Empirical studies in the field of mobility and transportation

Doctoral Thesis

Presented to the Faculty of Management, Economics and Social Sciences at the University of Fribourg (Switzerland), in fulfillment of the requirements for the degree of Doctor of Philosophy in Economics (Ph.D.)

by

Kevin Blättler
from Hergiswil NW

Accepted by the Faculty of Management, Economics and Social Sciences on September 23, 2024 at the proposal of
Prof. Martin Huber, Ph.D. (First Advisor) and
Prof. Beat Hintermann, Ph.D. (Second Advisor)

Fribourg, Switzerland, 2024

https://doi.org/10.51363/unifr.eth.2024.020

Acknowledgments

I would like to thank Martin Huber for the opportunity to write my dissertation under his supervision. I have greatly appreciated his supportive, inspiring and welcoming assistance. His methodological advice contributed substantially to the empirical work of the thesis presented here. I am also grateful for the enriching discussions at the various PhD seminars of the Department of Economics at the University of Fribourg. Special thanks to my PhD colleague Andreas Stoller for the enjoyable scientific and social exchange during my stays in Fribourg. Finally, I wish to thank Beat Hintermann for acting as my second supervisor.

Special recognition goes to my co-authors Hannes Wallimann, Widar von Arx, Sebastian Imhof and Silvio Sticher, who all work with me at the Competence Center for Mobility at the Lucerne University of Applied Sciences. Their complementary strengths and process guidance have enabled the success of the research projects in this thesis. Also thanks to Timo Ohnmacht, with whom I share the office. I have greatly benefited from the many discussions about the various mobility topics over the years.

Moreover, I would like to point out the importance of the practice partners in applied research projects. Without their positive attitude towards science, applied research of real-world cases would not be possible. In particular, I would like to thank Andreas Kronawitter, Sascha Venosta, Guido Buob, the hoteliers in Appenzell Innerrhoden and the staff at the Swiss National Library.

I am deeply grateful to my parents for their unconditional support and advice in all life situations. During the time of my PhD, I could share the delightful first years of my goddaughter's life. With her sharp mind, Noelia is my greatest inspiration. I also experienced challenging and rewarding moments with my football colleagues and lost one of my closest friends. I dedicate this doctoral thesis to Sven and all the people who accompanied me during the process of writing these four essays.

Contents

List of Figures

List of Tables

Introduction

This thesis is a collection of four empirical analyses in the field of mobility and transportation research. Mobility refers to the potential for movement within a given social and spatial context, while transportation is the actual movement that occurs, reflecting the demand on transport systems (Canzler and Knie, 1998). The four independent essays analyze transportation data in order to broaden scientific knowledge. The empirical analyses are either causal or predictive. The causal analyses in Chapters 1, 3 and 4 estimate the effect of public transport price reductions on either ridership, revenue or modal share, based on the potential outcome framework (see, for instance, Rubin, 1974). The predictive analysis in Chapter 2 estimates the likelihood of bookings for demand responsive transport using flexible statistical learning methods, also known as machine learning. Recently, scientific research developed approaches combining causal analysis with machine learning, such approaches are applied in Chapters 3 and 4 (see, for instance, Athey and Imbens, 2019). All essays are written in the context of Switzerland, where quality of public transport services and general living standards are relatively high. However, the regions analyzed in Chapters 1, 2, and 4 differ spatially, encompassing urban, rural, and touristic areas. Note that the studies are ordered chronologically, according to the time when the research projects were initiated.

In Chapter 1, co-authored with Hannes Wallimann and Widar von Arx, we analyze the public transport demand effects of a price reduction of annual season tickets, day tickets and hourly tickets (by up to 29%, 6% and 20%, respectively) in Geneva, an urban area in Switzerland. Considering a unique dataset based on transport companies' annual reports, we can observe the public transport demand of the main operator in Geneva as well as of other Swiss transport companies. By applying the synthetic control method and the synthetic difference in differences method, we construct a counterfactual that mimics the demand Geneva would have experienced in the absence of the price reduction. The methodology uses a data-driven procedure to create the synthetic Geneva from comparable Swiss transport operators. Furthermore, we propose an aggregate metric that inherits changes in public transport supply (e.g., frequency increases) to assess these demand effects, namely passenger trips per vehicle kilometer. We estimate a demand increase, on average over five years, of 10.6%. The corresponding 95% bootstrap confidence interval is [6.2%:12.8%]. In addition, we check the robustness of our results by using different study designs. Not blocking off supply changes leads us to a lower bound of the effect, amounting to an increase of 3.7%, with all bootstrap estimates being higher than zero. These findings are important for policy-makers as price reductions for public transport are being introduced and discussed in various European cities and countries.

In Chapter 2, co-authored with Sebastian Imhof, we assess the transferability of demand responsive transport (DRT) from an existing to a new perimeter in rural Switzerland. DRT services can run a more flexible schedule than fixed route services and hence have the potential to sustain/improve public transport frequency and accessibility in sparsely populated rural areas. We uncover the important spatial characteristics in the existing perimeter and test whether they can predict demand in the new perimeter. We focus on the random forest as the machine learner because of its functional flexibility and interpretability. Results indicate that the number of inhabitants and the distance to the train station are most important spatial characteristics for the prediction of DRT demand. The relation between distance to the train station and DRT demand is non-linear, with increasing demand prediction very close to the train station. In the planning process of new DRT services, these findings are essential for the definition of new perimeters. For a successful and viable DRT service in a rural setting, the inclusion of more densely populated areas as well as integrating a train station in the form of a hub station are crucial factors.

In Chapter 3, co-authored with Silvio Sticher, we explore the potential of Public Transportation Credits (PTCs) in a Swiss-wide context. PTCs are credits (or "allowances") that are greater in amount than their price and can be used to purchase public transportation tickets within a year. With the initial fixed payment, the subsequent use of the allowance and the eventual return to the standard fare, PTCs represent three-part tariff models. Against the background of the Swiss pricing structure, PTCs target customers with a medium-sized transport demand for which public transportation is comparatively more expensive than private cars. Consequently, a price reduction in this segment may lead to above-average demand effects. The study aims to identify the effect of the PTC on public-transportation revenue by analyzing a pilot study conducted by the Swiss public-transportation providers. In a randomized field experiment with 431,533 PTC invitees and 911 actual PTC buyers, we use the dispatch of invitations as an instrumental variable. However, due to the weak relationship between invitees and buyers the results remain insignificant. Therefore, we complement our analysis by comparing PTC buyers to customers in the control group conditional on observed consumption patterns in the year prior to the pilot study and personal characteristics. Under the assumption that the treatment is as good as randomly assigned conditioned on the observed characteristics, we find statistically significant evidence for a revenue increase of, on average, CHF 179.7 per PTC (approximately USD 200). The analysis suggests that well-designed price reduction policies can benefit both customers and public-transportation providers without needing government subsidies.

In Chapter 4, co-authored with Hannes Wallimann and Widar von Arx, we evaluate the effect of a fare-free public transport policy for overnight guests on travel mode choice to a tourism destination. While public transport free of charge within the destination during the stay is implemented in various tourism destinations, public transport free of charge for the arrival and departure to and from the destination on top of it—our policy of interest—is novel. To gather the relevant data, we conducted an online survey between May and October 2023. Our causal analysis takes advantage of the random element that the information on the offer from the hotelier to the guest varies in day-to-day business. Therefore, we can divide the guests with regard to the information status into a treatment and control group, i.e., informed and non-informed guests. To ensure the identification of the effect, we include only those guests who were not aware of this free arrival and departure offer at time of the booking process. As our analysis relies on observational (nonrandomized) data, we assume that we observe and control for all covariates that jointly influence potential outcomes and treatment, i.e., accommodation-specific characteristics, trip-related characteristics, mobility tools, and socio-demographic characteristics. We estimate a shift from private cars to public transport due to the policy of, on average, 14.8 and 11.6 percentage points, depending on the application of propensity score matching and causal forest, the latter being a causal machine learning approach. This knowledge is relevant for policy-makers, as the fare-free public transport policy for the specific group of overnight guests directly targets domestic transport to and from a destination, the substantial contributor to the CO_2 emissions of overnight trips.

The four essays reflect the scientific process of understanding context, making assumptions, applying empirical methods, and checking the robustness of the results to evaluate the effectiveness and transferability of transportation policies and products.

Chapter 1

Price reductions in urban public transport

A synthetic control approach

joint with **Hannes Wallimann** and **Widar von Arx***

Abstract

In this paper, we assess the demand effects of lower public transport fares in Geneva, an urban area in Switzerland. Considering a unique sample based on transport companies' annual reports, we find that, when reducing the costs of annual season tickets, day tickets and hourly tickets (by up to 29%, 6% and 20%, respectively), demand increases by, on average, over five years, about 10.6%. To the best of our knowledge, we are the first to show how the synthetic control method can be used to assess such (for policy-makers) important price reduction effects in urban public transport. Furthermore, we propose an aggregate metric that inherits changes in public transport supply (e.g., frequency increases) to assess these demand effects, namely passenger trips per vehicle kilometre. This metric helps us to isolate the impact of price reductions by ensuring that companies' frequency increases do not affect estimators of interest. In addition, we show how to investigate the robustness of results in similar settings. Using a recent statistical method and a different study design, i.e., not blocking off supply changes as an alternate explanation

*This chapter is based on a paper published in the journal *Transportation Research Part A: Policy and Practice* as Wallimann, Blättler, and von Arx (2023). We are grateful to the SBB Research Fund for financial support.

of the effect, leads us to a lower bound of the effect, amounting to an increase of 3.7%. Finally, as far as we know, it is the first causal estimate of price reduction on urban public transport initiated by direct democracy.

1.1 Introduction

The transport sector is a pivotal contributor to air pollution. Globally, approximately 27% of CO_2 emissions and energy consumption are caused by the transport sector; in the European Union, the figure amounts to about a third (Batty, Palacin, and González-Gil, 2015). Therefore, the transport sector causes negative externalities, which means a situation in which the action of a person imposes a cost on another person who is not a party to the transaction. Another important example is noise pollution. Private car use will lead to even greater levels of such negative externalities, which a shift in transport mode towards public transport could help reduce. Lower fares are a frequently discussed tool to motivate individuals to use public transport (see, e.g., Redman, Friman, Gärling, and Hartig, 2013).

Policy-makers must know how existing and potential customers respond to such lower fares. However, it is generally challenging to identify the causal effect of lower fares on public transport demand, as transport supply change over time. Therefore, we propose and discuss an aggregate metric that inherits a transport company's supply in public transport demand in this context. The metric is composed of passenger trips per vehicle kilometre. Moreover, considering CO_2 emissions, an increase in the metric points to an average emission decrease of each passenger.

In our comparative case study, we use this metric as the outcome variable to analyze lower fares empirically in the case of Geneva, an urban area in Switzerland. There, the electorate decided to reduce the price of state-owned public transport, which Geneva then introduced in December 2014. The reduction amounted to up to 29% for annual season tickets, 6% for day tickets and 20% for tickets valid for one hour. The case of Geneva is interesting for several reasons. First, Geneva is densely populated. Second, Switzerland has a high per-capita income, as does Geneva. Based on the first and second reasons, we resolve the puzzle of how lower fares cause demand when density and incomes are high, which is the case for many cities worldwide. And third, the public transportation sector in Switzerland is known for its high quality of service. Conclusions can thus also be drawn as to whether price reductions increase the demand for public transport in areas where the quality of the public transport sector is high.

To illustrate the price-reduction effect, we analyze the case of TPG, the main operator in the city of Geneva, and its agglomeration belt. To this end, we apply the synthetic control method (Abadie, Diamond, and Hainmueller, 2010, Abadie and Gardeazabal, 2003) to construct a synthetic TPG, a counterfactual that mimics the demand the company would have experienced in the absence of the price reduction. The methodology uses a data-driven procedure to create the synthetic TPG from comparable Swiss transport operators. Comparing the demand of TPG and its synthetic counterpart, we find that, on average, the price reduction increased the demand for public transport by 10.6% during the period 2015 to 2019, compared to 2014.

Furthermore, we set out to block off alternate reasons leading to our estimate through various robustness checks. For example, we find that the results are similar when increasing the length of the pre-treatment period or increasing the number of other operators to construct the synthetic TPG. Moreover, applying the recent difference in differences method of Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2019) does not question our findings. However, when we set out to assess the effect of our mechanism of interest, the effect of a price reduction on demand, using the total amount of passenger trips instead of the proposed metric, we are not able to construct a suitable synthetic TPG. The thing to notice is that when we re-estimate the effect with the, for this case, more appropriate synthetic difference in the difference method, we only get an effect of 3.7%. However, a corresponding 95% bootstrap interval amounts to [2%,12.4%], with all values being higher than zero. Moreover, this estimate relies mainly on control units with an upwards demand trend. Therefore, we conclude that this estimate serves as a lower bound of the effect. Summing up, our paper provides the first empirical evidence, at least for Geneva, that a fare-reduction policy can help increase passenger demand. Finally, note that such quasi-experimental evidence is crucial, as price elasticities are often based on Stated Preference or experimental surveys (in Switzerland, see, e.g., Weis, Vrtic, Axhausen, and Balac, 2016, Axhausen, Molloy, Tchervenkov, Becker, Hintermann, Schoeman, Götschi, Castro Fernández, and Tomic, 2021).

The rest of this paper proceeds as follows. Section 1.2 discusses the existing literature on pricing policies in public transportation. Section 1.3 describes the institutional background of the Geneva case study. In Section 1.4, we discuss the methodology and our strategy to identify the estimate of interest. Moreover, we present the underlying assumptions of our so-called natural experiment. Section 1.5 describes our unique data set, derived from the annual reports of Swiss transport companies and discusses our proposed aggregate metric. Section 1.6 applies the synthetic control method to our case and discusses the robustness of our results. In Section 1.7, we discuss our estimates by arguing how to achieve at a lower bound. Moreover, we debate about the so-called external validity. That is the ability of our study to produce an effect of the price reduction on demand, our theoretical mechanism of interest, to work in public transport settings. Section 1.8 concludes.

1.2 Literature review

Our study fits into the literature on fare-policy interventions in urban public transport systems. Bresson, Dargay, Madre, and Pirotte (2003) suggest that demand is less sensitive to fare changes in France's urban areas than in non-urban areas of England. Moreover, Bresson, Dargay, Madre, and Pirotte (2004) analyse French urban areas in greater depth and show that the effects of changing fares vary across areas. This heterogeneity is mainly explained by car ownership, urban sprawl, and the aging of the population. Recently, Kholodov, Jenelius, Cats, van Oort, Mouter, Cebecauer, and Vermeulen (2021) estimate the effect of a new fare policy in Stockholm and find varying effects across socioeconomic groups and different modes of public transport. Many other studies have examined fare policies in European cities by simulating fare changes (e.g., Parry and Small (2009) for London or Matas, Raymond, and Ruiz (2020) for Barcelona) or by analysing transport policy bundles (e.g., Buehler, Pucher, and Altshuler, 2017, for Vienna). We add to such studies by calculating the causal effect of fare-policy intervention in the interesting case in Geneva.

In the literature, causal analysis has mainly been conducted on fare-free policies rather than fare reductions, as in our case. In Europe, Cats, Susilo, and Reimal (2017) suggest that free fares increased public transport use by 14%. In addition, De Witte, Macharis, Lannoy, Polain, Steenberghen, and Van de Walle (2006) and Rotaris and Danielis (2014) investigate free-fare policies in Brussel and Trieste. The settings of Lee and Yeh (2019) in Taichung (Taiwan) and Shin (2021) in Seoul (South Korea) are the closest to ours. In Taichung, bus network and schedule improvements gradually increased bus use, which then grew further due to free-fare policies, leading to further adjustments on the supply side. Shin (2021) estimates there was a 16% increase in subway use by older adults after a fare-free policy was introduced for this age group in Seoul.

