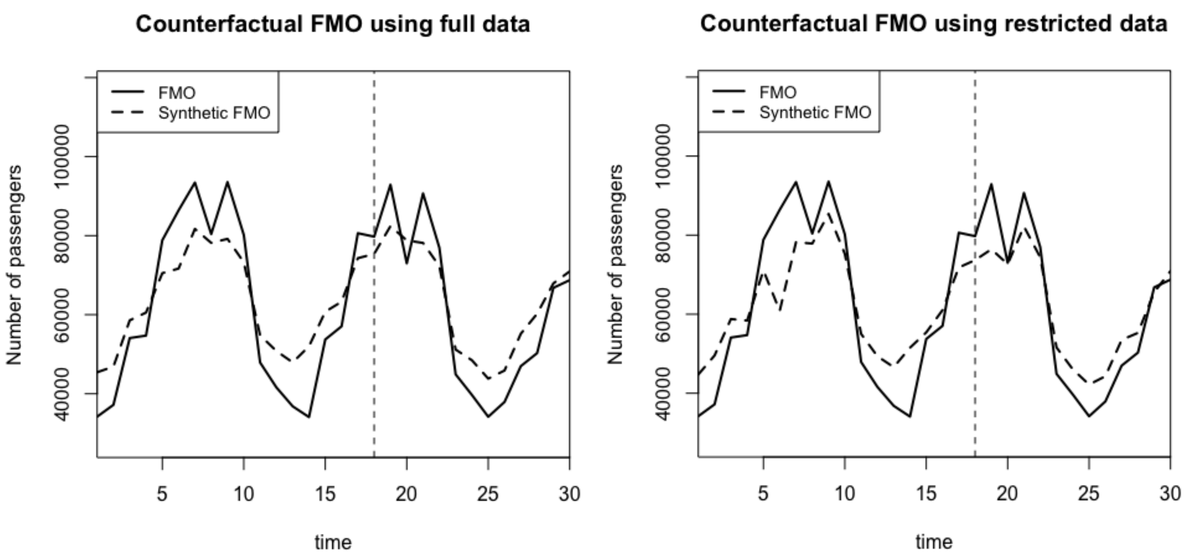


Figure 18: Counterfactuals for Münster-Osnabrück airport using full and restricted data

Münster-Osnabrück is a small airport in the German state of North Rhine-Westfalia. Similar to Groningen airport, there is high seasonality in the number of departing passengers. The possibility of Dutch passengers to use this airport may be more difficult, since it is located further away from the Dutch border compared to other German airports. According to the results, the Dutch aviation tax did not have an effect on the number of departing passengers in Münster-Osnabrück airport.

Table 15: Donor weights for Münster-Osnabrück

Specification	Donor weights
Specification 1 full data	Berlin Schönefeld (.019), Berlin-Tegel (.007), Bremen (.038), Dortmund (.038), Dresden (.042), Erfurt-Weimar (.055), Frankfurt-Hahn(.028), Friedrichshafen (.052), Hannover (.021), Karlsruhe (.049), Laage(.059), Leipzig (.038), Luebeck (.053), Nuremberg (.026), Paderborn (.047), Saarbrücken (.055), Sylt(.289)
Specification 1 restricted data	Dresden (.671), Erfurt-Weimar (.014), Friedrichshafen (.026), Karlsruhe (.055), Luebeck (.023), Paderborn (.147)

<u>Cologne-Bonn airport</u>

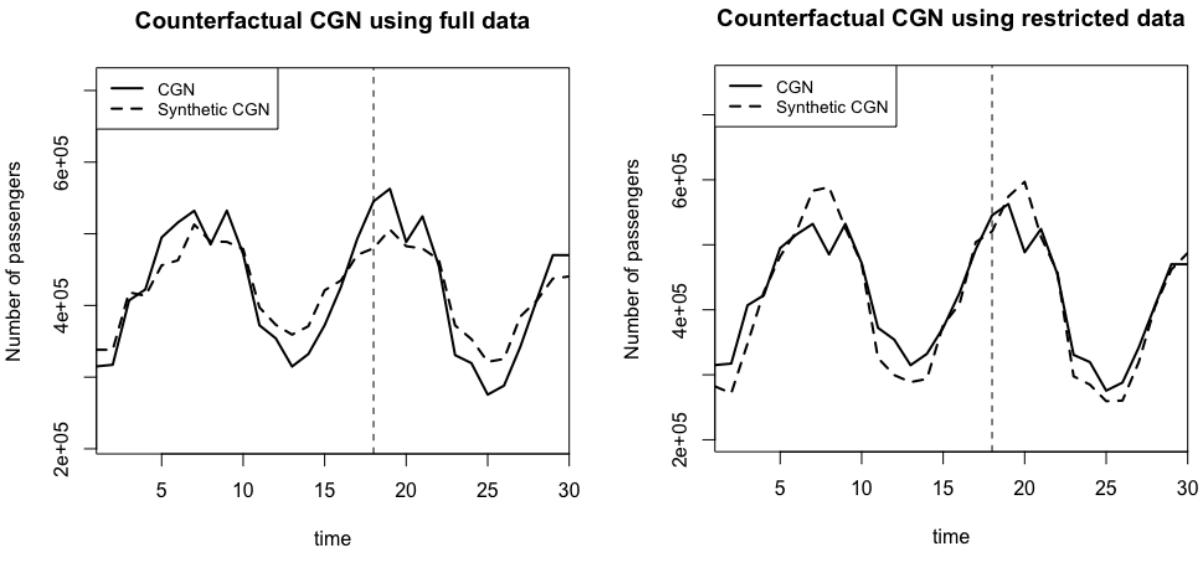


Figure 19: Counterfactuals for Cologne-Bonn airport using full and restricted data

Cologne-Bonn is a major international airport in Germany. Although it is not as close to the border compared to other airports, it is still a viable option for Dutch citizens. Figure 19 shows that the counterfactuals for the two datasets are quite distinct. Both counterfactuals have a good pre-treatment fit, but according to the analysis, there doesn't seem to be an effect of the Dutch aviation tax on the number of departing passenger in Cologne-Bonn.

Table 16: Donor weights for Cologne-Bonn airport

Specification	Donor weights
Specification 1 full data	Berlin-Tegel (.048), Berlin-Schönfeld (.043), Bremen (.040), Dortmund (.040), Dresden (.040), Erfurt-Weimar (.039), Frankfurt-Hahn (.041), Frankfurt-Main (.084) Friedrichshafen (.039), Hamburg(.047), Hannover (.042), Karlsruhe (.039), Laage (.040), Luebeck (.039), Munich (.062), Nuremberg (.041), Paderborn (.039), Saarbrücken (.039), Stuttgart (.045), Sylt(.039), Warsaw (.036)
Specification 1 restricted data	Berlin-Schönfeld (.025), Hannover (.015), Malaga-Costa del Sol (.10), Nice (.803), Palma de Mallorca (.049)

Brussels airport

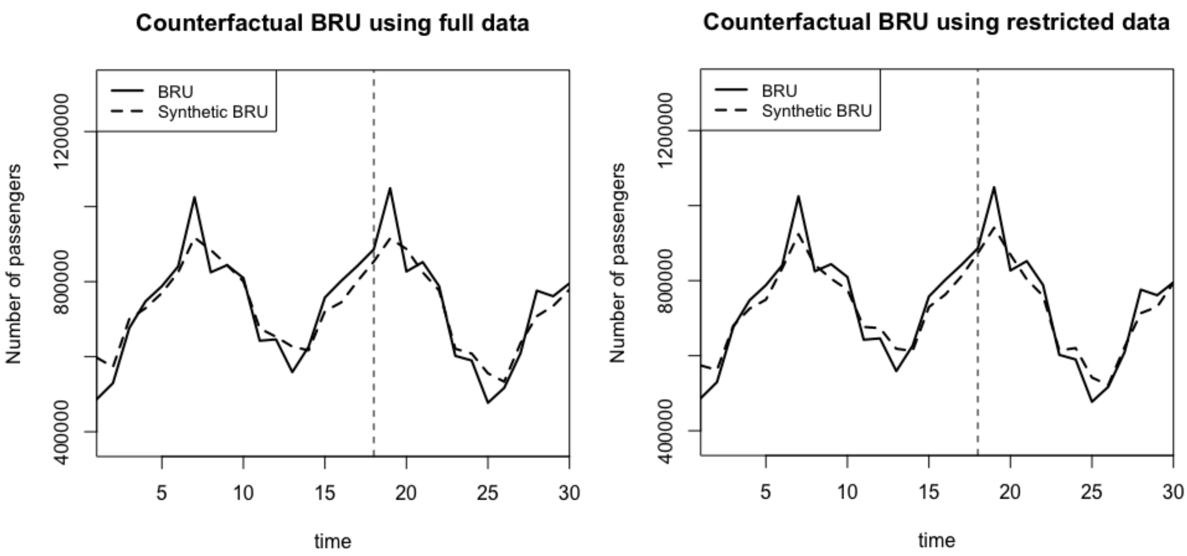


Figure 20: Counterfactuals for Brussels airport using full and restricted data

Brussels has the biggest airport in Belgium in terms of passenger numbers, and offers many international flights. Similarly to Dusseldorf, Brussels airport may offer an alternative to Dutch passengers for long-haul flights. The counterfactual is able to match the pre-treatment period relatively well, but it seems there was not effect of the tax on the number of passengers in Brussels.

Table 17: Donor weights for Brussels airport

Specification	Donor weights
Specification 1 full data	Athens (.005), Barcelona el prat (.010), Frankfurt-Main (.130), Katowice (.009), Krakow (.010), Paris-Charles de Gaulle (.071), Prague (.298), Warsaw (.063),
Specification 1 restricted data	Paris-Orly (.212), Prague (.418), Vienna (.356)

Charleroi airport

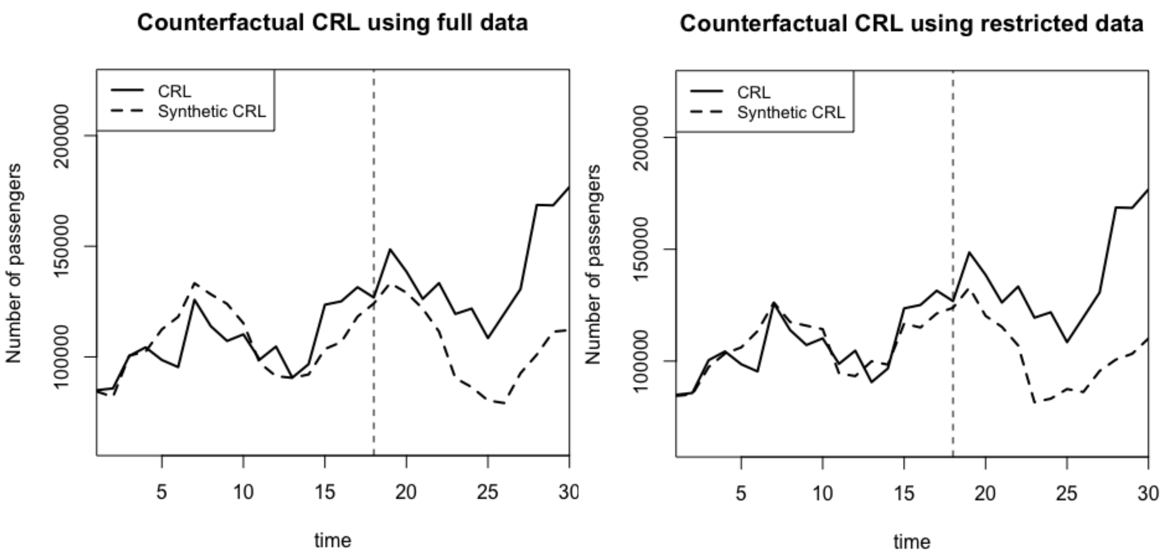


Figure 21: Counterfactuals for Charleroi airport using full and restricted data

Charleroi is a small airport located in Wallonia (Belgium). It is sometimes also called Brussels South airport as it also serves as a secondary airport to the Belgian capital. Even though this airport is located far away from the Dutch border relative to the rest of the neighboring airports in this study, it is still interesting to assess whether the tax had an impact on the number of departing passengers in Charleroi, because the airport offers many low-cost flights. This may attract price-sensitive passengers to fly from this airport instead of other Dutch airports. Although the pre-treatment fit is relatively poor, there is some indication of a positive treatment effect for Charleroi. This result will be discussed further in the next chapter.