Our study is also related to the rich literature on price elasticities in public transport. Price elasticities show the percentage change in demand due to a one percentage price change. For example, Holmgren (2007) exposes a short-run price elasticity of -0.75 and a long-run price elasticity of -0.91 in Europe. In line with Holmgren (2007), Brechan (2017) finds that increasing frequencies has a higher elasticity than reducing fares for public transport. Wardman, Toner, Fearnley, Flügel, and Killi (2018) show that the effects of price changes in public transport on car demand – the so-called cross-elasticities – are relatively low. Liu, Wang, and Xie (2019) add that changes to fare policy in Australia mostly increased the number of trips of existing users rather than attracted new users. That is why Litman (2004) suggests a relatively large fare reduction is crucial for car-users to switch to public transport. Redman, Friman, Gärling, and Hartig (2013) show that price can encourage car-users to use public transport. However, the reliability, frequency, and speed of public transport will determine whether their intentions are implemented and maintained. In Switzerland, where our case study of Geneva is located, price elasticities regarding the demand for public transport are typically low according to Citec Ingénieurs SA (2021). In a recent experimental study, Axhausen, Molloy, Tchervenkov, Becker, Hintermann, Schoeman, Götschi, Castro Fernández, and Tomic (2021) estimate a price elasticity of -0.31 in Switzerland.

More broadly, our study adds to the literature on price policies, inter alia with the goal of making mobility more sustainable. For instance, Kilani, Proost, and Van der Loo (2014) show that road-pricing combined with higher public transport fares in peak periods or discounts on off-peak tickets work in complementary fashion in Paris. Moreover, the effect of road-pricing (e.g., Percoco, 2015, for Milan) or peak-pricing (off-peak discounts) in public transportation alone is also analysed in recent literature (see, e.g., Rantzien and Rude (2014) for Stockholm and Huber, Meier, and Wallimann (2022) for Switzerland). Gkritza, Karlaftis, and Mannering (2011) assess the multimodal context of the urban public transport system with varying fare structures in Athens. For a review of public transport policies, see also Hörcher and Tirachini (2021).

Finally, we add to transportation studies applying the synthetic control method, according to Athey and Imbens (2017), *"the most important innovation in the policy evaluation literature in the last 15 years"* (p. 9). For instance, Percoco (2015), also previously mentioned, investigates the effect of road-pricing on traffic flows. Another example is Tveter, Welde, and Odeck (2017), who evaluate which transportation projects affect settlement patterns. Doerr, Dorn, Gaebler, and Potrafke (2020) estimate the extent to which new airport infrastructure promotes tourism. Studying ski-lift companies, Wallimann (2022) discusses the effect of radically discounting prices, while Xin, Shalaby, Feng, and Zhao (2021) investigate the impact of COVID-19 on urban rail-transit ridership. Closely related to our paper is also the study of Dai, Liu, and Li (2021) using the synthetic control method to investigate the effect of fare-free public transport policies in the post-COVID-19 era in three Chinese cities, Hangzhou, Ningbo, and Xiamen.

1.3 Background

Switzerland is densely populated and has one of the highest GDP per capita in the world.[1] The road and rail infrastructures are modern and well maintained. Public transport is reliable and frequent, and the tariff system is widely integrated. The mixture of short distances, high incomes and good quality drives the demand for mobility in Switzerland. For these reasons, the countries' residents are highly mobile. On the one hand, 1,000 residents own, on average, about 500 individual motorized vehicles.[2] Apart from a yearly fee of 40 Swiss francs[3] to use the highways, roads are free of charge. On the other hand, every second resident owns a public transport pass.[4] For example, about 2.7 million individuals (roughly 32% of the population) held a half-fare travel ticket in 2019.[5] With such a half-fare travel ticket, a person can buy Swiss-wide public transport tickets on a reduced tariff of 50%. Furthermore, Swiss residents bought more than one million subscriptions to regional tariff associations in 2019 (Verband öffentlicher Verkehr, 2020).

Switzerland is organized into 26 federal states, the so-called cantons. In Geneva, our canton of interest, 27.6% of the residents own a Swiss-wide public transport subscription. This is relatively low compared to other Swiss agglomerations. On the other hand, the proportion with a subscription from the regional tariff association is in Geneva rather large with 25.4% compared to other Swiss agglomerations (FSO, ARE, 2012). That is probably because of the urbanity and the small size of the canton of Geneva. For example, most journeys related to work are made within the canton (FSO, ARE, 2012).

Besides the federal system, the Swiss political system is a direct democracy. Therefore, electorates can decide on political issues at the communal, cantonal and federal state levels. In this political framework, the electorates of the canton of Geneva chose to reduce the prices of state public transport in 2013. This initiative originated from a senior citizens' association. At the request of Geneva's population, the tariff association in Geneva implemented a sharp price reduction in December 2014.[6] First, the full-fare hourly tickets were

[1] See https://data.worldbank.org/indicator/NY.GDP.PCAP.CD (accessed on November 9, 2021)

[2] See https://www.bfs.admin.ch/bfs/en/home/statistics/mobility-transport.html (accessed on November 9, 2021)

[3] At the time of writing, the Swiss francs and the Euro were close at parity.

[4] See https://www.bfs.admin.ch/bfs/en/home/statistics/mobility-transport.html (accessed on November 9, 2021).

[5] See https://reporting.sbb.ch/verkehr (accessed on November 9, 2021). Moreover, all under 16 years old (roughly 16% of the population) also travel with a price reduction of 50% and therefore do not need half-fare travel tickets.

[6] See https://www.srf.ch/news/schweiz/abstimmungen/abstimmungen/abstimmungen-ge/es-

reduced by 14.3% and the corresponding half-fare tickets by 20%. Second, the full-fare daily tickets were discounted by 5.7% and the corresponding half-fare tickets by 3.9%. Third, adults benefited from a price reduction of 28.6% on annual season tickets and seniors and juniors (people between 6 and 24 years) from a price reduction of 20% and 11%, respectively. Fourth, seniors additionally received a 10% discount on monthly season tickets, whereas adults and juniors received no discounts on monthly season tickets (Unireso, 2016). In 2014, the ticket categories who received a discount made up 65% of the total traffic revenue for 2nd class tickets.[7] Considering the revenue shares per ticket category of 2014, we assess an overall price discount of 12.6%. In Appendix 1.A we describe how we calculate this price change. Note that we do not account for substitution between ticket categories, which might lead us to an underestimation of the reduction. A final thing to notice regarding the regulation of urban traffic, the electorates in Geneva rejected the financing of park-and-ride facilities in the border regions in 2014.[8]

In summary, the policy intervention in December 2014 was the largest price reduction in a long time. The annual season ticket in Geneva now costs 500 Swiss francs for adults (previously 700 Swiss francs) and 400 Swiss francs for seniors and juniors (previously 500 and 450 Swiss francs respectively). These prices are more than 200 Swiss francs less than those charged by other Swiss cities. For instance, annual season tickets in Lausanne, Berne, Basel, and Zurich cost 740, 790, 800 and 782 Swiss francs respectively. The same is the case for single fare tickets amounting to 3 Swiss francs in Geneva. This shift away from the typical price level in Switzerland is the point of departure for our analysis. Using real-world data, we measure the effect of the price reduction on demand for public transport by comparing Geneva, where the political intervention occurred, with other regions of Switzerland.

In 2014, most of Geneva's tariff associations' revenue stemmed from TPG, a transportation company that transported about 197.1 million passengers that year.[9] The demand increased to 200.3 million passengers in 2015, which is an increase of 1.5% compared to 2014. From 2014 to 2015, TPG's traffic revenue fell from 153.7 million to 142.6 million Swiss francs (TPG, 2016). We present the annual traffic revenue of TPG in Table 1.3 in the Appendix 1.B. The TPG transport system depended on buses in the 20th century (FitzRoy and Smith, 1999). However, at the beginning of the 21st century,

bleibt-dabei-in-genf-fahren-senioren-billiger-tram-und-bus (accessed on Mai 16, 2022)

[7] 2nd class tickets account for almost the entire revenue.

[8] See https://www.srf.ch/news/schweiz/abstimmungen/abstimmungen/abstimmungen-ge/es-bleibt-dabei-in-genf-fahren-senioren-billiger-tram-und-bus (accessed on Mai 16, 2022)

[9] TPG also operates to a small extent outside the regional tariff association of Geneva (also outside Switzerland).

TPG started to expand its tram network, which grew from 14.5 kilometres in 2005 to 33 kilometres in 2012 (TPG, 2013). Overall, the number of vehicle kilometres increased from about 20 million in 2005 to about 29 million in 2013. Besides TPG, Geneva's tariff association consists of the Swiss Federal Railways, operating on the regional railway network, and Mouettes, which runs ferries.

1.4 Synthetic control method

In this section, we outline the synthetic control method used in our empirical analysis. Second, we present the assumptions underlying our analysis.

1.4.1 Methodology and implementation

Let D denote the binary treatment 'price reduction' and Y the outcome 'public transport demand'. The treatment D, the result of the initiative in Geneva, affects one unit (TPG). All the other units (transport companies) in our data are not exposed to the price reduction and thus constitute the control group. We can define the observed outcome of TPG, our unit of interest, as

$$Y_t = Y_t^N + \alpha_t D_t. \tag{1.1}$$

Y_t denotes the observed outcome, Y_t^N the outcome without the treatment, and α_t the treatment effect at time t. It is important to note that the treatment D takes the value 0 for all units during the period $t < T_0$, with T_0 indicating the introduction of the treatment. This is because also TPG was not exposed to the price reduction during the pre-treatment period. Only looking at the post-treatment period permits to define the treatment effect as

$$\alpha_t = Y_t - Y_t^N. \tag{1.2}$$

As we observe Y_t, we merely need to estimate Y_t^N, the public transport demand of TPG without the policy intervention. Using statistical parlance, Y_t^N is a counterfactual. That is the outcome one would expect if the intervention had not been implemented.

To determine Y_t^N, we use the synthetic control method of Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010). To construct the synthetic control unit (Y_t^N), the synthetic control method uses a data-driven procedure. In our study, the counterfactual Y_t^N, the synthetic TPG, is created out of already-existing companies of the control group, the so-called 'donor pool'. For this purpose, the methodology assigns a weight to each transport company in the control group. These weights are non-negative and sum up to one. On the one hand, we assign large weights to companies with a sizeable predictive power for TPG. On the other hand, transport companies in the control group with a low predictive power receive a small or a zero weight. The goal is to minimize the difference between TPG and the synthetic TPG in the period $t < T_0$, the pre-treatment period. To discuss the success of this goal, we calculate the mean squared prediction error (MSPE) of the outcome variable between TPG and the synthetic TPG.

To evaluate the significance of the results, we run placebo studies. To this end, we apply the synthetic control method to one transport company after another in the control group, all known to be untreated, using the remaining control companies as the donor pool. More precisely, we iteratively estimate placebo estimates of each unit with no price reduction considering it to be 'pseudo-treated'. If the estimated effect for TPG is similar to the placebo estimates, our result could have happened by chance. However, suppose the placebo investigations show that the effect estimated for TPG is enormous relative to the transport companies in the control group. In that case, like Abadie, Diamond, and Hainmueller (2010), we interpret our analysis as providing significant estimates of the treatment effect α_t. In implementing the synthetic control method, we use the *synth* and *SCtools* packages for the statistical software R by Hainmueller and Diamond (2015) and Silva (2020) respectively.

Moreover, we calculate the corresponding 95% bootstrap confidence intervals to the average treatment effect. Therefore, we randomly draw control units with replacement from our donor pool 2,000 times to arrive at these confidence intervals. In every sample, we construct a synthetic TPG and estimate the average gap between TPG and its counterfactual.

1.4.2 Assumptions

Identification requires statistical procedures, as explained in the previous chapter. However, on the other hand, ensuring that our calculation identifies the effect of the price reduction also relies on assumptions about how the world, here the world of public transportation, works (see, e.g., Huntington-Klein, 2021). Therefore, in this section, we discuss the contextual assumptions underlying our analysis (see also Abadie, 2021).

Assumption 1 (no anticipation):
Assumption 1 is satisfied when the public transport demand in Geneva did not change due to forward-looking customers reacting in advance to the policy intervention. To this end, the price reduction effect would be biased if TPG's travelers already use public transport before the intervention because they know that prices will fall later.

Assumption 2 (availability of a comparison group):
Assumption 2 requires a comparison group with similar characteristics to TPG. Therefore, we restrict our donor pool to transport companies that operate trams and buses primarily in cities with more than 50,000 inhabitants. The assumption is satisfied when controlling for pre-treatment outcomes and covariates is sufficient to model TPG's post-treatment potential outcome in the absence of the sharp price reduction by reweighting the outcomes of the transport companies in the comparison group (see, e.g., Huber, 2023).

Assumption 3 (convex hull condition):
Assumption 3 is satisfied when pre-treatment outcomes of the synthetic counterfactual can approximate the outcomes of the treated unit. Using statistical parlance, the pre-treatment outcomes of the treated unit are not 'too extreme' (too high or low) compared to the outcomes of the donor pool.

Assumption 4 (no spillover effects):
Assumption 4 is fulfilled when the price reduction has no spillover effects, eighter positive or negative, on other transport companies in the donor pool. An obvious failure of this assumption would be a decrease in public transport demand of other Swiss cities because their residents perceive the ticket costs as too high after the price reduction in Geneva.

Assumption 5 (no external shocks):
Applying the synthetic control method, we assume that no shocks occur to the outcome of interest during the study period (see, e.g., Abadie, 2021). In our case, this condition is challenging, since public transport companies expand the network from time to time, which typically affects the demand for public transport (see, e.g., Brechan, 2017, Holmgren, 2007). To account for such changes in supply, we propose an aggregate metric that breaks down the demand for public transport per company's supply, which we use as our outcome variable. More precisely, we calculate the ratio of passenger trips per vehicle kilometre, being robust against changes on the supply side. Additionally, to our knowledge, no large-scale road or parking policy was introduced in the areas of interest during the study period.

1.5 Data

To investigate the effect of the policy intervention in Geneva, we use the annual reports of Swiss transport companies, which the Swiss National Library systematically archives.[10] In these annual reports, the companies publish financial and non-financial performance indicators. We systematically gathered the most relevant performance indicators from public transport companies for our dataset. TPG operates mainly in the city of Geneva, the densest and second largest city in Switzerland, and its agglomeration belt. Using the synthetic control method, we have to choose each unit in the donor pool judiciously to provide a reasonable control for TPG, the treated unit (see Assumption 2 in Section 1.4.2). Therefore, we only consider transport companies that operate trams and buses primarily in cities with more than 50,000 inhabitants. These are Bernmobil (Berne), BVB (Basel), SBW (Winterthur), TL (Lausanne), TPL (Lugano), VB (Biel), VBL (Lucerne), VBSG (St Gallen) and VBZ (Zurich).[11]

First, we collected the number of passenger trips, which are standardized in Switzerland. The number of passenger trips counts how many passengers enter a company's vehicle per year. Passenger trips are essential, as we want to measure the increase in public transportation use, which, e.g., could be due to a mode shift from car use to mass transportation. Today, companies mainly count passengers automatically, but this was often done by hand in the past. This change of the counting system happened in Geneva from the years 2015 to 2016. Therefore, we adjust our TPG data from 2016 to 2019 based on the observed growth rate of the passenger trips to have a uniform panel dataset.[12] Since 2005, TPG has experienced the highest increase in passenger trips (compared to Swiss transport companies in the donor pool), followed by TL operating in Lausanne, another city in the French-speaking part of Switzerland. However, since 2005, TPG, together with VBSG (St Gallen), has also experienced the highest increase in vehicle kilometres. The increase results from the extension of tram routes. Therefore, to mitigate changes in supply, i.e., external shocks increasing company's networks (see Assumption 5 in Section 1.4.2), we use the previously discussed aggregate metric of passenger trips per vehicle kilometre as the outcome variable.

Consequently, companies with high-capacity utilization would have a high value in our dependent variable. Figure 1.1 shows the development

[10] See https://www.nb.admin.ch/snl/de/home.html (accessed on November 9, 2021). In this study, we focus on transport companies, as annual reports are not publicly available for tariff associations in the period of interest.