Table 18: Donor weights for Charleroi airport

Specification	Donor weights
Specification 1 full data	Berlin-Tegel (.006), Frankfurt-Main (.025), Hamburg (.003), Katowice (.005), Krakow (.005), Munich (.012), Ostend-Bruges (.678), Poznan (.135), Warsaw (.005)
Specification 1 restricted data	Bremen (.012), Dortmund (.160), Gdansk (.478), Torino (.278)

<u>Antwerpen airport</u>

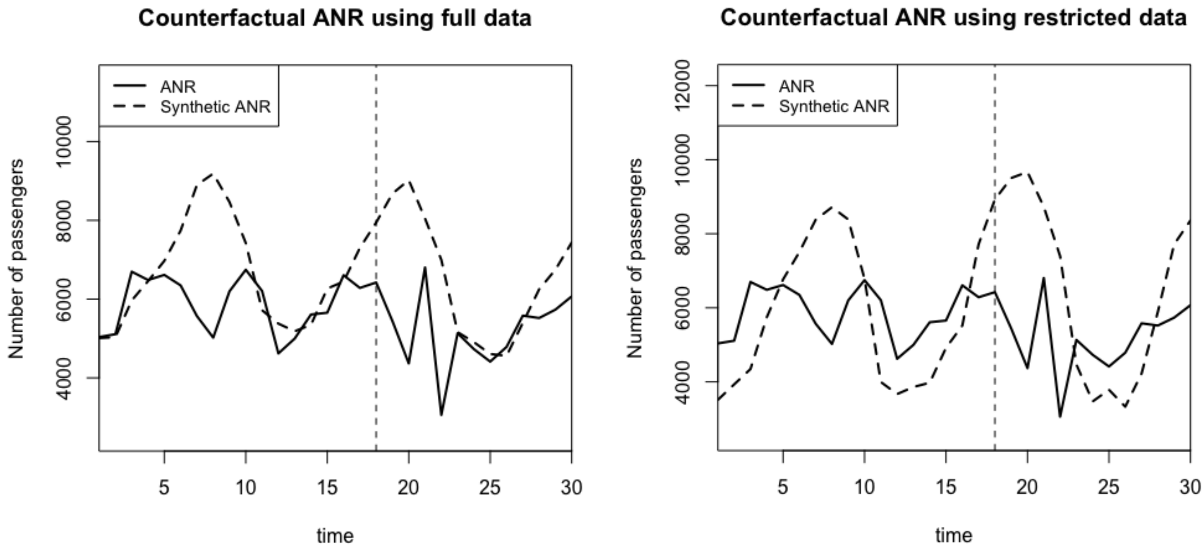


Figure 22: Counterfactuals for Antwerpen airport using full and restricted data

Antwerpen is a small international airport located in Northern Belgium, close to the Dutch border. Its location may be an advantage since it is close to major cities like Breda and Tilburg. Nevertheless, the number of departing passenger seem to follow an uncommon path, since the counterfactual has not been able to match the actual data very well. The pre-treatment fit seems to be a bit better for the full data compared to the restricted data.

Table 19: Donor weights for Antwerpen airport

Specification	Donor weights
Specification 1 full data	Astypalaia (.019), Chalons-Vatry (.074), Ikaria (.014), Kalymnos (.020), Karlovy Vary (.053), Kassos (.018), Skiros (.024), Syros (.644),
Specification 1 restricted data	Erfurt-Weimar (.012), Karlovy Vary (.0521), Karlstad (.031), Laage (.021), Lorraine (.012), Ostend-Bruges (.015), Stockholm-Vasteras (.016), Sylt (.311)

<u>Liege airport</u>

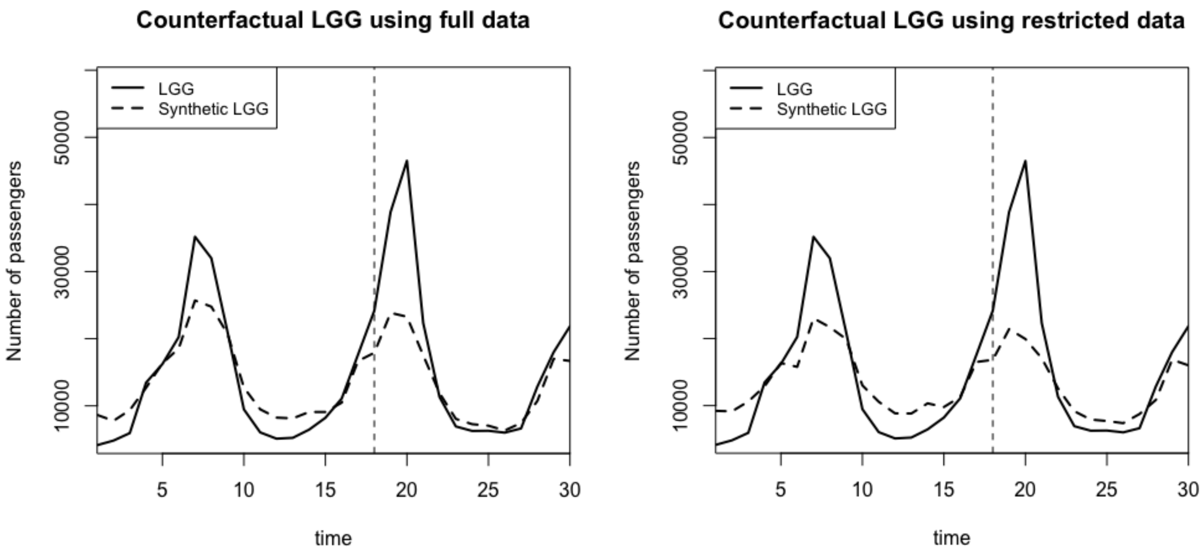


Figure 23: Counterfactuals for Liege airport using full and restricted data

Liege airport is a small airport in eastern Belgium. It lays close to Maastricht-Aachen airport, and thus, Dutch passengers in Maastricht may have used Liege airport instead. In figure 23 we observe, a rather unusual pattern of departing passengers in Liege.

Table 20: Donor weights for Liege airport

Specification	Donor weights
Specification 1 full data	Athens (.003), Iraklion (.003), Ostend-Bruges (.969), Thessaloniki (.003),
Specification 1 restricted data	Dresden (.087), Ostend-Bruges (.896), Paderborn (.003), Wroclaw (.004),

8.4 Placebo tests and inference

To evaluate the significance of the estimates, I apply the so-called placebo tests developed by Abadie et al. (2010, 2015). Because of the small sample setting of most applications of the synthetic control method, inference on the treatment effect is often difficult to apply. Placebo tests evaluate whether the results can be drawn entirely by chance. How often can we obtain results with similar magnitudes when we apply the method to units that are in fact not treated? The placebo tests consists of iteratively constructing counterfactuals using the synthetic control method to each of the control unit in the donor pool (Abadie et al., 2010). The iterative application of the synthetic control method to control units is also called placebo runs. Because the donor pool is untreated, the post-treatment period difference between the actual and counterfactual should just represent random noise. If the placebo runs create gaps of magnitude similar to the one estimated for the treated unit, we can conclude that there is not significant evidence for a strictly positive (or negative) treatment effect (Abadie et al., 2010).

After the placebo runs, The magnitude of the observed effect is normalized by dividing the mean square prediction error (MSPE) in the post-intervention period, with the MSPE in the pre-intervention period[a]. As explained in chapter 6, MSPE is the squared difference between the fitted and the actual values (Verbeek, 2017). P-values for each airport are constructed by calculating the likelihood of drawing a larger MPSE ratio out of a sample of RMPSE ratios from the placebo tests. For instance, if the MSPE ratio for the treated unit is larger than any MSPE ratio from all the control unit, we can be fairly confident that the treatment effect has not been drawn by chance, and therefore, the p-value in this case would be zero. The null hypothesis of no treatment effect is:

$$H_0\colon \tau_{1t} = y_{1t}^I - y_{1t}^N = 0 \tag{8.1}$$

[a] A different approach in the SCtools package is available, which consists of calculating the treatment effect of the treated unit and all the placebos. The advantage is that the corresponding distribution of the treatment effect is two-tailed (compared to the one-tailed distribution of the MSPE ratios), because it allows for both positive and negative effects. Nevertheless it does not take into account the pre-intervention fit. The MSPE ratio approach is also much more common in the synthetic control literature, which is why it was chosen.

Table 21: MSPE ratios and p-values from the placebo runs using both specifications.

Airport	Spec 1 MSPE ratio	Spec 1 p-value	Spec 2 MSPE ratio	Spec 2 p-value
Amsterdam Schiphol	1.290	0.401	1.233	0.259
Rotterdam/The Hague	2.099	0.293	2.135	0.310
Eindhoven	1.828	0.391	1.282	0.416
Groningen	0.979	0.857	1.071	1
Maastricht/Aachen	0.940	0.783	1.421	0.857
Dusseldorf	0.922	0.755	0.661	0.883
Weeze/ Niederrhein	7.587	0.016**	2.648	0.084*
Munster/Osnabrück	0.685	0.886	0.796	0.783
Cologne/Bonn	1.185	0.338	0.815	0.785
Brussels	1.221	0.306	1.250	0.250
Charleroi	11.646	0.004***	15.127	0.007***
Antwerpen	1.917	–	3.479	–
Liege	4.491	0.192	3.469	0.264

Table 21 shows the MSPE ratios and p-values for the treated unit using both specifications. The placebo runs are only applied to the full dataset, in order to make the p-values more robust, due to the bigger donor pool. The p-value measures how extreme a MSPE ratio is, given the sample of all MSPE ratios.

A very important caveat for the p-values is what to do with extreme values. Abadie et al. (2010, 2011) and Firpo & Possebom (2018) suggest to include only placebo units with a good pre-intervention fit when calculating p-values. More specifically, they propose to discard placebo units whose pre-intervention MSPE is five times or higher than that of the treated unit. This is because these placebo units are not informative of the relative rarity of the post-intervention effect of the treated unit. This recommendation is followed, and the p-values only change slightly. Most of the times the p-values change towards a more conservative (higher) one.

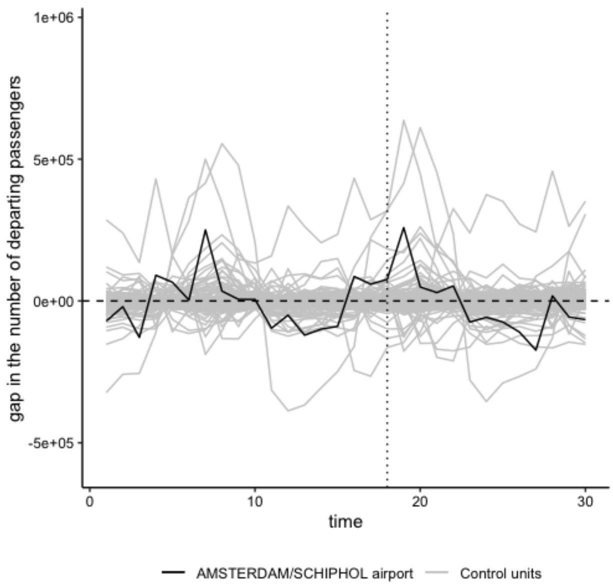


Figure 24: Placebo runs for Amsterdam-Schiphol airport

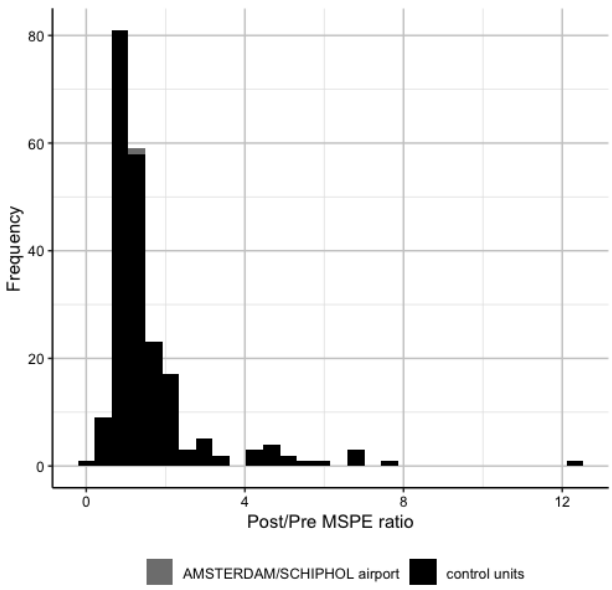


Figure 25: Distribution of the MSPE ratios

Figure 24 shows the placebo runs for Amsterdam-Schiphol. The lines represent the gap between the synthetic control and the actual data. Notice that the y-axis is presented in absolute terms, and thus the large deviations seen in the figure does not necessarily mean large differences between counterfactual and actual data, but rather regular-sized deviations but from airports with a large number of departing passengers. This is because although deviations are relatively small, they can be large in absolute terms when the number of departing passengers is also large.

Figure 25 shoes the distribution of the MSPE ratios. For illustrative purposes, we see where the MSPE ratio for Amsterdam-Schiphol (specification 1) lays in the distribution.

9 Discussion

This chapter provides an interpretation and discussion of the results, and puts them in the broader context of the literature. A separate section on the limitations of this study is provided, as well as a section on alternative methodological approaches that could have been used, within the synthetic control framework.

9.1 Interpretation and discussion of the results

This study aimed to quantify the impact of the Dutch aviation tax on the number of departing passengers. From the visual inspection of the counterfactuals, together with the MSPE ratios and p-values, it can be concluded that the analysis at hand did not find an effect of the Dutch aviation tax on departing passenger numbers.

Some of the treated units in the analysis have a relatively good pre-treatment fit. Inspecting the results a bit deeper, it is noticeable that most airports with a high number of departing passengers have a good pre-treatment fit. This suggests that large airports are more cointegrated among them, since their passenger numbers follow a closer pattern. On the other hand, smaller airports have a relatively poor pre-treatment fit. This is unfortunate, because an aviation tax is expected to have a larger effect on smaller airports, owning to the fact that these airports have normally a higher share of low-cost carriers (LCC), and therefore the passengers are more price-sensitive. Larger airports often have a larger share of business passengers, who are less price-sensitive. It is unfortunate then that we cannot be as confident with respect to a positive treatment effect on smaller airports due to the poor pre-treatment fit.

9.1.1 Effect on Dutch airports.

As mentioned in the previous chapter, the pre-treatment period fit for Amsterdam-Schiphol is relatively good. Nevertheless, the results are biased since the data contains the number of departing transfer passenger, to which the tax does not apply to. This becomes more apparent when we disaggregate the data and look into the types of passenger separately. In 2008, the year in which the Dutch aviation tax was introduced, the number of departing passengers decreased relative to the previous year, while the number of transfer passengers kept increasing (Schiphol, 2021). Investigating this disaggregated data is outside the scope of this thesis report, but it is an interesting direction for further research.

The Dutch aviation tax seems to not have an effect on Eindhoven and Rotterdam-The Hague. Eindhoven already had an upward trend if we look at figure 10. During the studied period (grey area) the passenger numbers stagnates, but we cannot concluded that this is due to the tax, the financial crisis, or a combination of the two. Rotterdam-The Hague airport has the largest MSPE ratio (2.099) out of the Dutch airports, according to the results, the passenger numbers of the airport have not significantly been impacted by the tax.

Gordijn & Kolkman (2011) point out that the supply in Groningen airport is primarily comprised by holiday travel packages, which explains the large increases in traffic during the summer season. Moreover, the tax comprises a small portion of the total price of the holiday package, which partly explains why, according to the result, the tax did not affect the number of departing passengers in Groningen.

A few months after the introduction of the tax, air passenger numbers decreased sharply in Maastricht-Aachen airport, and reached a low in January 2009. At a first glance, one would conclude that this sharp decrease is due to the introduction of the tax. Nevertheless, we are unable to conclude this according to the analysis, because of the very poor pre-treatment fit, and the MSPE ratio is lower than 1.

9.1.2 Effect on neighboring airports

The analysis in this thesis report does not find an impact of the Dutch aviation tax on the number of departing passengers. In Düsseldorf airport. The MSPE ratio is also very low, as it is lower than 1. Nevertheless, there is some anecdotal evidence that the number of Dutch passengers did indeed increase in Düsseldorf, as shown by Gordijn & Kolkman (2011). They show that the number of Dutch passengers increased substantially in 2008 and a further increase in 2009. At the same time, the overall number of passengers increased slightly in 2008 compared to the previous year and actually decreased in 2009. This is a possible explanation of why the analysis wasn't able to find a treatment effect on Düsseldorf airport. This evidence is only circumstantial and thus, we are still unable to conclude a positive treatment effect on Düsseldorf, but it does help explain the results of the analysis.

Weeze airport has one of the largest MSPE ratios, and a quick glance at the counterfactual may seem that the Dutch aviation tax did have an effect on the number of departing passenger. Nevertheless, figure 10 shows that Weeze airport already had an upward trend, which kept increasing after abolishing the tax. Furthermore, the pre-treatment fit is relatively poor, and Abadie et al. (2010, 2015) advise against reaching any conclusions when this is the case. When the pre-treatment fit is poor, it means that there is no control unit that is able to closely match the path during the pre-treatment period. The growth in Weeze airport during that time was quite unusual, which is why we are unable to conclude whether the Dutch aviation tax had an effect on the departing passenger numbers for this airport. The synthetic control method is therefore unfit to assess the impact of the tax for this case specifically.

For Münster-Osnabrück and Cologne-Bonn airport, we observe a good pre-treatment effect but no impact of the Dutch aviation tax. This might because they are relatively far away from the Dutch border, or the destinations offered by these airports where different from airports in the Netherlands, offering a poor substitution.

Brussels airport has a good pre-treatment fit, as it is one of the bigger treated airports. There is no effect of the Dutch tax however. On the other hand, Charleroi airport has the biggest MSPE ratio with a p-value lower than 0.01. The pre-treatment fit is relatively good, so everything points toward there being an effect of the tax on the number of departing passengers. Nevertheless, figure 10 shows that there was already an increasing trend in passenger numbers. Furthermore, there are two events that could have caused a large shock or an effect on the departing passenger numbers in Charleroi. The first one is the opening of a new terminal in January 2008 (Brussels South Charleroi Airport, 2021) which allowed for an increase in the supply of flights. Secondly, Witlox & Derudder (2010), as cited in Gordijn & Kolkman (2011), state that the growth can be attributed to the expansion of Ryanair.

Antwerpen airport has an unusual pre-intervention time period, which is why it is difficult to have a good fit. The lack of seasonality is due to the fact that most of the demand comes from business passengers, and there are no low-cost airlines. Moreover, Antwerpen airport has no p-value because all the placebo runs have a pre-treatment MSPE 5 times higher than that of Antwerpen. Liege airport lies very close to the Dutch border and the Dutch city of Maastricht. The passenger numbers seem to be highly seasonal, peaking in one of the summer months. Liege has a relatively big MSPE ratio, which would normally result in a statistically significant result of a p-value lower than 5%. However, we discard extreme placebos, which is why the current p-value is 0.192.

9.1.3 Donor and predictor weights.

The donor weights represent how much each control unit in the donor pool contributes to the counterfactual. Synthetic controls are typically sparse, meaning that only a few units in the donor pool contribute to the counterfactual (Abadie, 2020). Nevertheless, from table 5 we conclude that the convex hull condition is met for every treated unit, i.e. the pre-intervention predictors for the treated unit, $\boldsymbol{x_1}$ fall within the columns of the pre-intervention predictors for the untreated units, $\boldsymbol{X_0}$. When this is the case, the results may not be unique nor sparse. From the donor weight tables we see that the weights are indeed not sparse. More specifically the sum of many weights are far from 1, and some treated units have a high number of control units contributing to the counterfactual. This is not a problem per se, but it does decrease the interpretability of the results.

Table 22 shows summary statistics for all 52 sets ($13 \times 2 \times 2$) of predictor weights. Departing passengers is by far the most important predictor for constructing the counterfactual. It is fairly common in applications of the synthetic control method that the inclusion of the dependent variable as a predictor, results in the respective v-weight to be higher compared to the weights for the remaining covariates. Many applications ditch the covariates altogether, and only use the dependent variable. The reason why the covariates do not contribute as much to the counterfactual is because of the low correlation with the dependent variable. See appendix E for the correlation matrix.

Table 22: Summary statistics for predictor weights (Both specifications)

Variable	**Min**	**1st Q**	**Median**	**Mean**	**3rd Q**	**Max**
Departing passenger (mean or first lag)	0.0138	0.5912	0.8391	0.7230	0.9097	0.9995
Industrial output	0	0.0001	0.0349	0.0099	0.1121	0.5179
Ticket price	0	0.0001	0,0007	0.1088	0.1560	0.5300
Jet fuel price proxy	0	0.0002	0,0028	0.0689	0.0843	0.7133

9.1.4 Specifications and data used.

Table 21 shows the MSPE ratios and p-values for both specifications. The MSPE ratios do not differ much between the two cases, but it seems like the p-values tend to be slightly higher in specification 2 compared to specification 1. Nevertheless the same conclusions are reached in both of them.

The only way to compare the results between the full an the restricted data is the visual inspections of the counterfactual graphs. The difference between the two seem to be rather small, although in some cases it seems like the pre-treatment fit is better when using the restricted data.

9.1.5 Comparison to the literature

Chapter 4 provided a literature review on the econometric analysis of different impacts on the aviation sector. More specifically, 8 studies focus on the introduction of a tax or a change in the tax rate. Four studies found an effect, two found a small, almost negligible effect, while the two remaining studies didn’t find any effect. This study did also not find an effect of the tax. There are multiple reasons why this may be the case. For instance, Markham et al. (2018) believe that the Australian carbon tax did not have an effect on revenue passenger kilometers (RPKs), a measure for demand, because of the high competition between the two main airlines, which resulted in not passing the tax onto consumers. Nevertheless, a more plausible reason why the Dutch aviation tax did not have an effect is because the short life span of the tax and the low tax rate. Airline ticket prices are often quite volatile, and thus, it would be difficult for consumers to notice the increase in price due to the tax.