[11] The VBL (Lucerne) provided us with the VBL data, as it was not publicly available.

[12] We have verified our adjustments with the transport company TPG.

of passengers per vehicle kilometre for companies operating in a city with more than 50,000 inhabitants over time. As expected, our metric is mainly robust against changes on the supply side. Moreover, this variable also serves as a proxy for an average passenger load rate. Considering CO_2 emissions, this is also important, as the average emissions of each individual passenger decrease when the metric increases. Finally, we also observe that TPG is not extreme in the values of the outcome variable before the intervention. This is important to define a weighted subset of control companies that is comparable to TPG (see Assumption 3 in Section 1.4.2).

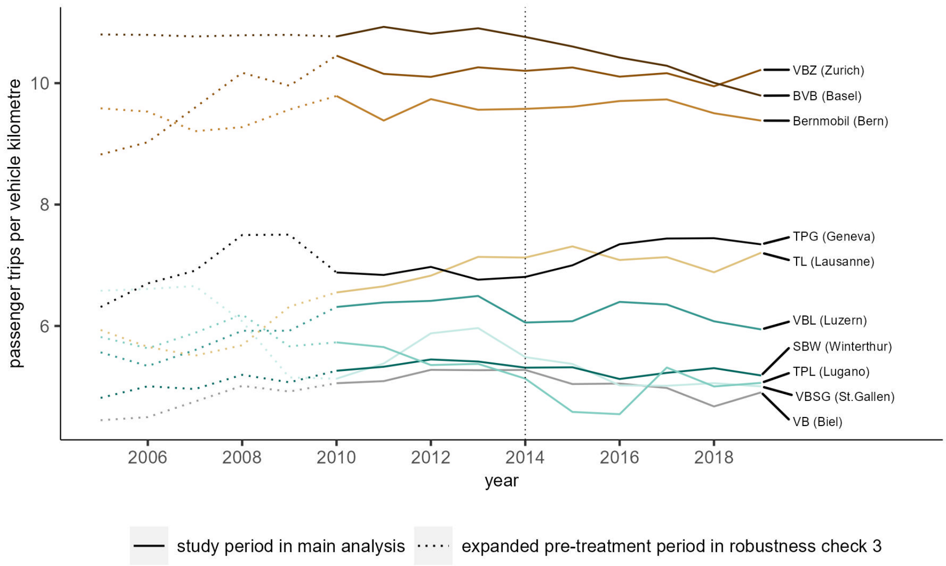


Figure 1.1: Passenger trips per vehicle kilometre. Note that we restrict our pre-treatment period to 2010 to 2014 (solid lines).

Controlling for supply changes also makes sense, as several studies show considerable effects of vehicle kilometers on demand. For instance, Holmgren (2007) estimates an elasticity of demand with respect to public transport supply (i.e., vehicle kilometres) amounting to 1.05. Based on this meta-analysis, we assume a considerable elasticity of demand with respect to public transport supply of about 1 when applying the ratio. However, and also a thing to notice in Figure 1.1 by looking at the period with the dotted lines, due to a substantial increase in vehicle kilometers plied by bus lines in Geneva's agglomeration belt from 2008 to 2010, the ratio in Geneva declined. This is because the aggregate change in TPG's supply occurred in the subarea where public transport is relatively poorly utilized. Therefore, we restrict our pre-treatment period to the years 2010 to 2014. However, collecting several observations on the unit of interest (TPG) and the donor pool is crucial before the price reduction (Abadie, 2021). Therefore, we also perform a robustness check with a more extended pre-treatment period. Moreover, we also oppose our results to estimations without the metric and thus use only passenger trips as the outcome variable. This robustness check is crucial, as unexpected low (or high) elasticity of demand with respect to public transport supply could be an alternate explanation of the treatment effect.

We match our outcome variable with predictors, forces working in a public transportation setting, to predict our outcome variable and build a valid synthetic TPG. We, therefore, gathered aggregate data about the share of public transport and individual motorized vehicles in Swiss urban areas from the Swiss Mobility and Transport Microcensus for 2010[13] and 2015[14]. We use these modal-split predictors to map the choice of transport modes in each urban area. In addition, we include variables for population growth and population density yearly provided by the association of cities.[15] These variables account for the potential demand for public transport in a given region. Finally, we use the average of pre-treatment outcomes for 2012 to 2014 (after 2011, the tram network of Geneva did not expand any further) for treated and control units as predictors.

1.6 Results

We subsequently present the results of applying the synthetic control method, evaluate their significance and investigate their robustness.

1.6.1 The effect of the price reduction

To construct the synthetic TPG, the synthetic control method assigns weights among the control group companies. VB (Biel) receives the highest weight with 0.400, while BVB (Basel) has the second-highest weight with 0.162, and the VBSG (St Gallen) has a zero weight.[16] Table 1.4 in Appendix 1.C shows the weights for each company in the donor pool. Figure 1.2 plots the

[13] See https://www.bfs.admin.ch/asset/de/su-d-11.04.03-MZ-2010-G07.3.1.1 (accessed November 9, 2021).

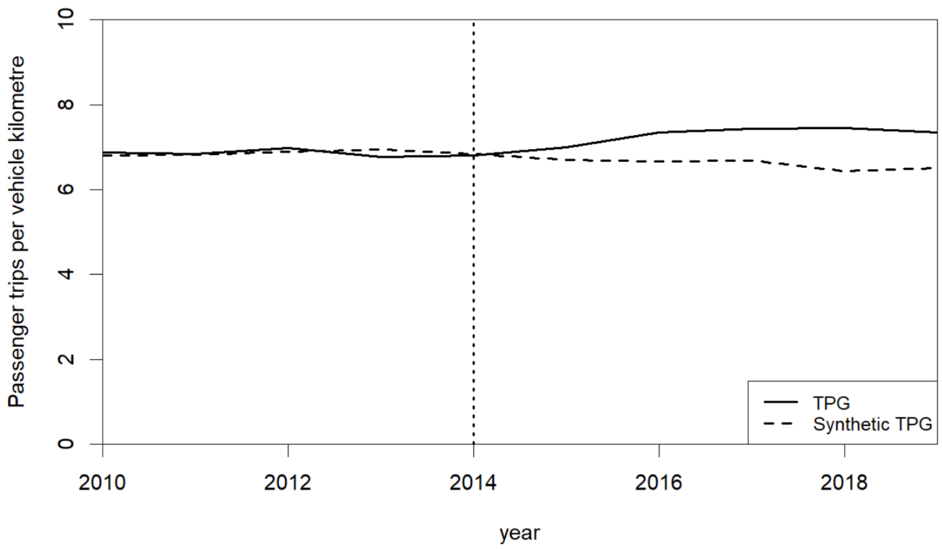
[14] See https://www.bfs.admin.ch/bfs/en/home/statistics/mobility-transport.html (accessed November 9, 2021).

[15] See https://staedteverband.ch/de/Info/publikationen/statistik-der-schweizer-stadte (accessed October 21, 2021).

[16] Note that in Biel, the aggregate supply increases from 2017 to 2019 by 14%. Accordingly, the number of passenger trips grows by 12%. Therefore, our ratio blocks off this aggregate supply change. In Basel, the aggregate supply remains constant during the study period.

outcome variable, equal to passenger trips per vehicle kilometre, of TPG and the synthetic TPG from 2010 to 2019. We can easily observe that the two trajectories track each other close in the pre-treatment period, i.e., the pre-price-reduction period. Thus, the mean squared prediction error (MSPE) of the outcome variable between TPG and the synthetic TPG amounts to a small figure of 0.009. Therefore, our synthetic TPG is a sensible counterfactual of the outcome we would expect if the intervention had not been implemented. While demand from customers of the synthetic TPG continued its slightly downward trend, the demand for TPG increased. This difference is relatively constant over four years, from 2016 to 2019.

Figure 1.2: Demand development of TPG and the synthetic TPG



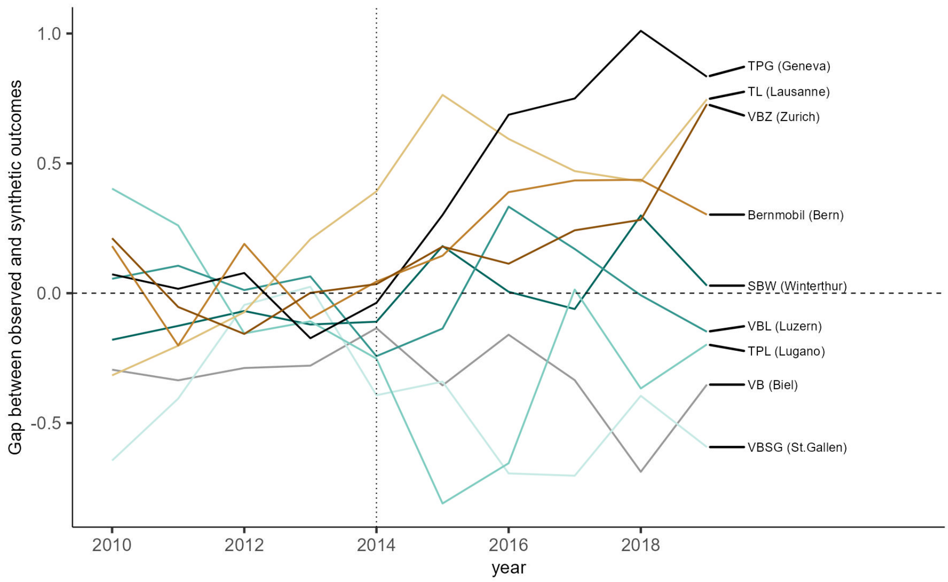
The estimate of our analysis indicates the effect of the policy intervention on demand in passenger trips per vehicle kilometre. More precisely, after the price reduction, this effect represents the yearly differences (gaps) between TPG and its synthetic counterfactual. On average, the demand (our ratio) increased by about 0.72 from 2015 to 2019. In other words, almost one additional passenger per vehicle kilometre boarded TPG's buses and trams due to the price reduction, an increase of about 10.6% compared to 2014.[17] Thus, we conclude that we can infer a positive effect on demand in Geneva due to the price reductions. Randomly drawing nine control units with a

[17]The effect on passenger trips per vehicle kilometre would be equivalent to the effect on passenger trips if the supply (i.e., vehicle kilometre) elasticity is about 1. In this simplification, the effect of passenger trips would be 10.6%, amounting to 20.9 million passenger trips.

replacement from our donor pool leads us to bootstrap confidence intervals. The corresponding 95% bootstrap confidence interval of the average estimated effect is [0.423; 0.870]. We present the distribution of the means of 2,000 samples in Figure 1.C.1 in Appendix 1.C.

The black line in Figure 1.3 illustrates the gap between the trajectories of TPG and the synthetic TPG. As we know from the results above, the MSPE of the outcome variable between TPG and the synthetic TPG is small. Hence the trajectories track each other closely in the pre-treatment period. However, they separate in the post-treatment period, and therefore we observe a causal effect of the treatment (price reduction) on demand (aggregate metric). We can now construct a synthetic counterfactual for all companies in our control group and compare these trajectories to the actual company's development. Suppose the trajectories from the 'pseudo-treated' companies and their synthetic counterpart fit well in the pre-treatment period and separate in the post-treatment period (even though they have not introduced a price reduction). Then, our effects calculated for TPG may be caused by chance rather than by the treatment (the price reduction). Finally, note that in Figure 1.3, we discard BVB (Basel) due to high pre-treatment MSPE and, therefore, insufficient fit (see also Assumption 3 (convex hull condition)).

Figure 1.3: Demand gaps of TPG and control companies



The other lines in Figure 1.3 summarize the results of iteratively applying our method to one transport company after the other by illustrating the gaps between the actual and the synthetic trajectories. The average MSPE among the companies amounts to 0.09, and the median amounts to 0.07, figures which are relatively small. Hence the trajectories track each other closely in the pre-treatment period. In other words, the methodology also provides mainly suitable counterfactuals for most companies in the control group. However, there remain a few lines that still deviate substantially from a zero-gap. From 2016 to 2019, the black line, the gap between TPG and its synthetic counterfactual, is further apart than all the other lines. Hence, the difference between the post-treatment MSPE and the pre-treatment period is the greatest among the companies. The ratio for TPG amounts to 66.0, while the companies with the second and third highest ratios are VBZ (Zurich) and TL (Lausanne), with 9.7 and 5.5 respectively. On average, the post-treatment MSPE divided by the pre-treatment MSPE amounts to 3.7 in the donor pool. Therefore, we conclude that the increase in demand for TPG due to the price reduction is not driven by chance.

1.6.2 Robustness analysis

In this section, we challenge our assumptions and our study design by performing robustness investigations. First, as a methodological robustness check, we apply a recent development of the synthetic control method, the synthetic difference in differences approach of Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2019), to demonstrate the goodness of our results. Second, we expand our pre-treatment period. Third, we expand our donor pool with companies operating in cities with fewer than 50,000 inhabitants. Fourth, we estimate the effect of the lower fares on the number of passengers (and not the number of passengers per vehicle kilometre). In the fourth robustness check, the synthetic TPG does not mimic TPG in the pre-treatment period appropriately. Therefore, in a final robustness investigation, we re-estimate the effect on the number of passengers using the synthetic difference in differences approach. We summarize the results in Table 1.1.

As a first robustness check, we use the synthetic difference in differences approach proposed by Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2019). In a nutshell, this methodology decides in a data-driven way (through minimization of the MSPE in pre-treatment periods) whether the synthetic control methodology or the conventional difference in difference model (see, e.g., Card and Krueger, 1994) is more appropriate for a case. However, this is a simplification. More precisely, it is an extension of the synthetic control method because it includes unit-specific fixed effects to control for constant differences in the demand level among the affected unit and the synthetic counterfactual. Hence, the demand level can vary by a constant. Therefore, it might be sufficient that the affected unit and the synthetic counterpart match each other in terms of changes or trends rather than levels (as the difference in differences model might be more appropriate). Moreover, the synthetic difference in differences method includes time weights. By weighting each period before the intervention, the synthetic difference in differences method is able to eliminate, in a data-driven way, the role of time periods considered to be inappropriate for the creation of the synthetic TPG. We use the *synthdid* package by Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2019) to implement the synthetic difference in differences method. Almost identical to our original result, the demand increases by 0.68, or 10.0%. Therefore, we can draw the conclusion that applying the synthetic difference in differences method—which includes unit fixed effects and time weights—leads to similar results as the synthetic control method.

Due to a significant increase in the vehicle kilometres of bus lines in Geneva's agglomeration belt from 2008 to 2010, we restricted our pre-treatment period to 2010 to 2014. However, it is crucial when applying the synthetic control method not to have a pre-intervention window that is too small. Therefore, in a second robustness check, we substantially expand our pre-treatment period to 2005 to 2014. In this analysis, the MSPE amounts to 0.1, which is slightly worse (but still decent) compared to our original estimation. The estimate amounts to 0.61, indicating an increase in demand of about 9% for TPG (compared to 2014). That is about 1.5 percentage points lower than the main result and is, therefore, almost identical to our original result.

Due to the risk of over-fitting, we only include transport companies operating in cities with more than 50,000 inhabitants in the control group. However, as the design of our donor pool might influence our results, we expand the donor pool in a third robustness check with transport companies from smaller cities that also primarily operate trams and buses and for which the necessary data are available. These are BBA (Aarau), BSU (Solothurn), MBC (Morges), STI (Thun), TPN (Nyon), Travys (Yverdon), VBG (Zurich agglomeration), VZO (Zurich agglomeration) and ZVB (Zug). The estimate amounts to 0.71, an increase in demand of 10.5% from 2015 to 2019 (compared to 2014). The pre-treatment mean squared prediction error (MSPE) of the outcome variable between TPG and the synthetic TPG is impressively low, amounting to 0.09. Therefore, we conclude that we construct a decent counterfactual and the estimate of our original study design is robust.