A more interesting comparison would be with Borbely (2019), who investigate the impact of the German aviation tax using the same methodology. This study offers some strengths over Borbely's (2019) paper. For instance, this study uses monthly data instead of yearly, so it would have been possible to identify effects happening within a year. This also allowed to have a higher pre-treatment period of 18, compared to the 8 pre-treatment periods in Borbely (2019). It is well known in the synthetic control method literature that a higher number of pre-treatment period is beneficial for the estimate. Furthermore, Borbely (2019) uses O-D passenger data, which is more aggregate than the data used in for this thesis report, which is departing passengers. Both the German and Dutch aviation tax applies on departing passengers excluding transfer.

Nevertheless, Borbely (2019) has a more in-depth selection strategy for the donor pools. One dataset consisting of airports in the EEA and a smaller subset based on airports in countries surrounding Germany. Out of these two sets, the donor pool is further limited to airports with passenger numbers that are at most twice or half times as large as the treated airport. The one with the best fit is reported. This thesis report used the entire dataset, and a subset based on airport type and proximity. Borbely (2019) also reports pre-treatment errors in percentage, and states that anything above 5% is a poor fit, and the result should be taken with care. Moreover, because Borbely (2019) uses annual passenger numbers, covariate data is available on a smaller geographical level. For instance, one of the covariates used is NUTS2 level GDP purchasing power per capita, while this thesis uses a country-level industry output index.

9.2 Limitations

Here I present some of the limitations and shortcomings of the current analysis. As mentioned in chapter 7, a subset of the entire data was also used to construct the counterfactuals. Using this subset is more fitting, since one of the methodological requirements is to restrict the donor pool to units that are similar to the treated unit (Abadie, 2020). In order to subset the data, the criteria from Malighetti et al. (2009) was used to create the donor pools. This study is one of the most comprehensive ones in the classifications of airports. The authors do not provide a full list of airports with their classification but rather, give some examples for each type of airport. The authors were contacted in order to provide this list but unfortunately, there was no response. The way the donor pool was actually chosen was to subjectively decide what units enter the donor pool based on the number of passengers and information searches of the airport, in order to conjecture what type of airport one might be. There is a possibility therefore, that the final donor pool was not optimally chosen, or that that this resulted in the introduction of subjectivity bias in the analysis.

Another limitation is that the current analysis is related to the data availability. It is likely that the Dutch aviation tax did have an effect on passenger numbers, albeit very small. Using aggregate data makes the possible effect of the Dutch aviation tax indistinguishable from random noise, since current impact evaluation methods are unable to differentiate it. Therefore, there is a need to use alternative methods or more disaggregated data. For instance, Gordijn & Kolkman (2011) use a rational choice model, as well as surveys, polls, and airport data, to assess the possible effect of the Dutch aviation tax.

A third shortcoming, is the lack of pre-treatment errors, which could have complemented the analysis very well. Borbely (2019) reports pre-treatment errors in percentage, and state states that anything above 5% is a poor fit.

Lastly it is important to keep in mind the possibility of bias in the calculation of the p-values. This is because placebos are not treated equally compared to the treated units. In the construction of the counterfactual for a treated airports in the Netherlands, the airports surrounding it are excluded, while this is not the case for the placebos. Closer airports are more likely to face similar macroeconomic and regional shocks, and thus, the counterfactuals for the treated and placebo units are handled differently.

9.3 Different approaches

This section provides alternative methodical approaches that this study could have applied, within the synthetic control framework. I first mention some of the many extension of the method that have been developed in recent years, and explain those that are relevant to the study at hand. Secondly, I explain ways to increase the robustness of the results, and lastly a criteria to choose the donor pool.

9.3.1 Extensions of the synthetic control method

The synthetic control literature has increased tremendously in the last decade, and many researchers have tried to expand the standard methodology in order to solve some of the issues that the methods brings. Here, I will discuss some of these extensions that are relevant to the case study of this thesis report, and may be used for further research.

One of these methods is the generalized synthetic control method by Xu (2017). It essentially links the SCM with regression-based analysis. The first step of this method is to estimate an interactive fixed effect (IFE) model using only control data, to obtain a fix number of latent factors. It then estimates factor loadings for each treated unit by linearly projecting pre-treatment treated values onto the space spanned by these factors. Finally, it calculates counterfactuals based on these estimated factors and factor loadings. This method relates to the SCM in the sense that it is a reweighting scheme. This method provides two advantages: Firstly, it allows the treatment to be correlated with time heterogeneities under reasonable modelling assumptions. Secondly, and most importantly to the context of this study, it generalizes the method to take into account multiple treated units at once, which contrasts with the standard synthetic control method to deal with treated units, by just calculating individual synthetic controls and stacking them up. This method has been applied – among others – to study the effectiveness of the Kyoto protocol (Maamoun, 2019), the evaluation of large-scale infrastructure projects (Kunimi & Seya, 2021) and the effect of short-term rental regulations on home-sharing platforms such as Airbnb (Chen et al., 2021).

Another relevant method for the case study of this thesis is the augment synthetic control method (ASCM) by (Ben-Michael et al., 2020). As explained by Abadie et al. (2010, 2015), a poor pre-treatment fit can introduce biases in the SC estimator. The augmented version tries to tackle this problem, by trying to estimate this bias using ridge regression and accounting for it in the estimate. Nevertheless, this estimator does allow for negative weights, which was one of the main advantages of the standard SCM. Regardless of this, the authors show substantial gains from this using extensive simulations. Because some results from this thesis report have a poor pre-treatment fit, this extension of the method can be applied in further research, with the aim to increase the robustness of the results. Some of the applications are the impact evaluation of crime-reducing policies (Kahmann et al., 2020), the effect of lockdown measures due to the COVID-19 pandemic in Chile (Bennett, 2021), and the impact this pandemic on air pollution and health in different cities in China (Cole et al., 2020).

The third and last of the methods discussed here is the multivariate synthetic control method using time series (MSCMT) by Becker & Klößner (2018), although computationally very hard, it offers three advantages over the standard SCM. Firstly, it can take into account various outcome of interests instead of only one. This is a very attractive feature, since policy interventions will likely affect multiple outcomes. In the context of this thesis, it may be interesting to also include carbon dioxide emissions as an outcome of interest (if such data is available), in order to investigate whether a potential decrease of passenger number due to the introduction of a tax also results in a reduction in CO_2 which is the ultimate goal if the tax has environmental purposes. A second advantage is that whole time series of predictor variables can be included. In the standard synthetic control method, the mean of predictors is often used as the numbers that need to be approximated by the synthetic control. By taking the mean (or any other arithmetic transformation), you discard part of the information given by your data, because the within variation (variation among time) is not taken into account. This method allows to include entire time series of predictors, meaning that counterfactuals could also be calculated for the predictor variables. Moreover, because more information is extracted from the dataset, the estimators can be more accurate. The third advantage is that the cross-validation approach used in Abadie et al. (2015) is improved and better defined. Klößner & Pfeifer (2018) apply this method to evaluate the impact of the German "Cash for Clunkers" program, which aimed to trade less-fuel efficient vehicles with more-efficient ones. They use two outcome of interests: vehicle registrations and carbon dioxide emissions.

9.3.2 Increasing robustness

To increase the validity of the results, multiple robustness checks can be implemented. In this thesis, the only robustness check performed is the placebo tests, which allowed to calculate MSPE ratios and p-values. In this section I mention additional checks that could potentially be applied to this case study.

One very simple robustness check is to construct and report counterfactuals with a different set of weights. This is done by Anderson et al. (2021), who study the impact of an hypothetical EU-ETS type scheme on CO_2 emissions in Australia, if it would have implemented one in 2005. Because of the small donor pool, the authors decide to construct counterfactuals based on equal weights, restricted least squares weights, etc. The results do not change significantly, and thus, conclude that the results are robust.

Another way of increasing robustness is by adding more specifications as suggested by Ferman et al. (2020). For the case study at hand, adding a specification in which the data is transformed to first-differences would be beneficial. Lu (2021) suggest to transform the data to first-differences when the data seems non-stationary. There are already some treated units in the data set with characteristics of non-stationary series, and this will rise if the time period is increased, because of the presence of clear trends in passenger numbers. Lu (2021) also shows that his results are more robust after the first-difference transformation.

Lastly, the synthetic control literature has expanded greatly in the last years in terms of inference. The original approach from Abadie et al. (2010, 2015) makes inference based on permutation distributions. A different approach is that of Chernozhukov et al. (2021a, 2021b). The method calculates t-statistics for the treatment effect, and is therefore able to calculate confidence intervals. Firpo & Possebom (2018) develops a method to analyze the null hypothesis of no treatment effect with multiple treated units. Cattaneo et al. (2021) presents a method to calculate prediction intervals. For this study specifically, it would be very interesting to calculate confidence intervals of the treatment effect.

9.3.3 Choosing control units

The original study by Abadie & Gardeazabal (2003) suggests to choose control units that are similar to the treated unit. This study follows this suggestion by constructing counterfactuals using a donor pool chosen on the basis of airport typology and proximity. Nevertheless, this study could also follow the suggestion from Harvey & Thiele (2020), who go a step further by proposing to restrict the donor pool to only units that are co-integrated with the treated unit. This "cointegration" method relates to the original synthetic control method, since it is argued by (Abadie, 2020) that the method is designed to exploit the co-movement among the treated and untreated units that are driven by common factors. Furthermore, this method formalizes the choice of control unit, since the method of selecting the donor pool suggested by Abadie & Gardeazabal (2003) remains a subjective choice. One further advantage is that it helps against specification searches.

10 Conclusion

This thesis investigated the effect of the Dutch aviation tax that was introduced in July 2008 and abolished one year later, on the number of departing passengers. The possible effect of the tax was investigated on Dutch airports, to which the tax applied to, and airports that are outside of the Netherlands, but close to the Dutch border, to investigate a substitution effect. This is because it was hypothesized that Dutch passengers would start using airports in neighboring countries. Nevertheless, the analysis of this thesis report has not been able to establish a causal effect of the tax on the number of departing passengers. Based on the results, we conclude that the tax was ineffective. Even though there might have been an effect of the tax, it likely to be very small, almost negligible. The large fluctuations in passenger numbers, as well as the differences in airport characteristics makes it a difficult task to detect the effect of the tax. A possible way forward is to use different methodology, or use more disaggregate data if available. A possible explanation for the results of this thesis report is that the tax was short-lived and too small to have any meaningful impact on the demand for air travel.

To answer the main research question, this thesis used the synthetic control method, a fairly recent method in the impact evaluation literature. The method combines elements of difference-in-differences and matching estimators. It involves the construction of a weighted combination of control units, to which the treated unit is compared to. These weights are chosen in way to minimize the pre-treatment difference between the treated unit and its counterfactual. The method has increased greatly in popularity, and is now an established method in the impact evaluation tool-kit. Furthermore, the numerous extensions on the synthetic control framework increases the desirability of the method.

The aviation sector contributes 2% of global GHGs, but is one of the fastest growing sources (Capoccitti et al., 2010). Its climate impact is even bigger because of the formation of contrails and cirrus clouds, as well as emissions of nitrogen oxides (Lee et al., 2009). There is a strong need for carbon taxes to slow down the growth of the aviation sector, as well as a way to correctly price the externality that the sector causes. Even though the number of aviation taxes have increased throughout Europe, it's likely that these taxes do not represent the true cost of the externality.

In conclusion, this study founds no effect of the Dutch aviation tax on the number of departing passengers. There might still be an effect of the tax, but it's likely to be very small. The Netherlands introduced another aviation tax in 2021. This tax is 7,845€ per passenger, so it's smaller than the tax investigated in this thesis report. Therefore, it is likely that this does not represent the true cost of the externality. The Netherlands could have learned from the 2008 tax and introduce meaningful and effective taxation in the aviation sector, that is needed to mitigate GHG emissions.

Appendix A: Derivation of the OLS estimator.

Consider the following regression equation:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \qquad (A.1)$$

The residual $\hat{\boldsymbol{\varepsilon}}$ is defined as $\hat{\boldsymbol{\varepsilon}} = \boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}}$. OLS minimizes the residual sum of squares, therefore:

$$\widehat{\boldsymbol{\beta}} = (\hat{\beta}_0, \hat{\beta}_1) = \arg\min\left\{\sum_{i=1}^{N} \hat{\boldsymbol{\varepsilon}}_{\boldsymbol{i}}^{\boldsymbol{2}}\right\} = \arg\min\left\{\sum_{i=1}^{N}\left(\boldsymbol{y}_{\boldsymbol{i}} - \widehat{\boldsymbol{\beta}}_{\boldsymbol{0}} - \boldsymbol{x}_{\boldsymbol{i}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{1}}\right)^2\right\} \qquad (A.2)$$

Using matrix notation:

$$\widehat{\boldsymbol{\beta}} = \arg\min\left\{\sum_{i=1}^{N} \hat{\boldsymbol{\varepsilon}}_{i}^{\boldsymbol{2}}\right\} = \arg\min\{\hat{\boldsymbol{\varepsilon}}'\hat{\boldsymbol{\varepsilon}}\} = \arg\min(\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}})'\,(\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}}) \qquad (A.3)$$

$$= \arg\min\left[\boldsymbol{y}'\boldsymbol{y} - \boldsymbol{y}'\boldsymbol{X}\widehat{\boldsymbol{\beta}} - (\boldsymbol{X}\widehat{\boldsymbol{\beta}})'y + \widehat{\boldsymbol{\beta}}'\boldsymbol{X}'\boldsymbol{X}\widehat{\boldsymbol{\beta}}\right] \qquad (A.4)$$

Since $\boldsymbol{y}'\boldsymbol{X}\widehat{\boldsymbol{\beta}}$ and $(\boldsymbol{X}\widehat{\boldsymbol{\beta}})'y$ have the same dimension, we can rewrite equation

$$\widehat{\boldsymbol{\beta}} = \arg\min\left[\boldsymbol{y}'\boldsymbol{y} - 2\boldsymbol{y}'\boldsymbol{X}\widehat{\boldsymbol{\beta}} + \widehat{\boldsymbol{\beta}}'\boldsymbol{X}'\boldsymbol{X}\widehat{\boldsymbol{\beta}}\right] \qquad (A.5)$$

Differentiate with respect to $\widehat{\boldsymbol{\beta}}$ and set equal to zero. The first term goes away, the second term only the beta goes away, and the rest of term can be expressed either way: $X'y = y'X$. The second part is a quadratic term, therefore, the result is:

$$\boldsymbol{y}'\boldsymbol{X} = \boldsymbol{X}'\boldsymbol{X}\widehat{\boldsymbol{\beta}} \qquad (A.6)$$

Assuming $X'X$ is invertible, multiply both parts by the inverse of this:

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{y}'\boldsymbol{X} \qquad (A.7)$$

Appendix B: List of excluded airports.

Table 23: Excluded airports

Airport	Country	Reason	Airport	Country	Reason
Martinique – Aimé Cesaire	France	French overseas	**Prestwick**	England	Doubled tax rate 2007
Cayenne – Félix Eboué	France	French overseas	**Scatsta**	England	Doubled tax rate 2007
La Réunion – Rolland Garros	France	French overseas	**Southampton**	England	Doubled tax rate 2007
Point-à-Pitre – Le Raizet	France	French overseas	**Stornoway**	England	Doubled tax rate 2007
Saint Martin – Grande Case	France	French overseas	**Sumburg**	England	Doubled tax rate 2007
Aalborg	Denmark	Danish tax 2007	**Tiree**	England	Doubled tax rate 2007
Aarhus	Denmark	Danish tax 2007	**Wick**	England	Doubled tax rate 2007
Billund	Denmark	Danish tax 2007	**Burgas**	Bulgaria	Oil import data missing
Borkhom/Ronne	Denmark	Danish tax 2007	**Sofia**	Bulgaria	Oil import data missing
Esbjerg	Denmark	Danish tax 2007	**Dubrovnik /Cilipi**	Croatia	Oil imp.& pax data missing
Karup	Denmark	Danish tax 2007	**Pula**	Croatia	Oil imp.& pax data missing
Kobenhavn/ Kastrup	Denmark	Danish tax 2007	**Split/Kastela**	Croatia	Oil imp.& pax data missing
Kobenhavn/ Rosklide	Denmark	Danish tax 2007	**Zadar/Zemunik**	Croatia	Oil imp.& pax data missing
Sonderborg	Denmark	Danish tax 2007	**Zagreb – Franjo Tudjman**	Croatia	Oil imp.& pax data missing
Cork	Ireland	Irish tax 2009	**Larnaka**	Cyprus	Oil import data missing
Dublin	Ireland	Irish tax 2009	**Pafos**	Cyprus	Oil import data missing
Ireland West	Ireland	Irish tax 2009	**Tallinn – Lennart Meri**	Estonia	Oil import data missing
Kerry	Ireland	Irish tax 2009	**Budapest – Liszt Ferenc**	Hungary	Oil import data missing
Shannon	Ireland	Irish tax 2009	**Riga**	Latvia	Oil import data missing
Luqa	Malta	Maltese tax 2008	**Kaunas**	Lithuania	Oil import data missing
Aberdeen/Dyce	England	Doubled tax rate 2007	**Palanga**	Lithuania	Oil import data missing
Barra	England	Doubled tax rate 2007	**Vilnius**	Lithuania	Oil import data missing
Belfast/ Aldergrove	England	Doubled tax rate 2007	**Luxembourg**	Luxembourg	Oil import data missing
Belfast City	England	Doubled tax rate 2007	**Alesund/Vigra**	Norway	Oil import data missing
Benbecula	England	Doubled tax rate 2007	**Alta**	Norway	Oil import data missing
Birmingham	England	Doubled tax rate 2007	**Bardufoss**	Norway	Oil import data missing
Blackpool	England	Doubled tax rate 2007	**Bergen/ Flesland**	Norway	Oil import data missing
Bournemouth	England	Doubled tax rate 2007	**Bodo**	Norway	Oil import data missing
Bristol	England	Doubled tax rate 2007	**Floro**	Norway	Oil import data missing
Campbelltown	England	Doubled tax rate 2007	**Harstad/Narvik/ Evens**	Norway	Oil import data missing
Cardiff	England	Doubled tax rate 2007	**Haugesund/ Karmoy**	Norway	Oil import data missing
Doncaster Sheffield	England	Doubled tax rate 2007	**Kirkenes/ Hoybuktmoen**	Norway	Oil import data missing
Dundee	England	Doubled tax rate 2007	**Kristiansand/**	Norway	Oil import data missing

			Kjevik		
Durham Tees Valley	England	Doubled tax rate 2007	**Kristiansund/ Kvernberget**	Norway	Oil import data missing
East Midlands	England	Doubled tax rate 2007	**Molde/Aro**	Norway	Oil import data missing
Edinburgh	England	Doubled tax rate 2007	**Moss/Rygge**	Norway	Oil import data missing
Exeter	England	Doubled tax rate 2007	**Oslo/ Gardermoen**	Norway	Oil import data missing
Glasgow	England	Doubled tax rate 2007	**Sandefjord/ Torp**	Norway	Oil import data missing
Gloucestershir e	England	Doubled tax rate 2007	**Stavanger/ Sola**	Norway	Oil import data missing
Humberside	England	Doubled tax rate 2007	**Tromso/ Langnes**	Norway	Oil import data missing
Inverness	England	Doubled tax rate 2007	**Trondheim/ Vaernes**	Norway	Oil import data missing
Islay	England	Doubled tax rate 2007	**Bucuresti – Henri Coanda**	Romania	Oil import data missing
Kirkwall	England	Doubled tax rate 2007	**Cluj Napoca – Avram Iancu**	Romania	Oil import data missing
Leeds Bradford	England	Doubled tax rate 2007	**Timisoara – Traian Vuia**	Romania	Oil import data missing
Lerwick/Tingw all	England	Doubled tax rate 2007	**Bratislava – Stefanik**	Slovakia	Oil import data missing
Liverpool	England	Doubled tax rate 2007	**Kosice**	Slovakia	Oil import data missing
London Gatwick	England	Doubled tax rate 2007	**Ljubljana/ Brink**	Slovenia	Oil import data missing
London Heathrow	England	Doubled tax rate 2007	**Basel**	Switzerland	Oil import data missing
London Luton	England	Doubled tax rate 2007	**Bern-Belp**	Switzerland	Oil import data missing
London Stansted	England	Doubled tax rate 2007	**Geneva**	Switzerland	Oil import data missing
LondonCity	England	Doubled tax rate 2007	**Lugano**	Switzerland	Oil import data missing
Londonderry/ Eglinton	England	Doubled tax rate 2007	**St. Gallen – Altenrhein**	Switzerland	Oil import data missing
Manchester	England	Doubled tax rate 2007	**Zurich**	Switzerland	Oil import data missing
Manston	England	Doubled tax rate 2007	**Kalamata**	Greece	Pax data missing
Newcastle	England	Doubled tax rate 2007	**Lappeenranta**	Finland	Pax data missing
Norwich	England	Doubled tax rate 2007	**Memmingen**	Germany	Pax data missing
Pantelleria	Italy	Pax data missing	**Perugia/ S. Franceso**	Italy	Pax data missing
Pardubice	Czechia	Pax data missing	**Savonlinna**	Finland	Pax data missing
			Zweirbruecke n	Germany	Pax data missing