In a fourth robustness investigation, we replace our metric with the original number of passenger trips. Remember, due to variation in vehicle kilometres of trams in Geneva in the study period and their effect on passenger trips, we define the ratio of passenger trips per vehicle kilometre as our outcome variable. When we analyse the impact on passenger trips alone, we arrive at similar patterns but a higher MSPE. Therefore, the trajectories of TPG and the synthetic TPG do not track each other as closely in the pre-intervention period as in our main study design (see also Figure 1.C.2 in Appendix 1.C). The reason for this is the positive demand shock in 2012 due to the finalization of the tram network extension. The estimate, however, is comparable amounting, to 18.0 million additional passenger trips. That points to a demand increase of about 9.1% for TPG compared to 2014, which is 1.4 percentage points lower than the main result. Note that these figures should be interpreted with much caution, as the pre-treatment fit is not decent, and TPG already starts (at 2014) at a higher value than the synthetic TPG. Moreover, an important thing to notice is that the outcome of TPG (passenger trips) is already higher than the synthetic counterpart (see Figure 1.C.2). Therefore, it might be that the effect due to the price reduction is lower than reported.

Adding to the fourth robustness check, we again estimate the price reduction effect on passenger trips. However, different from the previous investigation, we use the synthetic difference in differences approach instead of the synthetic control method. The recent methodology might improve as it is more sensitive to what is happening in the periods just before the intervention. Moreover, it permits the outcomes of TPG and the synthetic TPG to differ as it includes unit fixed effects. We find that the effect amounts to, on average, 7.3 million additional passenger trips. That is an increase of about 3.7% for TPG compared to 2014, which is lower than our original result. Hence, our result depends crucially on whether we consider the influence of the vehicle kilometres. Figure 1.C.3 in Appendix 1.C plots the effect estimated with the synthetic difference in differences approach. In our case, the methodology focuses on the parallel trend between TPG and TL (Lausanne), the company with the most favorable demand development among the unaffected transport companies. However, note that the corresponding 95% bootstrap confidence interval of the average estimated effect of the fifth robustness check is [3.9 million; 24.5 million]. That is an increase between 2.0% and 12.4%, with all values being higher than zero. However, these values should be interpreted with caution as the bootstrap distribution is not normal (see Figure 1.C.4 in the Appendix).

Table 1.1: Estimates summary of robustness checks

Check	**Modification**	**Price effect**
1	Method (SDID)	10.0%
2	Expanded pre-treatment period	9.0%
3	More units in the donor pool	10.5%
4	Passenger trips as outcome variable	Insufficient fit
5	Passenger trips as outcome and method (SDID)	3.7%

Note: In robustness checks 1, 2, and 3, we use passenger trips per vehicle kilometres as the outcome variable.

1.7 Discussion

We assess a demand effect of lower urban public transport fares and find that the price reduction in Geneva leads to a demand increase of about 10.6%. To isolate the effect of our mechanism of interest, the price reduction, we propose an aggregate metric inheriting supply changes of public transport networks. This makes sense as we are able to block off the effect of increasing and decreasing frequencies as an alternate explanation of demand-effects, being in the context of public transport of crucial importance. Moreover, robustness investigations show that the estimate is robust when we modify the study design, i.e., longer pre-treatment period or more companies in the donor pool, or applying the synthetic difference in differences approach.

The estimate is significantly lower when we consider the outcome variable passenger trips and do not isolate the price reduction effect from the supply effects. It amounts to 3.7% when we apply the synthetic difference in differences methodology, which is the more appropriate method to analyze the outcome variable passenger trips. However, it should be noted that when using the outcome variable passenger trips, Assumption 5 (no external shocks) is violated regardless of the methodology. A demand increase of 3.7% is even lower than naively comparing the passenger trips of TPG after and prior to the price discount, amounting to 5.7% additional trips.[18] This is because the estimate of the robustness check 5 mainly relies on control units with an upwards trend. Moreover, when calculating bootstrap estimates of the effect, we do not get any negative values and the 95% bootstrap confidence interval of the average estimated effect points to an increase of between 2.0% and 12.4%, inclusive. Therefore, we conclude that the effect of 3.7% additional demand is a potential lower bound of the effect.

Using the metric passenger trips per vehicle kilometre, we assume a high elasticity of demand with respect to public transport supply, i.e., about 1, due to findings in the literature (Holmgren, 2007). On the other hand, as a word of caution, the elasticity of demand with respect to public transport supply might be lower when public transport quality is high, see, e.g., Axhausen and Fröhlich (2012). In such a case, increasing or decreasing vehicle kilometres could influence the metric and, therefore, the estimate of interest. However, looking at Geneva, as well as Biel and Basel, the two units with the highest weight in the donor pool, we observe a high elasticity of demand with respect to public transport supply. Concrete, when vehicle kilometres go up, passenger

[18] This increase is also due to an additional railway cross-country train line between Geneva and France, coming alongside an increase of vehicle kilometers of TPG. The latter also increases demand. However, note that we can control for this effect using our proposed aggregate metric.

trips go up. Therefore, in light of blocking off vehicle kilometres as an external shock influencing the estimate of interest (Assumption 5), we suggest in future natural experiments to use a metric controlling for supply changes, together with a presentation of a lower bound.

As the price change from 2014 to 2015 amounts to 12.6%, we can calculate corresponding point elasticities of demand. In Appendix 1.A, we describe how we assess the price elasticities. We get average elasticities of -0.84 and -0.29 of our main result and the lower bound, respectively. These estimates are in line with the literature. In particular, Holmgren (2007) proposes that the often stated rule of thumb of a price elasticity amounting to –0.3 only holds when vehicle kilometres are treated exogenous, but not when vehicle kilomteres are treated endogenously. In the latter case, Holmgren (2007) suggests a short-run price elasticity of -0.75 and a long-run price elasticity of -0.91 in Europe. In Switzerland, where our case study of Geneva is located, Axhausen, Molloy, Tchervenkov, Becker, Hintermann, Schoeman, Götschi, Castro Fernández, and Tomic (2021) estimate in a recent experimental study a price elasticy of -0.31. We complement this research, since our study differs in essential elements. First, our estimate is based on a natural experiment and includes longer-term adjustments. Second, whereas regular car use was a condition for participation in the investigation of Axhausen, Molloy, Tchervenkov, Becker, Hintermann, Schoeman, Götschi, Castro Fernández, and Tomic (2021), we cannot identify different customer groups. Third, we analyze a price reduction and Axhausen, Molloy, Tchervenkov, Becker, Hintermann, Schoeman, Götschi, Castro Fernández, and Tomic (2021) a price increase.

One limitation of the study is that we did not analyze the influence of the COVID-19 outbreak. Future studies should investigate a more extended period and also take into account the impact of the pandemic. A thing to notice is that TPG is a company that operates on a cross-border territory. In Switzerland, and thus in the donor pool, we only have BVB (Basel) and TPL (Lugano) with a comparable situation. Therefore, we can not completely exclude that the price reduction has a different effect on TPG's measures than on companies in the donor pool, which might lower the external validity of our result. Moreover, it is again essential to mention the extension of the tram network in Geneva, which, as a quality improvement, could still have had after-effects on demand. Thus, using statistical jargon, we do not know whether we completely isolated the effect of the supply increase, even when applying our metric.

Finally, note that we only present a point estimate of demand changes. Therefore, any generalizations from our findings should consider this factor. Moreover, we have considered the price reduction effect as a policy intervention and not the impact of the size of the discount. E.g., Brechan (2017) finds no significant relationship between the size of the price reduction and the demand reaction. Therefore, e.g., using similar study designs to discuss different effect sizes (if present) is on the agenda for future research. In addition, the price reduction was not the same for all age groups and ticket sentiments. Therefore, future studies could also investigate demand effects for specific client groups, e.g., seniors.

In summary, we show that price reductions in urban areas with high-quality public transport attract customers. However, the demand effect is too small to compensate for the loss of revenue due to lower prices. Therefore, future studies should also analyze whether the increased number of trips stems from existing or new customers.

1.8 Conclusion

In this study, we answered the question of whether a public transport price discount leads to increasing demand. Therefore, we have applied the synthetic control method to assess the demand effects of lower fares in Geneva, a Swiss urban area. The methodology is ideal for such quasi-experimental settings of price reductions (in urban areas). It constructs a counterfactual that mimics the demand a treated unit would have experienced without the price reduction in a data-driven way. Following a democratic vote, the regional tariff association in Geneva introduced a price reduction of 28% for annual season tickets and of 20% for hourly tickets. To the best of our knowledge, our study is the first causal analysis of this case and of price reductions due to direct democracy in general. We created a unique data set of annual reports from Swiss transport companies to identify the increase in demand. In addition, we proposed a metric for aggregate demand to block off increasing networks as an alternate explanation of demand-effects, being in the context of public transport of crucial importance (Brechan, 2017, Holmgren, 2007). This metric breaks down the demand for public transport per company's supply. We found that the lower fares caused an increase in demand of 10.6% from 2015 to 2019 for TPG, by far the biggest operator in the Geneva tariff association. The result remains robust when performing several robustness checks. However, when changing study design by looking at the effect and applying the synthetic difference in differences method, we were able to provide a lower bound of the effect's estimate amounting to an increase of 3.7% additional passenger trips.

Appendices

1.A Price elasticity

Taking a demand change and a price change together, we can estimate a price elasticity of demand:

$$\text{Price elasticity of demand} = \frac{\text{Demand change in \%}}{\text{Price change in \%}} \tag{1.A.1}$$

To define the price change on aggregate level, we consider the revenue share of each ticket category and their price change. We calculate the price change on aggregate level, the so-called overall price change, based on the revenue share before the price intervention:

$$\text{Relative price change} = \sum_{n}^{i=1} \text{revenue share}_{i,2014} * \frac{price_{i,2015} - price_{i,2014}}{price_{i,2014}} * 100 \tag{1.A.2}$$

where i denotes the ticket categories. Moreover, 1 stays for the first an n for the last category.

1.B Descriptive statistics

Table 1.2: Key figures of TPG and the control group (in millions)

	TPG			**Control group (mean)**		
year	metric	passengers	vehicle kilometers	metric	passengers	vehicle kilometers
2019	7.3	217.9	29.7	7.0	90.4	10.9
2018	7.4	210.7	28.3	6.9	89.3	10.9
2017	7.4	207.9	27.9	7.1	89.2	10.6
2016	7.3	204.5	27.8	7.1	88.5	10.5
2015	7.0	200.3	28.6	7.1	88.5	10.3
2014	6.8	197.1	28.9	7.2	88.1	10.3
2013	6.8	196.6	29.1	7.4	88.5	10.2
2012	7.0	192.3	27.6	7.3	87.6	10.2
2011	6.8	177.1	25.9	7.2	85.3	10.1
2010	6.9	172.1	25.0	7.2	84.4	9.8

Note: Metric denotes our aggregate ratio being passenger trips per vehicle kilometers.

Table 1.3: Traffic revenues of TPG (in millions)

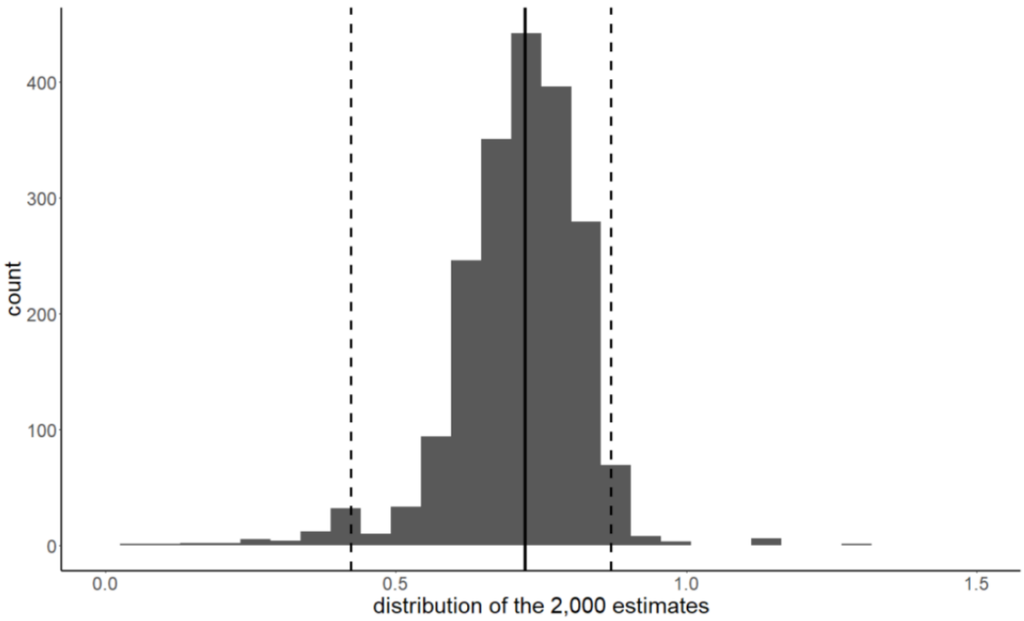
year	TPG
2019	153.8
2018	150.7
2017	146.1
2016	145.3
2015	142.6
2014	153.7
2013	152.1
2012	144.3
2011	135.2
2010	127.9

1.C Further tables and figures

Table 1.4: Company weights for the synthetic TPG

Company	Weight
Bernmobil (Bern)	0.055
BVB (Basel)	0.162
SBW (Winterthur)	0.080
TL (Lausanne)	0.079
TPL (Lugano)	0.091
VB (Biel)	0.400
VBL (Lucerne)	0.083
VBSG (St Gallen)	0.000
VBZ (Zurich)	0.049

Figure 1.C.1: Bootstrap estimates



Note: values greater than 1.5 are not displayed in this Figure.