There is a total of 117 excluded airports

Appendix C: R codes

C1. R code data cleaning

```
data_airports <- read_dta(file = "/Users/benjamin/R/data_thesis.dta")

#filter to have the relevant time period
data_airports2 <- filter(data_airports, time == "2007M01:2009M06" )
#select relevant variables
data_airports2 <- select(data_airports, air_number, airport, country, time, pax,
prod_industr_agg, tick_pr, oil_import_pr_mon)
# exclude airports in the UK, Ireland, Denmark and Malta
data_airports2 <- filter(data_airports2, !country == "United Kingdom" &
!country == "Ireland" & !country == "Denmark" &
!country == "Malta")

#There were missing values in oil exports for some countries, even though the
#data was available in Eurostat. Replace these NA's with their value
missing_values <-readxl::read_excel("/Users/benjamin/R/missing_countries
_oil_imports.xls")
library(tidyr)
replace(data_airports2$oil_import_pr_mon, ifelse(is.na(data_airports2$oil_import_pr_mon))
)
is.na(data_airports2$oil_import_pr_mon)
data_airports2$oil_import_pr_mon <- ifelse(data_airports2$country == 'Greece' &
is.na(data_airports2$oil_import_pr_mon),
missing_values$Greece,
data_airports2$oil_import_pr_mon)
data_airports2$oil_import_pr_mon <- ifelse(data_airports2$country == 'Austria' &
is.na(data_airports2$oil_import_pr_mon),
missing_values$Austria,
data_airports2$oil_import_pr_mon)
data_airports2$oil_import_pr_mon <- ifelse(data_airports2$country == 'Finland' &
is.na(data_airports2$oil_import_pr_mon),
missing_values$Finland,
data_airports2$oil_import_pr_mon)
data_airports2$oil_import_pr_mon <- ifelse(data_airports2$country == 'Portugal' &
is.na(data_airports2$oil_import_pr_mon),
missing_values$Portugal,
data_airports2$oil_import_pr_mon)
data_airports2$oil_import_pr_mon <- ifelse(data_airports2$country == 'Poland' &
is.na(data_airports2$oil_import_pr_mon),
missing_values$Poland,
data_airports2$oil_import_pr_mon)


#Exclude the following countries for missing values
data_airports2 <- filter(data_airports2, !country == "Croatia" &
!country == "Cyprus" & !country == "Bulgaria" &
!country == "Estonia", !country == "Hungary",
!country == "Latvia", !country == "Lithuania",
!country == "Luxembourg", !country == "Norway",
!country == "Romania", !country == "Slovakia",
!country == "Slovenia", !country == "Switzerland")

#Exclude the following airports for missing values/ invalid
data_airports2 <- filter(data_airports2, !airport == "AIME CESAIRE/MARTINIQUE airport",
```

```
!airport == "CAYENNE-FELIX-EBOUE airport",
!airport == "LA REUNION-ROLAND GARROS airport",
!airport == "POINTE-A-PITRE/LE RAIZET/GUADELOUPE airport",
!airport == "SAINT MARTIN, GRAND CASE, GUADELOUPE airport")
data_airports2 <- filter(data_airports2, !airport == "KALAMATA airport",
!airport == "LAPPEENRANTA airport",
!airport == "MEMMINGEN airport",
!airport == "PANTELLERIA airport",
!airport == "PARDUBICE airport",
!airport == "SAVONLINNA airport",
!airport == "ZWEIBRUECKEN airport")
data_airports2 <- filter(data_airports2, !airport == "PERUGIA/S. FRANCESCO airport")

#Filter treated and untreated airports
airports_var_treated <- filter(data_airports_var, airport == "AMSTERDAM/SCHIPHOL airport"|
airport == "EINDHOVEN airport"| airport == "GRONINGEN/EELDE airport" |
airport == "MAASTRICHT/AACHEN airport" | airport == "ROTTERDAM airport" |
airport == "ANTWERPEN/DEURNE airport" | airport == "BRUSSELS airport" |
airport == "CHARLEROI/BRUSSELS SOUTH airport" | airport == "LIEGE airport"|
airport == "DUESSELDORF airport"| airport == "NIEDERRHEIN airport"|
airport == "MUENSTER/OSNABRUECK airport" | airport == "KOELN/BONN airport")
airports_var_untreated <-filter(data_airports_var, !airport == "AMSTERDAM/SCHIPHOL
airport",
!airport == "EINDHOVEN airport", !airport == "GRONINGEN/EELDE airport",
!airport == "MAASTRICHT/AACHEN airport", !airport == "ROTTERDAM airport",
!airport == "ANTWERPEN/DEURNE airport", !airport == "BRUSSELS airport",
!airport == "CHARLEROI/BRUSSELS SOUTH airport", !airport == "LIEGE airport",
!airport == "DUESSELDORF airport", !airport == "NIEDERRHEIN airport",
!airport == "MUENSTER/OSNABRUECK airport", !airport == "KOELN/BONN airport")
```

C2. R code synthetic control method.

Instead of providing the full R code, examples will be given for the sake of reducing the length of this appendix:

In order to create a counterfactual for one treated unit, dataprep( ) will be used first, followed by synth ( ):

```
dataprepoutAMS11 <- dataprep(foo = type1,
                           predictors = c("pax", "prod_industr_agg", "tick_pr",
"oil_import_pr_mon"),
                           predictors.op = "mean",
                           time.predictors.prior = 1:18,
                           dependent = "pax",
                           unit.variable = "air_number",
                           unit.names.variable = "airport",
                           time.variable = "time3",
                           treatment.identifier = 7,
                           controls.identifier = 1:6,
                           time.optimize.ssr = 1:18,
                           time.plot = 1:30)
synth.outAMS11 <- synth(dataprepoutAMS11)
```

This example calculates the counterfactual for Schiphol using the restricted data and specification 1. In order to calculate specification 2, we need to use the special.predictor argument:

```
dataprepoutAMS21 <- dataprep(foo = type1,
                             predictors = c( "prod_industr_agg", "tick_pr",
"oil_import_pr_mon"),
                             predictors.op = "mean",
                             time.predictors.prior = 1:18,
                             special.predictors = list(list("pax", "mean", 18)
                             dependent = "pax",
                             unit.variable = "air_number",
                             unit.names.variable = "airport",
                             time.variable = "time3",
                             treatment.identifier = 7,
                             controls.identifier = 1:6,
                             time.optimize.ssr = 1:18,
                             time.plot = 1:30)
synth.outAMS21 <- synth(dataprepoutAMS21)
```

This is how the counterfactual for Schiphol was calculated, using the restricted data and specification 2. Notice that the special.predictors argument is used, taking the mean in period 18, which is equivalent to taking the first lag of the number of passengers. In order to make the process faster however, the multiple.synth( ) was used many times. This function automates the process with many treated unit, and is especially useful when the same donor pools is used for all the treated units. The following example shows the R code for calculating the counterfactual for all 13 treated units using specification 1 and the full data set:

```
multiple.synth.out1 <- multiple.synth(foo = airports,
                predictors = c("pax", "prod_industr_agg", "tick_pr"),
                predictors.op = "mean",
                special.predictors = list(list("oil_import_pr_mon", 1:18, "mean")),
                time.predictors.prior = 1:18,
                dependent = "pax",
                unit.variable = "air_number",
                unit.names.variable = "airport",
                time.variable = "time3",
                treated.units = 216:228,
                control.units = 1:215,
                time.optimize.ssr = 1:18,
                treatment.time = 19,
                time.plot = 1:30)
```

This makes the analysis much simpler, because it applies all 13 dataprep and synth functions in one command. The result of this is a multi-list of which the relevant objects can be extracted from. The following example shows how to extract dataprep and synth for Schiphol:

```
synth.outAMS1 <- multiple.synth.out1[["df"]][[1]][["synth.out"]]
dataprepoutAMS1 <- multiple.synth.out1[["df"]][[1]][["dataprep.out"]]
```

You can extract and then assign to an object in R. The number 1 in the code refers to the position of the treated unit, since Schiphol is the first treated unit in the list. In order to make the graphs, the Synth package has a convenient function for it called path.plot( ). The following example shows the code for plotting the counterfactual for Schiphol using the full data and specification 1:

```
path.plot(synth.res = synth.outAMS1, dataprep.res = dataprepoutAMS1,
          Ylab = "Number of passengers", Xlab = "time",
          Legend = c("AMS", "Synthetic AMS"),
          Legend.position = "topleft",
          Main = "Counterfactual AMS using full data")
abline(v = 18, lty = 2)
```

The only needed arguments are the dataprep and synth objects. The rest of the information is related to naming the x and y axis, a title for the graph as well as a legend and its position. The W weights are extracted as follows:

```
W_AMS1 <- round(synth.outAMS1$solution.w, 2)
```

Here I rounded the weights up to two decimals, because many control units do have a positive weights, although very small, so they become irrelevant.

In order to generate the placebos I use the generate.placebo( ) function:

```
placeboAMS <- generate.placebos(dataprepoutAMS1, synth.outAMS1, Sigf.ipop = 2)
```

To plot the placebos I use plot_placebos():

```
plot_placebos(tdf = placeboAMS, ylab = "gap in the number of departing passengers",
              xlab = "time")
```

And finally, to get the MSPE ratio and p values I use mspe.test():

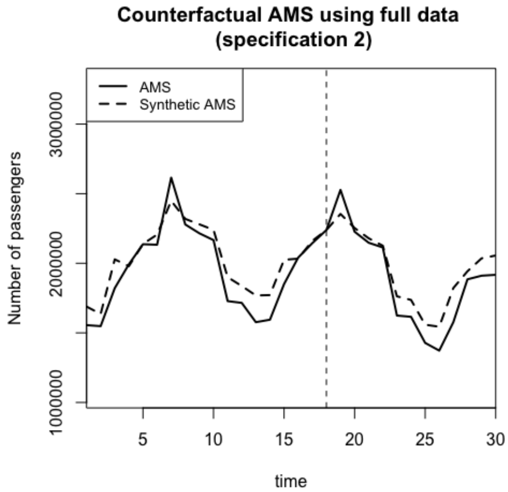
```
mspeAMS1 <- mspe.test(placeboAMS)
```

Appendix D: Correlation matrix of the predictor variables

Table 24: Correlation matrix of predictor variables

	Departing passengers	Ticket price	Industrial output	Oil imports
Departing passengers	1	-0.048	-0.080	0.046
Ticket price	-0.048	1	-0.294	0.073
Industrial output	-0.080	-0.294	1	0.248
Oil imports	0.046	0.073	0.248	1

Appendix E: Counterfactuals for Specification 2



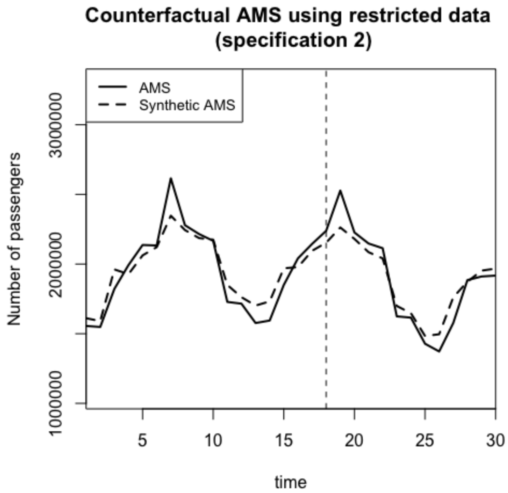


Figure 26: Counterfactuals for Amsterdam-Schiphol airport using full and restricted data (Specification 2)

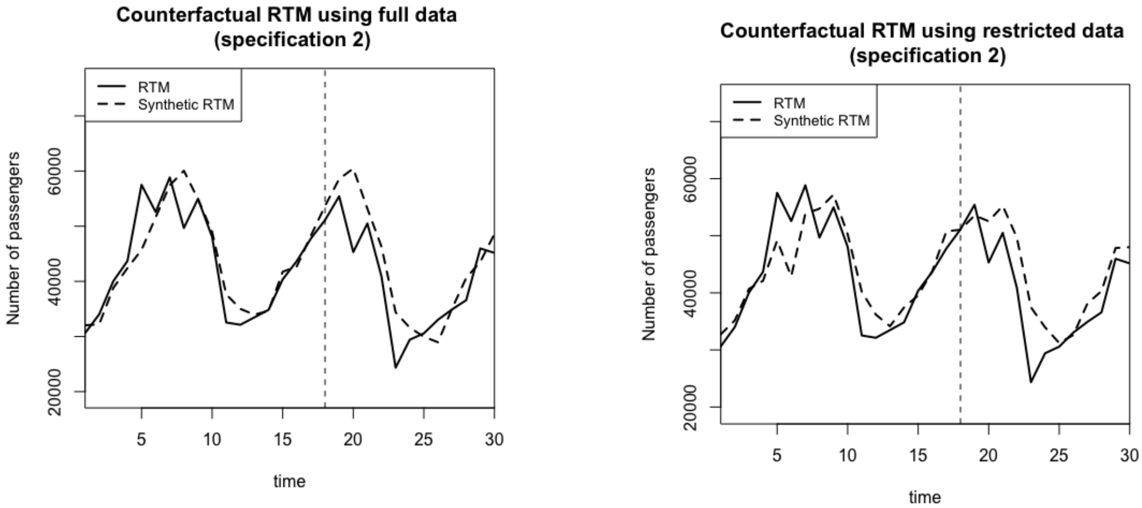


Figure 27: Counterfactuals for Rotterdam-The Hague airport using full and restricted data (Specification 2)

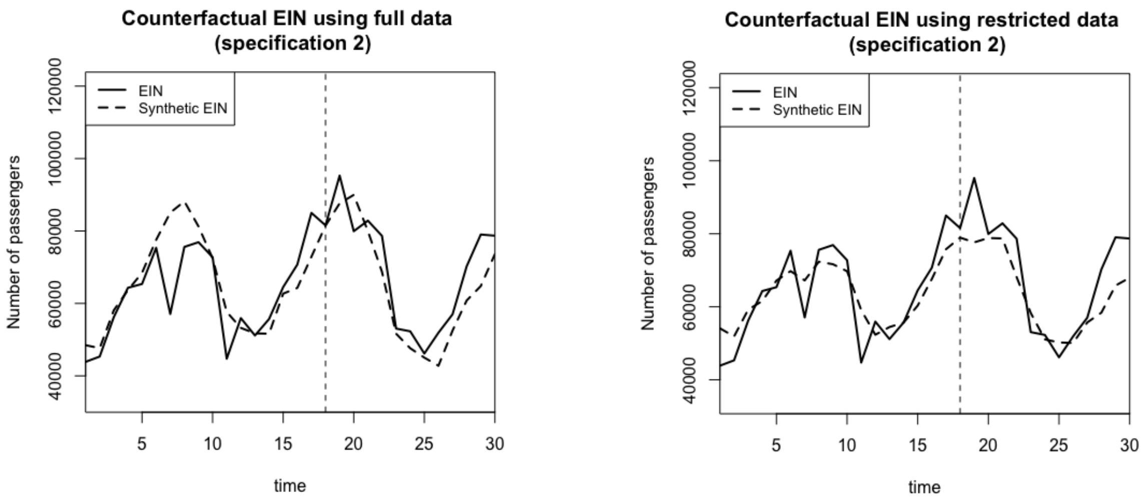


Figure 28: Counterfactuals for Eindhoven airport using full and restricted data (Specification 2)

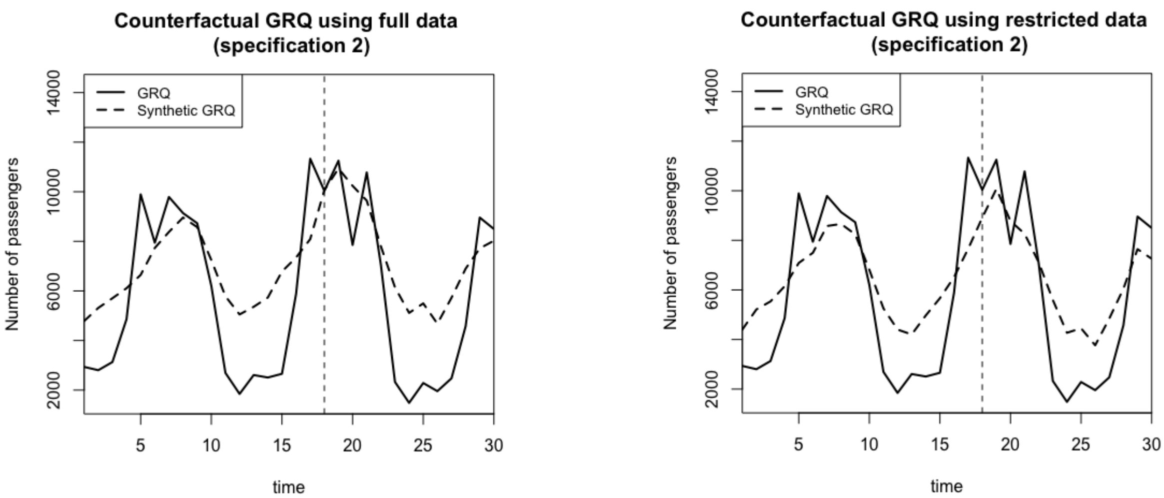


Figure 29: Counterfactuals for Groningen airport using full and restricted data (Specification 2)

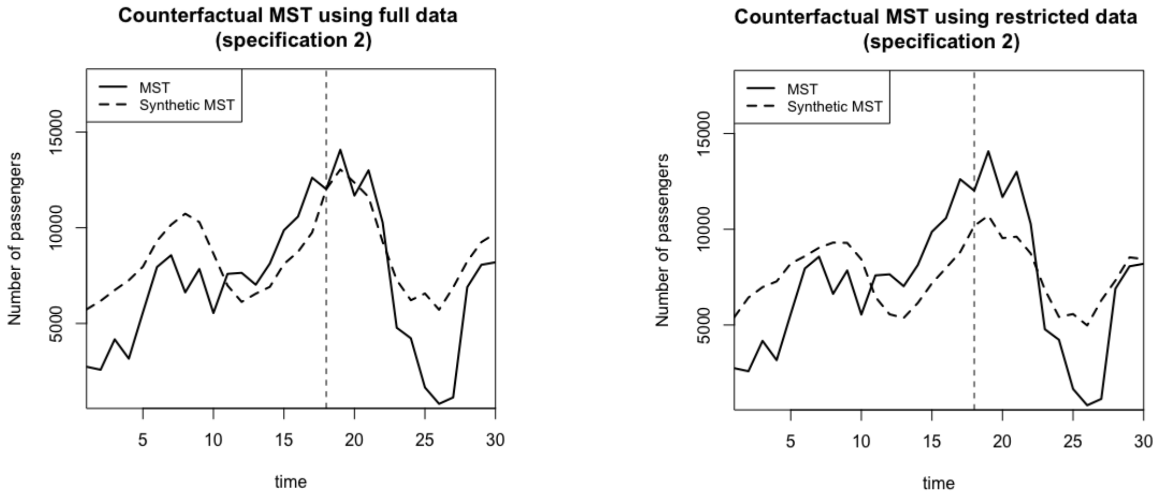


Figure 30: Counterfactuals for Maastricht-Aachen airport using full and restricted data (Specification 2)

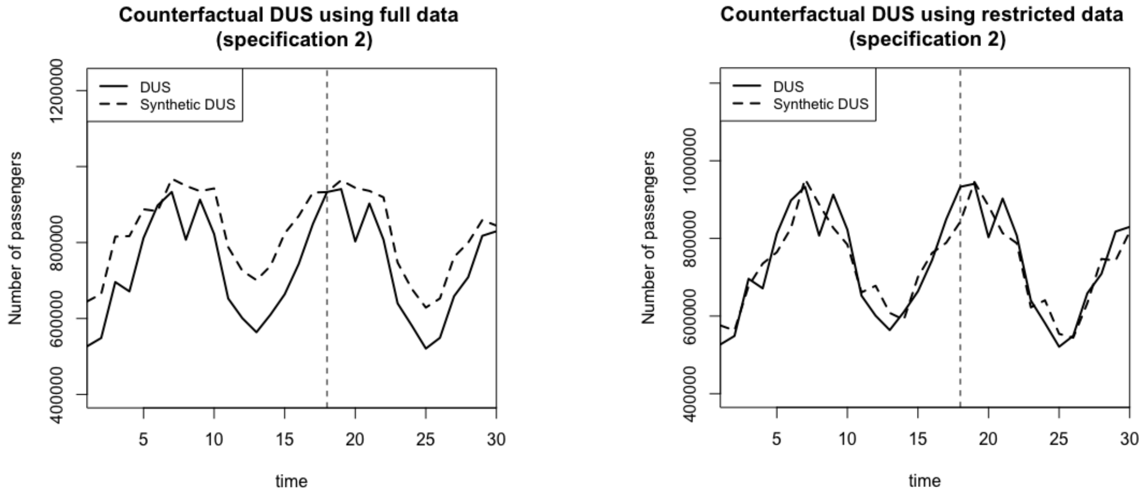


Figure 31: Counterfactuals for Düsseldorf airport using full and restricted data (Specification 2)

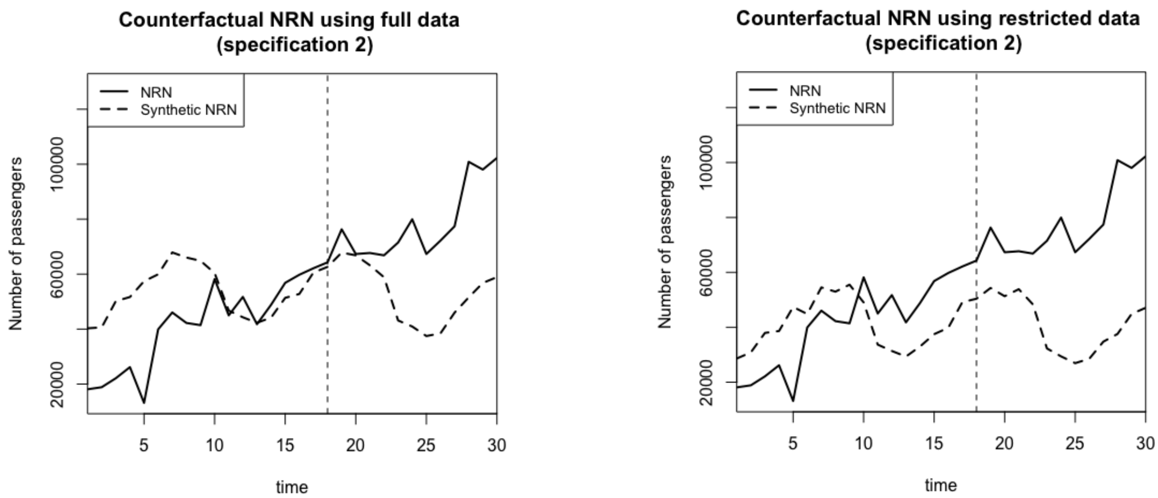


Figure 32: Counterfactuals for Weeze-Niederrhein airport using full and restricted data (Specification 2)