Figure 1.C.2: Gap between TPG and the synthetic TPG of robustness check 4

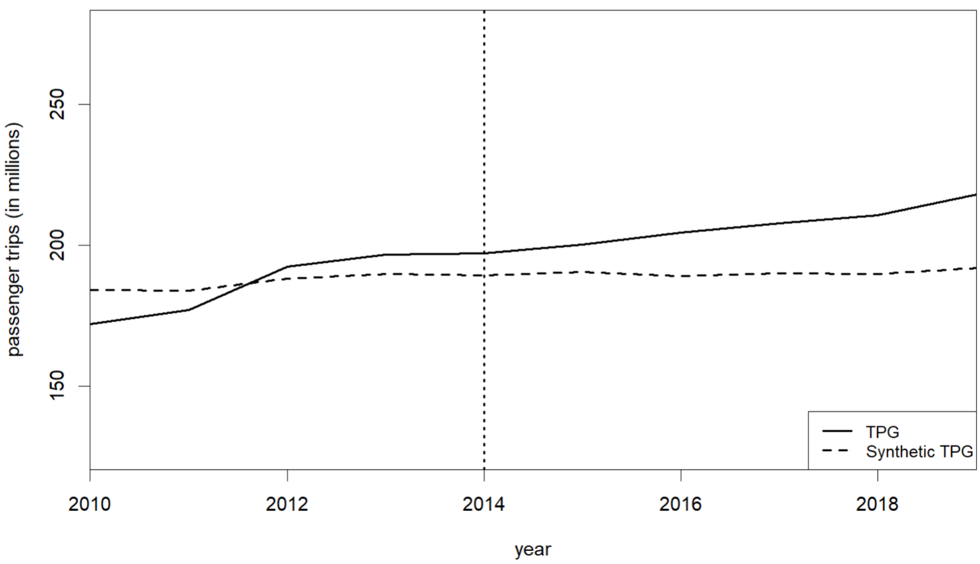


Figure 1.C.3: Effect on passenger trips estimated with the synthetic differenece in differences approach

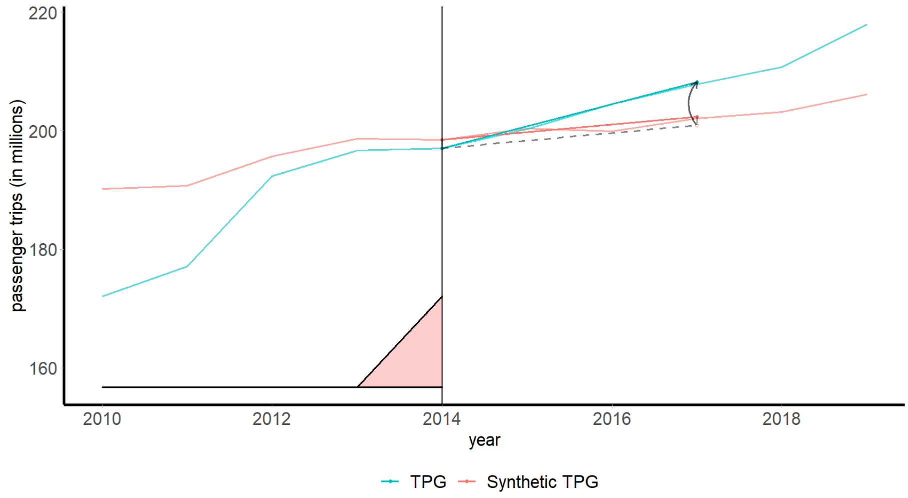
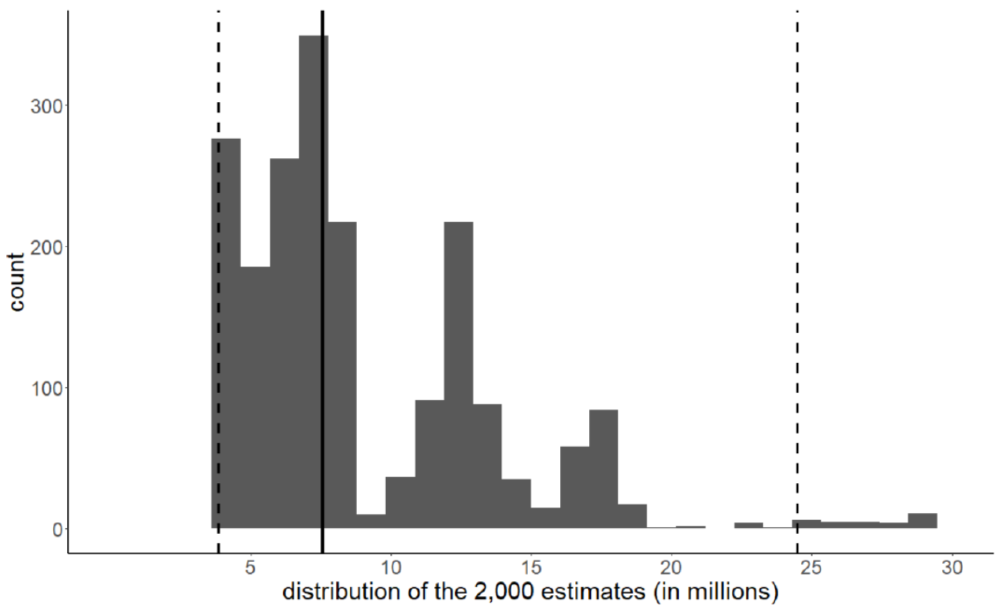


Figure 1.C.4: Bootstrap estimates of robustness check 5



Chapter 2

Predicting DRT demand in rural Switzerland

Assessing spatial characteristics

joint with **Sebastian Imhof***

Abstract

The niche market segment of demand responsive transport (DRT) services is meant to overcome structural economic problems of currently cost ineffective public transport (PT) services in rural areas. Simulation studies for mainly urban DRT services showed that demand for DRT trips is correlated with spatial characteristics. More knowledge of spatial characteristics of rural settings and their influence on DRT trips is necessary. In this study, trip data of a rural DRT service called mybuxi is used. Machine learning is applied for a better understanding of spatial characteristics of DRT demand in two different rural settings of the mybuxi service. Here in, the transferability from one mybuxi setting to the other is then tested. Results indicate that the number of inhabitants and the distance to the train station are the most important spatial characteristics for the prediction of DRT demand. The study suggests that both DRT service areas experienced an increase in accessibility. For future transport planning, the increase in accessibility by DRT services in different rural areas must be taken as a legitimation for these services to be implemented instead of line-bound PT services.

*This chapter is based on a paper published in the journal *Research in Transportation Economics* as Imhof and Blättler (2023).

2.1 Introduction

Public transport (PT) operators face the problem that sparse population and extensive surface area only allow low service frequency which in the end leads to an unattractive service availability for the population. Rural PT services can be highly cost-ineffective, and the operators need additional public subsidies to maintain the services (De Jong, Vogels, van Wijk, and Cazemier, 2011). Mounce, Beecroft, and Nelson (2020) call this set of circumstances the "rural mobility problem". To overcome this problem, flexible demand-responsive transport (DRT) services gained the interest of PT operators as well as researchers. DRT services are meant to strengthen rural transport services, as they allow a higher accessibility in rural areas compared to fixed route services with buses (Avermann and Schlüter, 2019, Coutinho, van Oort, Christoforou, Alonso-González, Cats, and Hoogendoorn, 2020). Especially in the case of transport agencies trying to sustain a certain service level for the passengers despite low ridership, DRT services may be a better solution than fixed route services (National Academies of Sciences, Medicine, et al., 2019). DRT services so far are considered niche services that either operate as a replacement or in concurrence to traditional public transport services (Sharmeen and Meurs, 2019). Important success factors of DRT services are their integration in a public transport mix and their ability to fill gaps in accessibility in areas with low PT demand (Daniels and Mulley, 2012). A combination of future autonomous DRT services with existing mass transportation services such as commuter railways may help to increase PT ridership in rural areas (Imhof, Frölicher, and von Arx, 2020).

Due to their higher flexibility, DRT services can specifically contribute to a decrease in personal car usage in rural areas (Sörensen, Bossert, Jokinen, and Schlüter, 2021) and to reducing social exclusion of mobility-disadvantaged persons (Nykiforuk, Glenn, Hosler, Craig, Reynard, Molner, Candlish, and Lowe, 2021, Vitale Brovarone, 2022). Previous studies showed that, in general, persons with low income (Kuhnimhof, Buehler, Wirtz, and Kalinowska, 2012), specifically young adults (se.g. Buehler and Hamre, 2015, Molin, Mokhtarian, and Kroesen, 2016, Schulz, Böhm, Gewald, and Krcmar, 2021) and retired persons (Scheiner, Chatterjee, and Heinen, 2016) can profit from easy PT access and are more aware for multimodal trips (Buehler and Hamre, 2015) which is important for trips combining DRT and PT like train services. In Switzerland, Thao, Imhof, and von Arx (2023) found that especially elderly people and people without access to a car, use DRT services in rural areas more often compared to adults in working age and people with access to a car. In effect, governments see in DRT a mean to increase accessibility and social inclusion at the same time (Davison, Enoch, Ryley, Quddus, and Wang, 2012).

However, research showed that many current rural DRT services are not economically viable (Currie and Fournier, 2020). Spatial characteristics can be influential on the number of trips realized in certain areas, yet research on spatial characteristics of flexible transport services so far concentrated mainly on simulations and statistical models of large-scale flexible transport services' trip data in urban areas (Guidon, Reck, and Axhausen, 2020, Zwick and Axhausen, 2022). Population and job density as well as the distance to a city center were found to be crucial factors influencing trip origins and destinations in DRT services (e.g. Weckström, Mladenović, Ullah, Nelson, Givoni, and Bussman, 2018, Zwick and Axhausen, 2022). Jain, Ronald, Thompson, and Winter (2017) additionally showed that, for the Greater Melbourne region, spatially differing socio-demographic patterns as well as PT performance are essential factors to be considered for predicting the usage of a DRT service. Yet, it is still unclear whether accessibility measures influence the usage of a particular DRT service.

To further understand how rural DRT services can be scaled up, more knowledge of spatial characteristics in rural settings and their influence on DRT demand are needed. In this study, trip data of the rural DRT service called mybuxi is used. We predict DRT demand with spatial characteristics using the machine learning algorithm 'random forests'. We use this model to test the transferability from one mybuxi setting to another by training the algorithm in a perimeter, where the service is established and then predict demand in a new perimeter.

So far, several studies using simulation methods have highlighted the importance of spatial characteristics on the performance and quality of DRT services. According to a simulation by Ronald, Thompson, Haasz, and Winter (2013), the level of service of a DRT service is affected by the spatial distribution of demand. Diana, Quadrifoglio, and Pronello (2007) found that DRT services, compared to PT services, have lower emissions where demand is low and high levels of service quality sought. The usage of small vehicles may therefore outperform line-based services. Scott (2010) highlights the suitability of DRT services where transport demand is low. He distinguishes between following factors influencing low demand: time of day; day of week; low-density land-use patterns like suburban or rural areas. Spatial characteristics further influence the pooling rate of flexible transport solutions such as DRT. Brown (2019), Gehrke, Huff, and Reardon (2021), Li, Pu, Li, and Ban (2019) all found that in areas of high population density there is a greater likelihood that a pooled service option will be chosen by passengers. For a Swiss ridesharing scheme in a rural context, Thao, Imhof, and von Arx (2021) found no association between land-use diversity and demand for ridesharing trips.

These studies using simulations do not offer more in-depth information on which spatial patterns of demand are found in real-world DRT services and to their influence on the sustained operation of the service. Currently, only sparse literature on this topic exists. Sörensen, Bossert, Jokinen, and Schlüter (2021) highlight the spatial patterns of a rural DRT service in Germany and found that trip frequency related to the population size of neighboring villages or cities. In their case study, the topography had an impact on the resulting corridors that developed. Alonso-González, Liu, Cats, Van Oort, and Hoogendoorn (2018) showed that users of a DRT service in the Netherlands experienced a high improvement in accessibility compared to traditional PT services, highlighting that the accessibility gains are the highest in underserved areas. Throughout the present article, accessibility is understood as a multi-dimensional concept that takes into account, how members of society can reach their desired destinations (Mulley, Nelson, Teal, Wright, and Daniels, 2012).

The rest of this paper is structured as follows: in Section 2.2, the data sources for this study are presented, followed by descriptive statistics on the data. Section 2.3 is dedicated to the chosen methodological approach. Results in Section 2.4 then describe the findings on the spatial interactions of the two chosen mybuxi service areas and whether the findings on one service area are transferrable to the second service area. The paper then concludes with a discussion of the key findings as well as the limitations of the study.

2.2 Context and data description

2.2.1 Context

Mybuxi is a start-up company dedicated to providing rural DRT services. The company was founded in 2018 and set up four different DRT services in rural Switzerland, so far. Two services in rural parts of the canton of Berne are examined in this paper. Both services use virtual stops based on which passengers can choose origin and destination stops individually. The virtual stops are evenly distributed over the entire service area in populated areas as well as places of touristic interest. Upon requests of the local population and enterprises, virtual stops can be added or eliminated in the mybuxi system. Operating in areas where car dependency is high mainly because of lack of highly frequent PT services, the main goal of the mybuxi service is to provide an alternative to the private car usage. Especially elderly people or school children in rural areas are target groups of the service.

The first service started in April 2019 in the Herzogenbuchsee Region in the municipalities of Herzogenbuchsee and Niederönz. Two municipalities, Bettenhausen and Thörigen, joined the service two years later. However, in these two municipalities mybuxi operates only in the evening and with fixed stops. For keeping a consistent dataset, we exclude these two municipalities of the analysis. In the analysis of the Herzogenbuchsee area, 46'389 trips were included.

The second perimeter lies in the Emmental Region with six rural municipalities involved. There, the service started in September 2020. Due to political regulations, the operation is different in the municipality of Burgdorf compared to the other five municipalities (e.g. pick-ups from the train station are not allowed before 19 o'clock). Therefore, we also exclude this municipality from the analysis. However, we include the municipality of Burgdorf in a robustness check in Appendix 2.A. In the Emmental area, 6'485 trips were included in the statistical analysis.

Both service areas are important pilot services for mybuxi to gain helpful experience for future expansions to other rural areas. The continuation of both services after the first two pilot years underscores the current success of mybuxi in these areas. In both perimeters, the service started with one minivan to cover the demand; in the Herzogenbuchsee area, a second vehicle was necessary after the first year of service. In the Emmental area, a second vehicle is used to cover peak-time demand. Today, the service is not economically viable and is therefore relying on public subsidies and private sponsorships. In Switzerland, the public subsidies for DRT services are lower than subsidies for traditional bus services.

The service in both areas is reliant on volunteer drivers, receiving 50 Swiss Francs for a shift of 4 to 5 hours. For the Herzogenbuchsee area, a user must pay 4 Swiss Francs per trip; for the Emmental area, a trip costs a user 10 Swiss Francs. Average trips in the Emmental area are much longer than in the Herzogenbuchsee area. Currently, there is no possibility to integrate a DRT service in the public transport system and the nationwide ticket fare system due to regulatory constraints.

2.2.2 Data description

Input data were collected from various sources. The DRT operator mybuxi provided the demand data for all trips in both regions examined. For the spatial data, we used data provided by the Federal Statistics Office (FSO) as well OpenStreetMap (OSM) data (OpenStreetMap Contributors, 2022). Additionally, we gathered data from geospatial analysis for distance measurements (Openrouteservice, 2022).

For both service areas, we created a 300x300-meter raster covering both service areas. This resulted in 175 zones in the perimeter of the Herzogenbuchsee area as well as in 915 zones for the perimeter of the Emmental area. For each zone, pick-ups and drop-offs with the mybuxi DRT service were plotted. The pick-ups and drop-offs per zone are the dependent variables. We use the number of trips, since we assume that pooling rather happens in areas with higher population density. However, we use the number of passengers as dependent variable in a robustness check in Appendix 2.A. The spatial data per zone acts as predictor. Table 2.1 lists the spatial data used.

Data	**Data source**
Population size per hectare	(Federal Statistical Office (FSO) 2021b)
Number of employees per hectare	(Federal Statistical Office (FSO) 2021a)
Number of workplaces per hectare	(Federal Statistical Office (FSO) 2021a)
Quality of PT ordered into five categories: A) Very good PT coverage B) Good PT coverage C) Moderate PT coverage D) Poor PT coverage E) No PT coverage	(Federal Office for Spatial Development (FOSD) 2022)
Points of interest - Hotels - Restaurants (incl. bars) - Health care - Schools - Shops	(OpenStreetMap Contributors 2022)
Distance to next train station (in km)	Based on Openrouteservice (2022)

Table 2.1: Independent variables: spatial data

A centrality variable was introduced to better understand in which way rural land-use patterns are explaining demand for DRT services. We therefore calculated the distance between each zone's centroid and the nearest train station, with the distance as result of the variable "Distance to next train station (in km)". The introduction of the variable "Quality of PT" additionally gives an indication on the accessibility of each zone with PT. PT stops are not included in the model, as they are covered by the PT quality in each zone.

2.2.3 Descriptive statistics

Table 2.2 describes the number of pick-ups and drop-offs per zone –the dependent variables - for the Herzogenbuchsee and Emmental areas. In the Herzogenbuchsee area, the mean for pick-ups and drop-offs per zone is higher. In the Emmental area, comparatively more zones do not have any pick-ups or drop-offs. That is, the distribution of pick-ups and drop-offs is more left skewed compared to that of the Herzogenbuchsee area.

Variable	Min	Q1	Median	Mean	Q3	Max
Herzogenbuchsee area						
Number of pick-ups per zone	0	0	1	267.5	69.5	18,078
Number of drop-offs per zone	0	0	2	265.1	103	8,996
Total 46,389 trips recorded from April 2019 to Mai 2022.						
Emmental area						
Number of pick-ups per zone	0	0	0	7.2	0	1,944
Number of drop-offs per zone	0	0	0	7.1	0	984
Total 6,485 trips recorded from September 2020 to Mai 2022.						