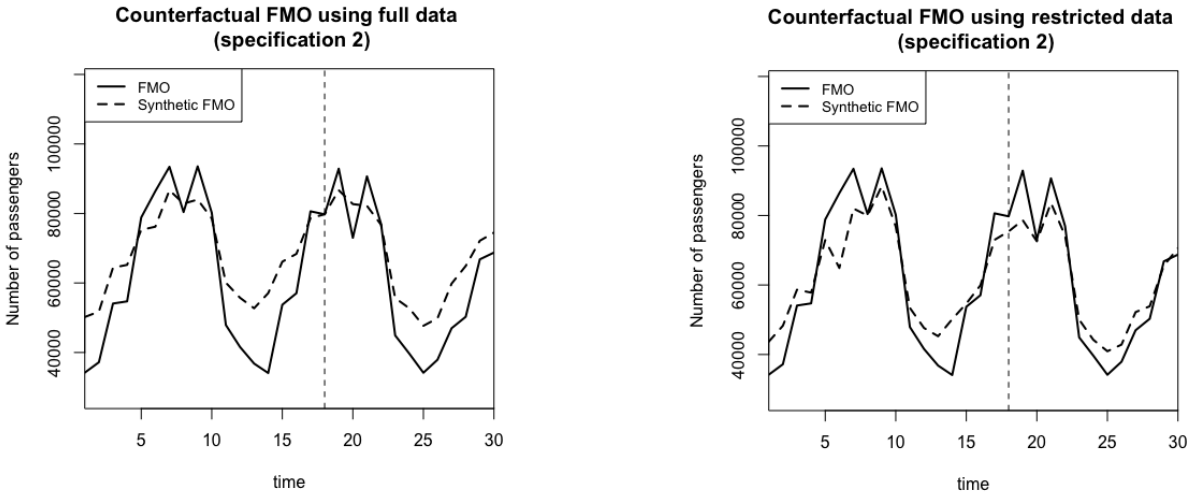


Figure 33: Counterfactuals for Münster-Osnabrück airport using full and restricted data (Specification 2)

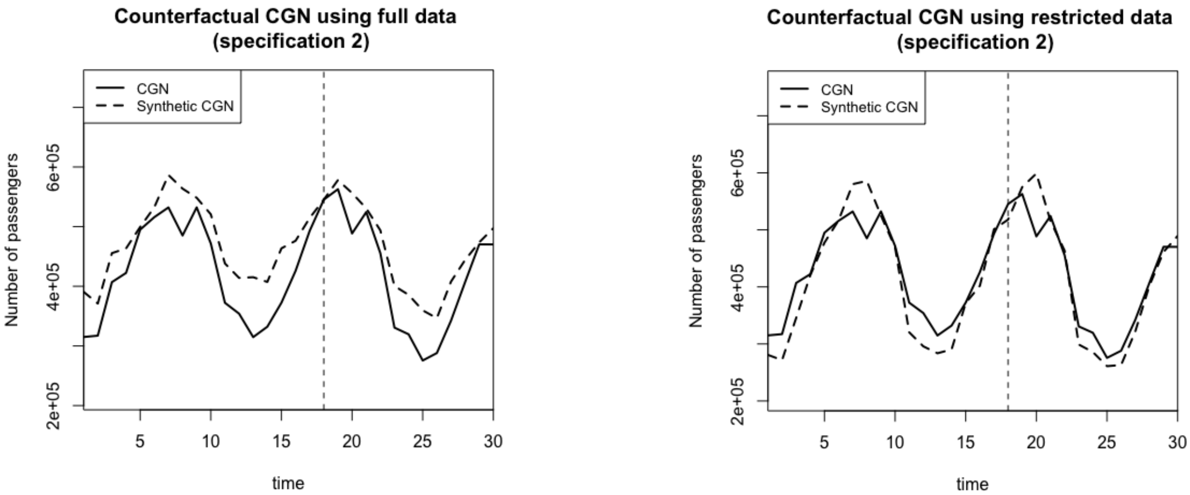


Figure 34: Counterfactuals for Cologne-Bonn airport using full and restricted data (Specification 2)

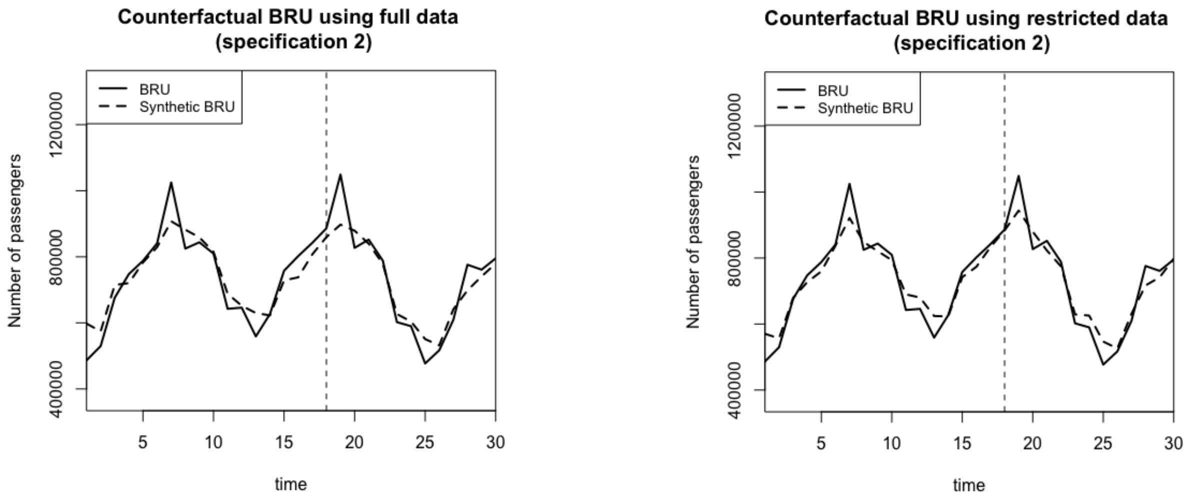


Figure 35: Counterfactuals for Brussels airport using full and restricted data (Specification 2)

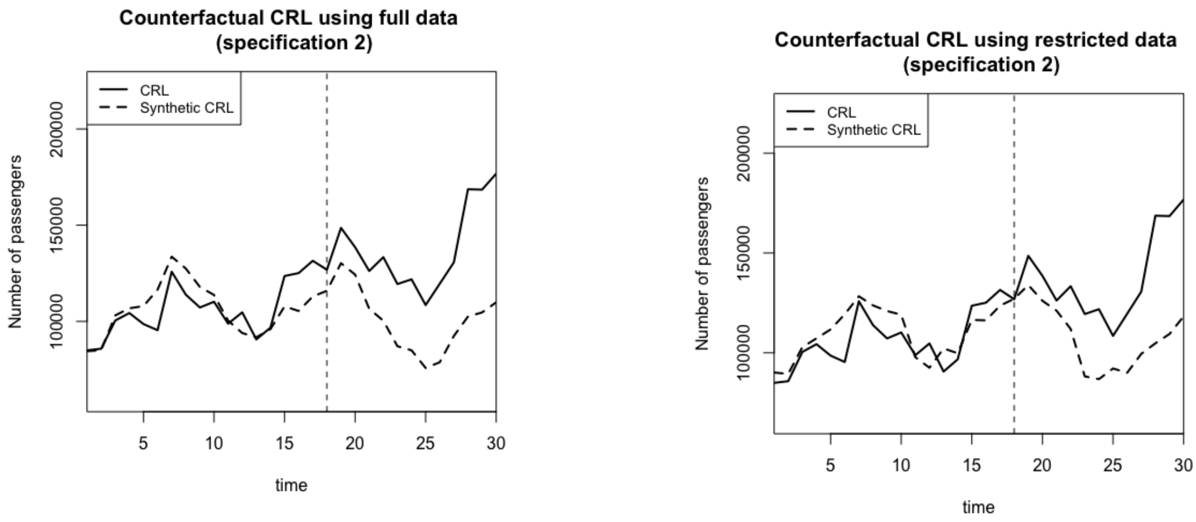


Figure 36: Counterfactuals for Charleroi airport using full and restricted data (Specification 2)

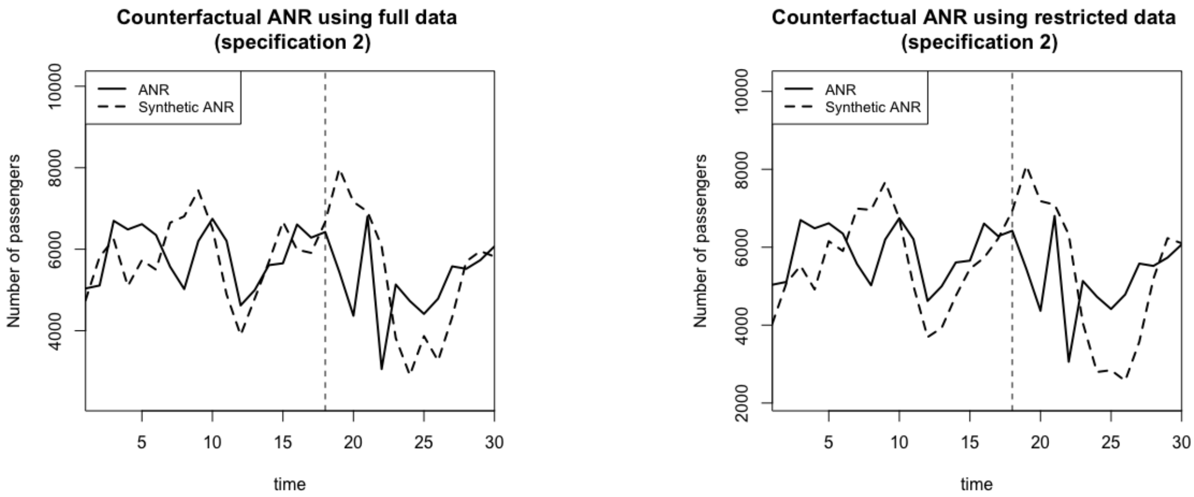


Figure 37: Counterfactuals for Antwerpen airport using full and restricted data (Specification 2)

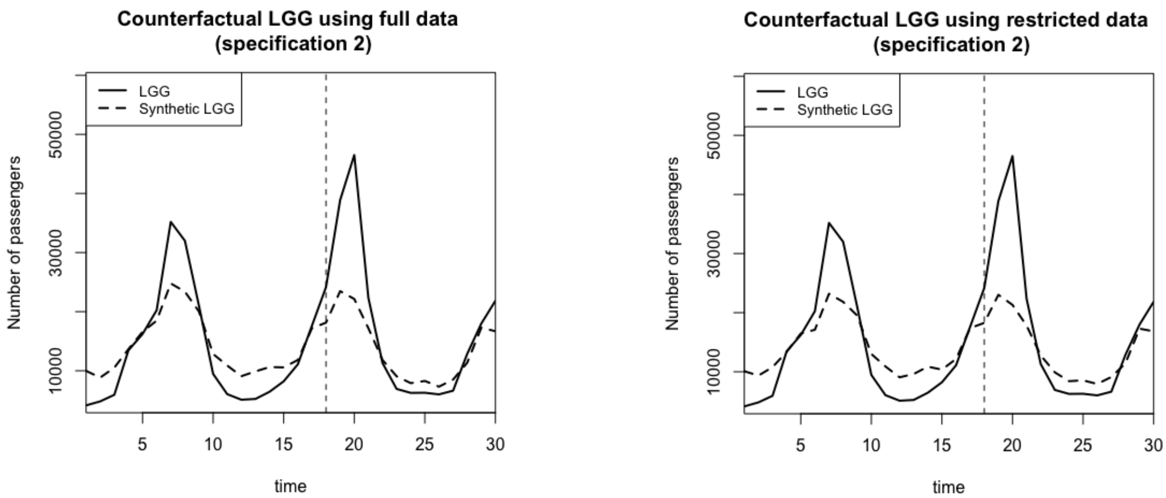


Figure 38: Counterfactuals for Liege airport using full and restricted data (Specification 2)

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