Table 2.2: Description of pick-ups and drop-offs in Herzogenbuchsee and Emmental areas

Figure 2.2.1 shows the population density in both examined areas, the Herzogenbuchsee and Emmental areas, and Table 2.3 describes the statistical distribution of the population as well as the employees per zone. The Herzogenbuchsee region is populated densely with a higher concentration of the population around the train station in the middle of the area. At the boundaries of the perimeter, population density is fading out. Overall, the mean population (see Table 2.3) is higher, the mean employees per zone lower than in the Emmental area. In the Emmental area, the population is more dispersedly distributed. Around both train stations in the Emmental area, the population density is the highest, like in the Herzogenbuchsee area. Inside the Emmental area, due to a topographically complex situation, many zones have no or small populations. The perimeter of the Emmental area is dominated by a hilly topography with many farms, resulting in a scattered settlement structure. The scattered distribution of small farms explains the slightly higher number of employees per zone in the Emmental area.

Variable per area	**Min**	**Q1**	**Median**	**Mean**	**Q3**	**Max**
Population size per zone						
Herzogenbuchsee	0	0	0	51.6	26.5	483
Emmental	0	0	3	11.1	8	377
Number of employees per zone						
Herzogenbuchsee	0	0	0	2.4	0	303
Emmental	0	0	0	5	4	296

Table 2.3: Statistical distribution of population size and employees per zone

Figure 2.2.1: Population distribution in the Herzogenbuchsee (left) and Emmental (right) areas.

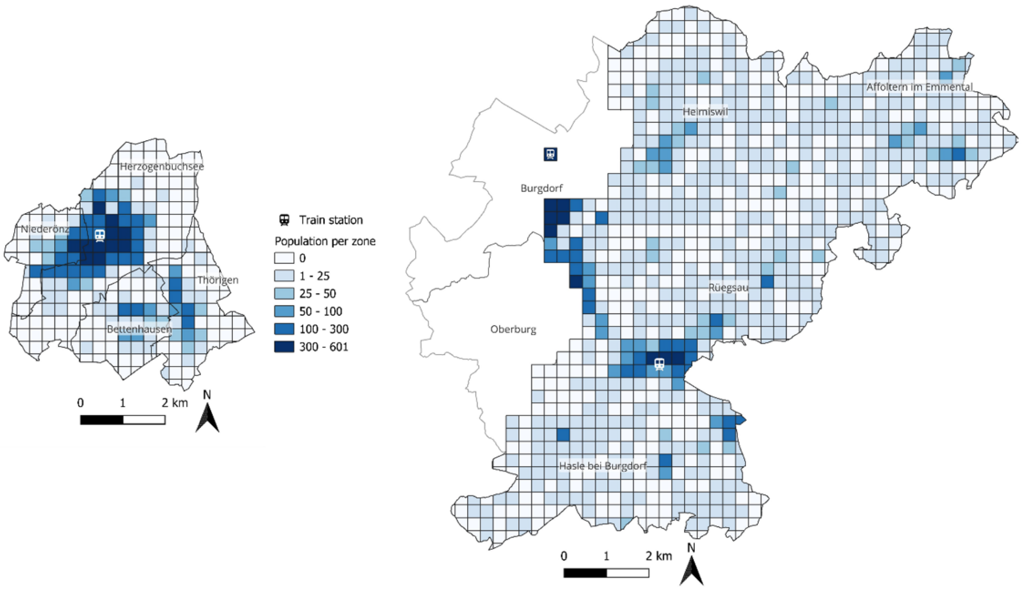


Figure 2.2.2 shows the geographical distribution of drop-offs in both perimeters studied. In both perimeters, the zone in which the train station is situated has the most drop-offs (Herzogenbuchsee area: 8'996 drop-offs; Emmental area: 984 drop-offs at South-Eastern train station). The same pattern is observed for pick-ups (2.2.3) (Herzogenbuchsee area: 18'078 pick-ups; Emmental area: 1'935), therefore the presence of a train station appears to be a factor for increased pick-ups and drop-offs.

The much denser distribution of pick-ups and drop-offs in the Herzogenbuchsee area than in the Emmental area (see Figure 2.2.2 and Figure 2.2.3) may be explained by the dense settlement structure (see Figure 2.2.1) . The demand for trips in the Emmental area is more disperse. Additionally, due to the larger perimeter in the Emmental area, trips are comparatively longer in time and distance than in the Herzogenbuchsee area.

Figure 2.2.2: Spatial drop-off distribution in the Herzogenbuchsee (left) and Emmental (right) areas.

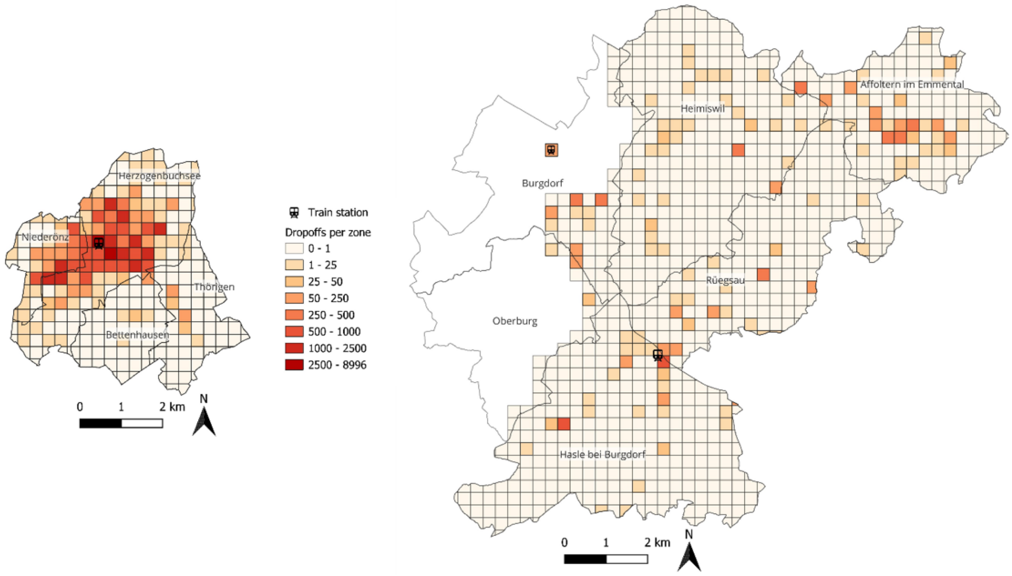
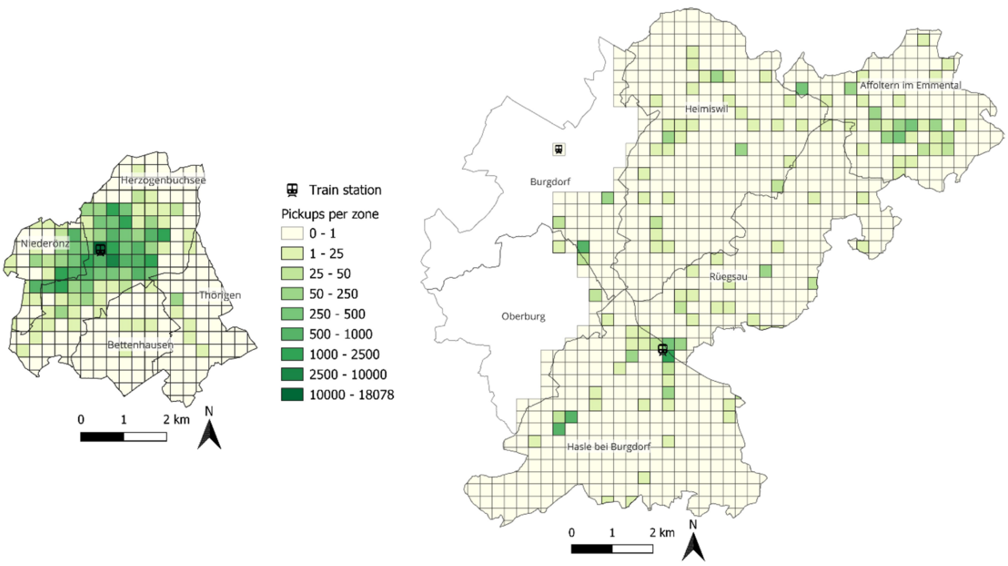


Figure 2.2.3: Spatial pick-up distribution in the Herzogenbuchsee (left) and Emmental (right) areas.



2.3 Methods

We use the random forests algorithm to predict demand for the DRT services within and across areas. Random forests are created by bootstrap aggregating ("bagging") single decision trees. Decision trees split the set of possible values of the predictors into nonoverlapping subregions based on a goodness-of-fit criterion, e.g., minimizing the mean squared error (MSE) across the newly created subregions. The average outcome in the subregions is then the prediction for all observations within the subregions. Bagging the decision trees then decreases variance. To reduce the correlation between the trees, random forests are built using only a random subset size m of predictors p, e.g., $m = p/3$ (James, Witten, Hastie, Tibshirani, et al., 2013, Breiman, 2001).

The importance measure for each predictor variable is computed by randomly permuting the values for this variable. For predictions within a perimeter, the variable importance measure is calculated by permuting the variable in the out-of-bag data.[1] For predictions across the perimeters, the variable importance measure is computed by permuting the variable in the test data. The variable importance measure is then the difference between the mean squared errors when the predictor variable is permuted and when it is not permuted, expressed as percentage change.

We point out that we do not analyze the causal effects of the spatial variables on demand, but simply their capability of forecasting demand. The predictive power of the spatial variables do not imply causal effects, because they can be prone to regularization and selection bias (see, e.g., Langen and Huber, 2023). We use the randomForest package in R to implement random forests based on growing 500 decision trees. Due to the medium size sample, results are obtained using bootstraps to prevent possible overfitting. We present the distribution of the means of 100 samples.

To equalize the level of observed values, we subtract the mean and divide the result by the standard deviation when analyzing the predictive power across perimeters. With this approach, we get standardized values, such that all variables have a mean of zero and a standard deviation of one. Additionally, no zone has a PT quality classified as A in the Herzogenbuchsee area. Therefore, when testing the transferability from Herzogenbuchsee to Emmental, we bound the quality indicator of PT at the upper limit, such that the quality classes A and B are merged.

[1] The variable importance measure within perimeters follows the default procedure of the RandomForest package in the statistical software `R` when applying the `importance`-command.

2.4 Results

First, we split the dataset from the Herzogenbuchsee and Emmental areas into a training and test set separately to recognize spatial patterns within areas. Second, we use the Herzogenbuchsee area as training set and the Emmental area as test set and display which spatial characteristics predict DRT demand across perimeters the best.

2.4.1 Prediction within perimeters

Table 2.4 shows the importance of the spatial variables to predict the number of pick-ups and drop-offs in the Herzogenbuchsee area. Within this perimeter, the most important variable is the number of inhabitants, followed by the distance to the train station. Among the points of interests, restaurants and health care facilities have some predictive power. The quality indicator of PT has low predictive power. Finally, patterns between pick-ups and drop-offs are similar.

A look at the aggregate measures shows that the spatial variables have overall rather moderate predictive power. The mean absolute error (MAE) is 290.73 for pick-ups and 233.96 for drop-offs, which is similar to the mean of pick-ups (267.5) and drop-offs (265.1) per zone in Herzogenbuchsee.

Predictor variable	**Pick-ups**		**Drop-offs**	
	Increase of MSE in %	Relative importance	Increase of MSE in %	Relative importance
Population	12.53	1	16.21	1
Distance to train	8.13	0.65	9.08	0.56
Restaurant	4.12	0.33	5.87	0.36
Health care	3.90	0.31	5.40	0.33
Shop	3.59	0.29	3.90	0.24
Quality of PT	2.37	0.19	2.72	0.17
School	1.98	0.16	1.76	0.11
Hotel	0.00	0.00	0.00	0.00
Employees	-0.77	-	-0.67	-
Aggregate measures				
MSE	2333959.80		610691.77	
MAE	290.73		233.96	

Table 2.4: Variable importance in the Herzogenbuchsee area

Figure 2.4.1 illustrates how demand prediction changes, when the values of the important predictors alter. First, The more inhabitants live in a zone, the higher the demand prediction. Second, whereas the partial relationship between population size and DRT demand is approximately linear, we observe a non-linear relationship between the distance to the train station and the DRT demand. Figure 2.4.1 shows that demand prediction increases tremendous right at the train station. Third, the prediction goes up with the occurrence of a restaurant; however, the quantity of restaurants does not seem to matter. That is, if this predictor is used for a splitting rule, the data is mostly split between zones with and without restaurants.

Figure 2.4.1: Partial dependence plots for the relatively most important variables in the Herzogenbuchsee area

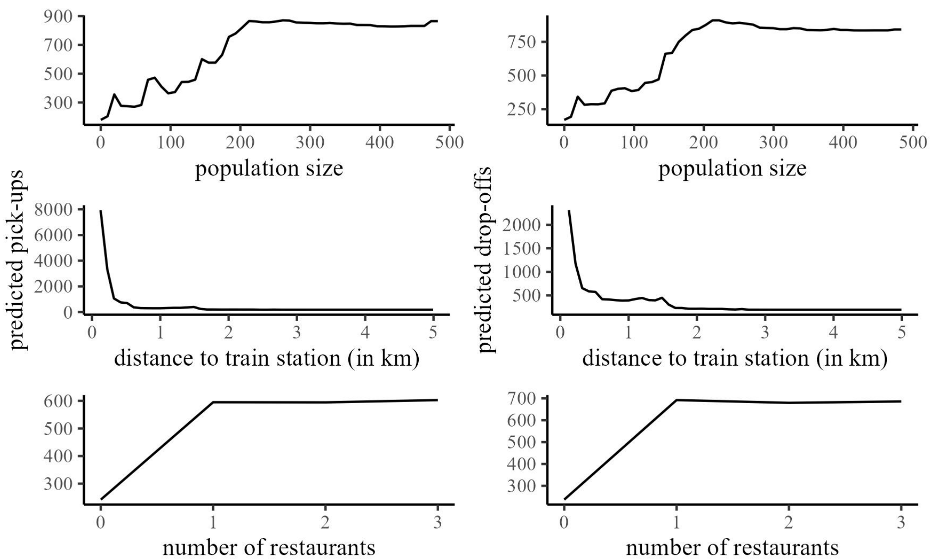


Table 2.5 shows the importance of the spatial variables to predict the number of pick-ups and drop-offs in the Emmental area. Within this perimeter, the most important spatial variables are the number of restaurants, the number of employees and the number of inhabitants. Again, the quality indicator of PT has low predictive power and patterns between pick-ups and drop-offs are similar. With a word of caution, we excluded the municipality of Burgdorf, where the main health facility in the region is located. However, we include the municipality of Burgdorf in a robustness check in Appendix 2.A.

The aggregate measures display that the spatial variables have overall rather moderate predictive power. The mean absolute error (MAE) amounts to 10.18 for pick-ups and 9.83 for drop-offs, which is again similar to the mean of pick-ups (7.2) and drop-offs (7.1) per zone in the perimeter.

Predictor variable	**Pick-ups**		**Drop-offs**	
	Increase of MSE in %	Relative Importance	Increase of MSE in %	Relative Importance
Restaurant	7.94	1	9.25	1
Employees	6.96	0.88	8.22	0.89
Population	4.88	0.62	7.19	0.78
Distance to train	4.19	0.53	6.03	0.65
Shop	3.37	0.42	4.11	0.44
Quality of PT	1.25	0.16	2.80	0.30
Hotel	0.95	0.12	1.09	0.12
School	0.28	0.04	-0.14	-
Health care	0.00	0.00	0.00	0.00
Aggregate measures				
MSE	5269.34		2264.23	
MAE	10.18		9.83	

Table 2.5: Variable importance in the Emmental area

2.4.2 Prediction across perimeters

Finally, we test whether DRT demand can be predicted from one perimeter to another perimeter. Therefore, we use the pioneer perimeter in Herzogenbuchsee for training a model and test the accuracy of the predictions in the Emmental perimeter. Table 2.6 shows that DRT demand in Emmental is not accurately predicted based on the trained model in Herzogenbuchsee. The dense settlement structure or the well-established DRT service in Herzogenbuchsee may introduce noise, which prevents accurate predictions for other perimeters. To use all the observations for training and testing, we switch the training and test set. When the zones in Emmental represent the training set and the zones in Herzogenbuchsee the test set, the importance measures of the predictor variables number of inhabitants, distance to the train station and presence of restaurants increase a lot. The link between prediction accuracy and definition of training set suggests that more perimeters are needed to determine to what extend spatial variables can predict DRT demand across perimeters.

Looking at the aggregate measures shows that the mean absolute error is similar when using Herzogenbuchsee and Emmental as training sets. However, the mean squared error is smaller, when using Emmental as training set, reflecting the increase in the variable importance measures. This may be due to outlier zones that are more accurate predicted from Emmental to Herzogenbuchsee than vice versa.

Training set	Herzogenbuchsee		Emmental	
	Pick-ups	Drop-offs	Pick-ups	Drop-offs
Predictor variable	Increase of MSE in %			
Population	1.91	8.06	10.51	53.26
Distance to train	2.64	2.68	123.21	63.58
Restaurant	0.76	2.53	25.10	52.95
Shop	3.69	5.26	8.10	12.53
Quality of PT	0.97	0.57	1.98	11.54
School	-0.18	0.28	-0.05	0.77
Health care	0.20	0.14	0.00	0.00
Hotel	-0.01	-0.02	-0.02	-1.04
Employees	-0.11	-0.34	-1.04	-1.51
Aggregate measures				
MSE	0.91	0.89	0.59	0.60
MAE	0.15	0.28	0.24	0.40

Table 2.6: Variable importance across perimeters

2.5 Discussion & Conclusion

This paper examined the spatial demand characteristics of the rural DRT service called mybuxi in two of its operating perimeters. Machine learning was used for a better understanding of spatial characteristics of DRT trips in these two rural areas with different settings (dense vs. sparse populations, small and flat vs. large and hilly areas). Unlike other simulation studies in this field of research, these two rural cases are analyzed using data of a real-world DRT service. Further on, the paper showed how random forests algorithms can be used in the context of such rural DRT services. In particular, the transferability from one mybuxi setting to the other was investigated.

Overall, the number of inhabitants was found to be the most important spatial characteristic to predict DRT demand across perimeters. Increasing number of inhabitants per zone lead to higher demand predictions. This may be explained as increasing the number of inhabitants increases the number of potential users, underscoring the principle of the "rural mobility problem" caused by low population size and density (see Mounce, Beecroft, and Nelson, 2020). The finding on the interrelation between population density and demand for trips is in line with previous research on urban flexible transport services (e.g. Weckström, Mladenović, Ullah, Nelson, Givoni, and Bussman, 2018, Zwick and Axhausen, 2022).

The second important variable was found to be the distance to the train station. We observe a non-linear relationship between the distance to the train station and the number of trips, with demand greatest closest the train station. This observation is in line with the literature that highlights the importance of integrating DRT into a PT mix (Daniels and Mulley, 2012). In the planning process of new DRT services, these first two findings are important for the definition of new perimeters. For a successful and viable DRT service in a rural setting, the inclusion of more densely populated areas as well as integrating a train station in form of a hub station are crucial factors. If a region is even less populated than some parts of the Emmental area, there may additional factors (e.g. tourism) that could determine the demand for trips in a perimeter that were not examined in this study. Here, further research on spatial characteristics of new perimeters with other spatial preconditions will be necessary.

Among points of interest, the presence of restaurants has the most predictive power. That may be interlinked with the location of restaurants, as they are often situated in areas where social life takes place. They are often close to the village center, tourist attractions or healthcare facilities. This finding may be important for the planning of the service area of a new rural DRT system, too, especially when virtual stops in an app instead of physical stops like with buses are being used. Restaurants can be important pick-up and drop-off stops in these systems, also regarding the ability to pool rides. And for restaurants and shops around them, for their customer base the reachability may be increased. Especially in rural areas, where restaurants and shops often face economic pressure, DRT services may help to keep or increase their business. The quality indicators of PT were all found to have low or no predictive power as the predictions for zones with poor, moderate and good PT quality are similar. Based on this finding, we draw the conclusion that the DRT services increase the accessibility of all zones within the two perimeters. Additionally, the robustness checks in Appendix 2.A indicate links between the train stations and zones with low or no public transport coverage.

In conclusion, the DRT service shows similar patterns as PT services in different rural settings. Therefore, understanding the spatial characteristics is crucial to optimize benefit from schedule flexibility and small vehicle size of DRT services and hence, increase not just cost efficiency but also accessibility. For research and future policies on rural DRT services, this is a crucial finding. Future research must continue to examine the interaction between rural DRT services and bus transport services. Especially the increase in accessibility with a DRT service legitimates future public subsidies and if enough capacity is available, the DRT services may replace the traditional bus services. Future research should continue to examine further potentially influential spatial factors such as touristic spots or sport sights that may influence the demand for a rural DRT system.

2.6 Limitations

Our interpretation of the success factors for DRT services is based on the capability of predictors to forecast demand and not on the analysis of causal effects. In other words, we show that some spatial characteristics (e.g., restaurants) can predict demand DRT, but we do not analyze whether these spatial characteristics caused the DRT trip (e.g., people going into the restaurant after drop-off). The important spatial characteristics may be interlinked with other non-observable spatial characteristics (e.g., restaurants are often situated where other activities take place).

Additionally, by fitting spatial to demand patterns, we can hint towards increasing accessibility within perimeters, however we cannot quantify the number of trips that were made complementary and supplementary to the PT service. Future studies should focus on this research question.

Another limitation is that mybuxi operates in the Emmental area with less virtual stops, around 200 of them, than the Herzogenbuchsee area with around 1'000 virtual stops. Therefore, we cannot be sure that the trip before the pick-up and after the drop-off starts respectively ends within the same zone. If that is not the case, the predictions would be misleading. Spatial regression algorithm that account for spatial dependencies might resolve this concern.

Appendices

2.A Robustness checks

In our analysis in Section 2.4, we aim to predict DRT demand from an existing perimeter (Herzogenbuchsee) to a new perimeter (Emmental) and vice versa. In the following robustness checks, we challenge our empirical research design. The results are presented in table 2.7.

In Section 2.4, we use the number of trips as outcome to account for passengers pooling for the same trip. However, the number of passengers is also of key interest regarding economic efficiency. Therefore, in robustness check (1), we replace the outcome variable with the number of passengers. Since the vast majority of trips are not pooled, we obtain similar results regarding the importance of the spatial characteristics.

In Section 2.2 we describe the data and show that in both perimeters, the zone in which the train station is located has by far the most drop-offs and pick-ups. In robustness check (2), we examine the influence of this outlier zone by only considering the subsample of drop-offs at the train station to predict pick-ups and the subsample of pick-ups at the train station to predict drop-offs. By examining the origins and destinations of trips to and from the train station, we can gain additional insight into origin and destination relationships. First, the importance of number of inhabitants increases. Second, the quality indicator of PT shows some importance, predicting more pick-ups in zones with low or no public transport coverage.

In robustness check (3), we use again the subsample of trips to and from the train station (similar to robustness check (2)). However, we switch training and test set, training the model in the Emmental perimeter (similar in robustness check (3)). In this design, the most important variables are the number of inhabitants, the quality indicator of PT and the number of restaurants.

In the final robustness check (4), we include the municipality of Burgdorf in the sample. So far, we have excluded Burgdorf due to different political regulations, which limit pick-ups and drop-offs at the train station. However, Burgdorf is a populous municipality on the Emmental perimeter, where a train station and the regional hospital is located. These points of interest could influence the estimation. Table 2.7 illustrates that the importance of distance to the train station decreases compared to the analysis in Section 2.4, reflecting the political restrictions. Moreover, the importance of the number of inhabitants increases, mirroring the added populous municipality.

Table 2.7: Variable importance across perimeters (robustness checks 1 through 5)

Check	1	2	3	4
Predictor variable	Increase of MSE in %			
Training set	Herzogenbuchsee		Emmental	
Sample	all	train station	train station	all
Pick-ups				
Population	2.03	14.72	68.01	24.35
Distance	2.56	5.79	3.07	81.20
Restaurant	0.83	0.10	3.07	23.59
Health care	0.20	0.07	0.00	0.08
School	0.11	0.01	0.47	-0.07
Shop	3.85	-0.00	0.82	-3.81
Quality of PT	0.97	7.75	26.98	-2.86
Hotel	-0.01	0.00	0.00	0.05
Employees	-0.13	-0.57	2.49	-1.99
Aggregate measures				
MSE	0.91	1.16	1.00	0.66
MAE	0.17	0.45	0.61	0.28
Drop-offs				
Population	7.89	19.35	29.52	75.45
Distance	2.47	2.86	-8.25	39.23
Restaurant	2.30	2.41	23.45	42.20
Health care	0.12	0.06	0.00	-0.02
School	0.22	0.04	0.23	1.66
Shop	5.18	0.64	1.01	8.21
Quality of PT	0.49	3.06	8.08	4.10
Hotel	-0.02	0.01	0.00	0.04
Employees	-0.37	-0.34	-1.88	-6.84
Aggregate measures				
MSE	0.89	1.03	1.29	0.73
MAE	0.29	0.41	0.66	0.46

Chapter 3

The potential of Public-Transportation Credits

Three-part tariffs in public transportation

joint with **Silvio Sticher***

Abstract

In December 2023, public-transportation providers in Switzerland introduced Public-Transportation Credits (PTCs). PTCs are credits (or "allowances") that are greater in amount than their price and can be used to purchase any type of public-transportation tickets within a year. With the initial fixed payment, the subsequent use of the allowance and the eventual return to the standard fare, PTCs represent three-part tariff models. We explore the potential of PTCs to target particularly elastic segments of the demand curve, simultaneously allowing for increased consumption and higher revenue. To assess the revenue impact of the PTC empirically, we analyze a pilot study conducted by the Swiss public-transportation providers. In a randomized field experiment with 431,533 PTC invitees and 911 actual PTC buyers, we use the dispach of invitations as an instrumental variable. However, this result is insignificant due to the weak relationship between invitees and buyers. Therefore, we complement our analysis with a selection-on-observable approach, utilizing machine-learning techniques to match PTC buyers to customers in the control group. This way, we reveal a highly significant

*This chapter is based on a paper published in the journal *Transportation Research Part A: Policy and Practice* Journal as Sticher and Blättler (2024).

treatment effect, indicating a revenue enhancement of CHF 179.7 per PTC (approximately USD 200). Leveraging our comprehensive dataset and insights from a non-buyer survey, we predict a demand of around 200,000 units for the market-launch version of the PTC.

3.1 Introduction

Following its announcement in autumn 2022 (SRF, 2022, Alliance SwissPass, 2022), in December 2023, the association of public-transportation companies in Switzerland, "Alliance SwissPass" (ASP, henceforth referred to as "public-transportation providers"), implemented a novel pricing model. It consists of a product range which we henceforth call "public-transportation credits" (PTC).[1] For a price P_{PTC}, a customer receives an allowance of value V_{PTC} (whereas $V_{\text{PTC}} > P_{\text{PTC}}$). This non-transferable allowance can then be used to purchase a wide range of public-transportation tickets (but not season tickets) during one year. Since the PTC can be summarized by the fixed-price component, the allowance, and the (standard) fare upon completion of the allowance, it can be categorized as a three-part tariff, as defined, for instance, in Lambrecht, Seim, and Skiera (2007).

Prior to fully introducing the new product range, the alliance mandated its major member, the Swiss Federal Railways (SBB) to pilot a stripped-down version of the PTC between December 2021 and March 2023 (SBB, 2021), which is the basis of the present study.[2]

Pricing measures in public transportation such as the introduction of the PTC are used by public-transportation providers to tackle a variety of goals—revenue optimization being only one of them. For instance, even with moderate price elasticities, lower prices allow for a higher modal share of public transportation, a typical component of performance agreements. Furthermore, and somewhat counter to the aforementioned point, by attracting former season-ticket holders, excessive zero-marginal-cost usage could be curbed—even more in times of home office gaining currency.

To varying degrees, trade-offs abound. In particular, applying the often-cited rule-of-thumb price elasticity in public transportation of -0.3, passenger-count goals conflict with revenue goals—even in the short run, where production cost is (virtually) unaffected by increased demand.

However, according to an unpublished preliminary experimental study conducted by ASP in 2020, the introduction of a PTC actually appears to increase revenues. This is puzzling in the sense that the PTC merely introduces a new (volume) discount, which is de facto a price reduction. How is this in line with price elasticities ϵ with $\epsilon < 1$?

[1] The pricing model is marketed by the public-transportation providers under the name "Halbtax PLUS" ("Half Fare Travelcard PLUS"). See https://www.sbb.ch/en/tickets-offers/travelcards/half-fare-travelcard-plus.html.

[2] One of the authors worked for SBB until June 2022 as head of strategic pricing, where he conceptualized the PTC. He was granted access to the anonymized data of the complete pilot study by SBB and ASP.

For a possible explanation, it is worth disentangling (aggregate) price elasticities into customer-specific ones. Also, some key information about the landscape of existing public-transportation tickets in Switzerland is necessary: At the end of 2021, 0.41 million out of 8.74 million people in Switzerland were in possession of a "GA Travelcard" (GA). The GA is a season ticket, covering most[3] of public transportation in Switzerland.[4] This number does not include the many more season tickets (of about 20 regional tariff networks) in circulation, which mirror the GA within a smaller perimeter. Further 2.83 million Swiss inhabitants owned a "Half Fare Travelcard" (HF), which—as the name implies—generally allows to buy tickets at half their price (SBB, 2022, BFS, 2022).[5]

With such an unusually high "membership", all but general price movements must be analyzed with cross-price elasticities in mind—or, alternatively, public transportation may be studied as a single good with a somewhat intricate, non-linear pricing structure. This is the approach we follow in Section 3.3. There we argue that the current price schedule is comparatively unfavorable to customers on the brink between the HF and GA travelcard: For "heavy users", the GA is highly competitive versus the customers' major outside option, car ownership. For individuals with very low mobility needs, non-discounted tickets (combined with the HF, if applicable), public transportation stands out thanks to low fixed costs. For customers with a medium-sized mobility demand, however, public transportation is comparatively expensive against the background of today's pricing structure which in turn leads to increased price sensitivity. Consequently, a targeted price reduction in this segment can lead to above-average demand effects, potentially outweighing any decrease in yield rates. In our case, this targeted price reduction is achieved through the introduction of the PTC.

Examining the data from the pilot study, we indeed find evidence supporting a revenue-enhancing property of the PTC. While we are unable to measure demand for public transportation for all customers, we can consistently measure their expenditures.[6] In a randomized field experiment,

---

[3] Notable exceptions only concern touristic lines.

[4] At the end of 2019, that is, prior to the Corona Pandemic, even 0.50 million inhabitants possessed a GA.

[5] Also, 1.40 million children (below the age of 16) in Switzerland were automatically granted the HF price.

[6] Given that a significant proportion of public-transportation consumption relies on season tickets, we cannot consistently measure demand in terms of passenger kilometers. Consequently, we are also unable to determine price elasticities quantitatively. However, since public transportation is not a Giffen good, we can safely assume that demand will increase with the introduction of the PTC. If revenue increases at the same time, $\epsilon > 1$ immediately follows.

utilizing the distribution of pilot-study invitations as an instrument, we observe a substantial albeit statistically insignificant treatment effect. The primary reason for this insignificance lies in the weak relationship between the instrument and the treatment (i.e., the purchase of the PTC). Out of 431,533 invitees, only 911 individuals purchased a PTC, with 893 completing the pilot study. However, matching these buyers with a control group based on a selection on observables approach yields a statistically highly significant result: On average, PTC buyers increased their yearly expenditures on public transportation by over 10 percent, rising from CHF 1,680.4 to CHF 1,860.1. The confidence interval of this CHF 179.7 increase ranges from CHF 115.0 to CHF 244.4. Accordingly, while the pilot study reached only a small fraction of customers, those who participated exhibited price elasticities with $\epsilon > 1$.

We structure the rest of our paper as follows: In Section 3.2, we provide a brief overview of the transportation literature concerning the impact of (targeted) price reductions, supplemented by insights from the economics literature on three-part tariffs. In Section 3.3, we present a theoretical overview of the PTC, discussing its impact on customers' expenditures and, consequently, public-transportation providers' revenue. In Section 3.4, we outline the design of the pilot study and our field experiment. We present a detailed description of the involved treatment and control groups and the collected data in Section 3.C. In Section 3.5, we present the treatment effect observed in the field experiment, while in Section 3.6, we extend our analysis beyond the purely experimental setting by employing an selection on observables approach, matching the 893 PTC buyers with participants from the control group based on observable characteristics. In Section 3.D, we explore the demand for a more "mature" market-launch version of the PTC, utilizing supplementary data obtained from a survey conducted among non-buyers from the pilot study. In Section 3.7, we conclude with a brief discussion of our assumptions and results, as well as recommendations for implementation.

3.2 Literature Review

Our paper adds to the broad literature in transportation economics, analyzing the relationship between fares, demand, and revenue. As revenue effects depend on the interaction between fares and demand, empirical studies often focus on price elasticities. As mentioned in Section 3.1, we are not able to measure demand for all types of customers due to the prevalence of season tickets. Hence, we are also not able to compute price elasticities quantitatively. However, under very generic circumstances, a potential revenue gain arising from the introduction of the PTC (a discount) can only be explained with a (local) price elasticity with $\epsilon > 1$.

In the European transportation sector, (general) price elasticities are usually estimated to be below $\epsilon = 1$. In a meta analysis, Holmgren (2007) estimates short-run price elasticities of up to $\epsilon = 0.75$ and long-run price elasticities of up to $\epsilon = 0.91$, but only as long as vehicle kilometers are treated as endogenous.

In the Swiss context, a recent field experiment conducted in urban areas estimates the short-run price elasticity to be $\epsilon = 0.31$ (Axhausen, Molloy, Tchervenkov, Becker, Hintermann, Schoeman, Götschi, Castro Fernández, and Tomic, 2021). This aligns with the commonly cited rule of thumb for the price elasticity in public transportation, which is approximately $\epsilon = 0.3$. Wallimann, Blättler, and von Arx (2023) examine a price-reduction initiative in the city of Geneva, Switzerland. They find that reducing the prices of annual season tickets, day passes, and hourly tickets by up to 29 percent, 6 percent, and 20 percent, respectively, led to a 10.6 percent increase in demand over a five-year period. Thommen and Hintermann (2023) analyze discounts for off-peak train tickets and obtain an (own) price elasticity of $\epsilon = 0.7$.

Price elasticities closer to and even above $\epsilon = 1$ are found when limiting attention on individual submarkets and segments (as in our case): Kholodov, Jenelius, Cats, van Oort, Mouter, Cebecauer, and Vermeulen (2021) utilize smartcard data from public-transportation systems to calculate price elasticities for distinct public-transportation modes. They find that demand fo trains exhibits a larger price elasticity ($\epsilon = 0.90$) compared to the demand for buses ($\epsilon = 0.56$) and metros ($\epsilon = 0.45$). Additionally, they find above-average price elasticities for long-distance journeys. Isolated instances with $\epsilon > 1$, however, seem to be artifactual and are deemed outliers by the authors themselves. Wardman (2022) estimates price elasticities above $\epsilon = 1$ for rail trips taken for leisure purposes. Most comparable to our result is the finding of Liu, Wang, and Xie (2019), who discover revenue gains from a price reduction in Australia due to increased consumption from existing customers.

The theoretic literature on transportation economics discusses the constraints of welfare-oriented pricing.[7] It compares first-best pricing with second-best and non-linear pricing, two-part tariffs being an prototype of the latter. A main result of the corresponding literature, which goes back to Carbajo (1988), states that combined tariffs prove to be more efficient that uniform fares because they allow to encourage frequent travelers' demand without forgoing revenue from infrequent users.

More recent pricing literature outside the transportation field adds to non-linear pricing by discussing the concept of three-part tariffs (e.g., Lambrecht, Seim, and Skiera, 2007, Fibich, Klein, Koenigsberg, and Muller, 2017). Such tariffs consist of a fixed-price component, the number of free units (allowance), and the price per unit above the number of free units. With customer heterogeneity, as we clearly have regarding the demand for public transportation, Fibich, Klein, Koenigsberg, and Muller (2017) show that firms should offer multiple three-part tariff plans, targeting light and heavy users separately. Hence adding the PTC "between" the HF and the GA should allow to increase revenue.

Three-part tariffs are commonly deployed in the telecommunications industry (think of mobile plans with monthly allowances of free minutes and/or gigabytes). Ascarza, Lambrecht, and Vilcassim (2012) examine the transition from a two-part tariff to a three-part tariff in the telecommunication market. They find that the inclusion of an allowance led to an increase in consumption beyond what might be expected from the change in their budget constraint, resulting in higher revenue. In contrast, Malone, Turner, and Williams (2014), who investigate the behavior of subscribers to three-part tariffs compared to those with unlimited plans, discover that subscribers with three-part tariffs have lower usage, particularly among heavy users. Nevo, Turner, and Williams (2016) ascertains that customers subscribing to three-part tariffs respond to the fraction of their monthly allowance used and the number of remaining days in the billing cycle.

In the transportation sector, Caiati, Rasouli, and Timmermans (2020) find that customers generally prefer three-part tariff pricing schemes over two-part tariff schemes for e-car rentals. However, it is worth noting that while their study encompasses different modes of transportation, they do not include three-part tariff options for public transportation. In addition, various studies explore mobility budgets (Zijlstra and Vanoutrive, 2018, Millonig, Rudloff, Richter, Lorenz, and Peer, 2022). Typically provided to employees, these budgets can be likened to "freemium" pricing models, which represent a specific instance of three-part tariffs with a zero-fixed-price component. While the mobility-budget literature predominantly concentrates on human-resource

[7] For an overview, see Hörcher and Tirachini (2021).

management and corporate sustainability, our work focuses on price incentives and revenue. Consequently, we consider our research a pioneering effort in examining the impact of three-part tariffs in public transportation.

3.3 Product Design

In this section, we analyze the theoretical revenue effect from the introduction of the PTC based on its product design. To do so, we first examine the status quo of the public-transportation providers' pricing structure (prior to the implementation of the PTC).

3.3.1 Point of Departure

Consider Figure 3.3.1, which presents a stylized illustration of the ticket choices available to public-transportation users in Switzerland, specifically concerning the national perimeter.[8]

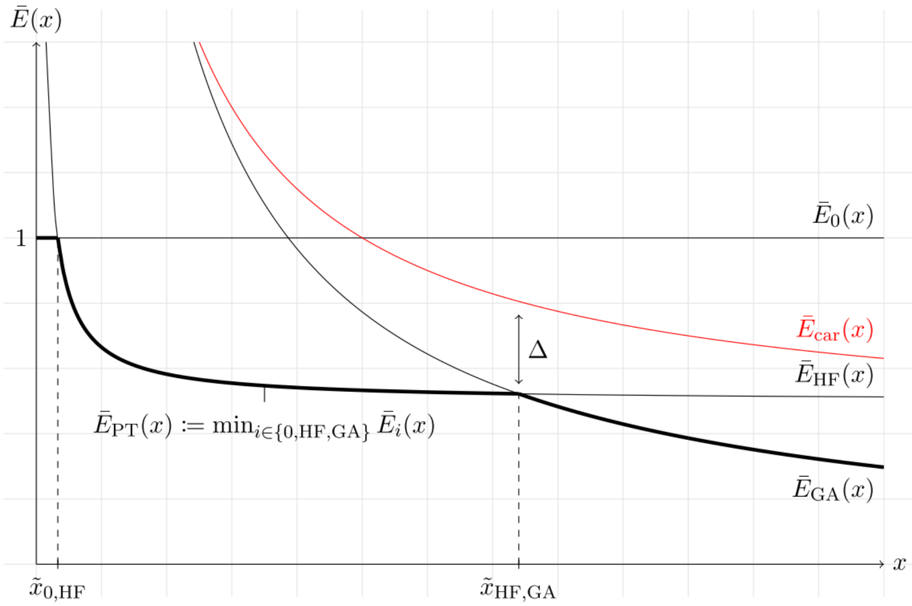


Figure 3.3.1: Average expenditures with public-transportation tickets and car ownership

[8]Note that most of the qualitative analysis that follows is also applicable to "regional" public-transportation customers in Switzerland, who benefit from lower fares for single journeys and season tickets due to shorter distances. For the purpose of this section, we disregard travel classes and (third-degree) price differentiations among customer segments to simplify the exposition.

Here, x refers to the amount of public transportation consumed. We describe this amount by the (hypothetical) annual expenditure for public transportation that would accrue if only non-discounted tickets would be bought.[9] That is, $E_0(x) = x$, where $E_0(x)$ is the expenditure function regarding non-discounted tickets. The according average-expenditure function, $\bar{E}_0(x)$, is thus a flat line of height 1. $E_{\text{HF}}(x)$ refers to the expenditure function when possessing the HF, which—with an annual price tag of CHF 185 (roughly \$ 200) or less—is an auto include for most regular users of public transportation in Switzerland (see Section 3.1). The hyperbolic average-expenditure function $\bar{E}_{\text{HF}}(x)$ follows from the HF being a two-part tariff. $\bar{E}_{\text{HF}}(x)$ approaches 0.5 for $x \to \infty$. Finally, $E_{\text{GA}}(x)$ represents the expenditure function when purchasing the GA. Due to the GA only consisting of a fixed-price component, $\bar{E}_{\text{GA}}(x) \to 0$ for $x \to \infty$.

Regarding public transportation as a whole, only $\bar{E}_{\text{PT}}(x) \min_{i \in \{0,\text{HF},\text{GA}\}} \bar{E}_i(x)$, is relevant. For sufficiently small $x \leq \tilde{x}_{0,\text{HF}}$, non-discounted tickets (without a fixed-price component) minimize expenditure. For sufficiently large $x \geq \tilde{x}_{\text{HF,GA}}$, the GA (without a variable-price component) minimizes expenditure. In between (for $\tilde{x}_{0,\text{HF}} \leq x \leq \tilde{x}_{\text{HF,GA}}$), the two-part-tariff HF minimizes expenditure.

Note the "spike" at $\tilde{x}_{\text{HF,GA}}$. At this level of consumption, buying a GA starts getting worthwhile. But unlike at higher levels of x, at $\tilde{x}_{\text{HF,GA}}$, average expenditure with the GA equals average expenditure with the HF—a product aimed at occasional users.

Compare this to $\bar{E}_{\text{car}}(x)$, the average-expenditure curve for car owners. In general, $\bar{E}_{\text{car}}(x)$ exceeds $\bar{E}_{\text{PT}}(x)$ (BFS, 2022). Furthermore, annual car-related expenses also consist of both fixed and variable components (comparable to two-part tariffs). The actual extent of $\bar{E}_{\text{car}}(x)$ is obviously case dependent (starting with the vehicle choice), and comparing it with $\bar{E}_{\text{PT}}(x)$—as we do in Figure 3.3.1—ignores the fact that private and public transportation modes are all but perfect substitutes. However, the circumstance that $\bar{E}_{\text{car}}(x) - \bar{E}_{\text{HF}}(x)$ decreases with x and $\bar{E}_{\text{car}}(x) - \bar{E}_{\text{GA}}(x)$ increases with x indicates that public transportation is least competitive at $\tilde{x}_{\text{HF,GA}}$.[10] Vice versa, by specifically approaching (potential) customers with a consumption level around $\tilde{x}_{\text{HF,GA}}$,

[9] One might also interpret x as number of journeys or passenger kilometers. By using the non-discounted ticket price equivalent, however, we neither have to worry about trips of varying lengths nor do we have to take into account the (typically degressive) price function for single trips.

[10] To formalize the argument: Write $E_{\text{HF}}(x)$ as $\alpha_{\text{HF}} + \beta_{\text{HF}} x$, $E_{\text{GA}}(x)$ as α_{GA}, and $E_{\text{car}}(x)$ as $\alpha_{\text{car}} + \beta_{\text{car}} x$. Then, $\bar{E}_{\text{car}}(x) - \bar{E}_{\text{HF}}(x) = (\alpha_{\text{car}} - \alpha_{\text{HF}})/x + (\beta_{\text{car}} - \beta_{\text{HF}})$, which clearly decreases in x. Similarly, $\bar{E}_{\text{car}}(x) - \bar{E}_{\text{GA}}(x) = (\alpha_{\text{car}} - \alpha_{\text{GA}})/x + \beta_{\text{car}}$ increases in x for $\alpha_{\text{GA}} > \alpha_{\text{car}}$. Since the (financial) fixed-price components of car ownership and GA ownership are of similar magnitude, $\alpha_{\text{GA}} > \alpha_{\text{car}}$ is likely to hold once non-financial

public-transportation providers could leverage the advantage of particularly elastic demand.

As an illustration, consider the options available to public transportation to simultaneously enhance its modal share and its revenue. Price increases are clearly not viable, and so are general price decreases, as mentioned above. This leaves us with the option of isolated price decreases.[11]

One approach is to lower the price of the GA, which could attract customers in the "critical region" around $\tilde{x}_{\mathrm{HF,GA}}$. However, as previously observed, the GA is most competitive among customers with a very high demand for mobility. Therefore, reducing its price would primarily benefit existing customers who already heavily utilize public transportation, i.e., the inframarginal customers.

On the other hand, most HF customers rely on public transportation only occasionally. As formalized in Footnote 10, it is unlikely that car ownership would serve as a substitute for such consumption patterns.[12]

However, there are also potential customers with a mobility demand of less than (but closer to) $\tilde{x}_{\mathrm{HF,GA}}$, who consider the current offer as relatively expensive. Part-time commuters serve as an example. The rationale behind the PTC is to specifically lower public-transportation prices around $\tilde{x}_{\mathrm{HF,GA}}$, where the usual trade-off between yield and quantity is most likely to be suspended.

3.3.2 Introduction of the PTC

In our study, participants in the treatment group were given the option to purchase either a "small" or a "large" PTC, or alternatively, they could opt not to participate. While the specific details of the study design are discussed in Section 3.4, here we focus on describing the product from a customer's perspective, with the large PTC as our illustrating example.[13]

With the (large) PTC, a customer pays CHF 2,000 and receives a public-transportation allowance of CHF 3,000 in return. This allowance is valid for 12 months and can be used for various public-transportation tickets,

opportunity costs of possessing a GA (instead of a car) are taken into account. Think, e.g., of the lack of spontaneity.

[11] In the following, we omit the consideration of possible price reductions for non-discounted tickets, as the argument against such a measure mirrors the one regarding the HF.

[12] It is more reasonable to assume that car ownership is already established in these cases, and public transportation is used as a supplementary mode for non-financial reasons, such as sharing a vehicle within the household or going out for some drinks.

[13] In brief: The small PTC costs CHF 800 and includes an allowance of CHF 1,000. There are also plans to introduce an additional "intermediate" PTC with an allowance of CHF 2,000 and an as-yet-undisclosed price. As there is a progressive volume discount, the exposition in this section remains applicable even with these additional PTC variations in mind.

including single tickets and day passes. The reimbursement conditions are quite generous, ensuring that purchasing a PTC carries no financial risk: After 12 months, remaining allowance up to the price of the PTC is refunded.[14]

So when is it advantageous to purchase the PTC, and how strong is the incentive to do so? To simplify the discussion (and also because it is generally-speaking true), suppose that the areas of validity of the HF, the GA, and the PTC are the same. Given the above-mentioned reimbursement conditions, buying the PTC weakly dominates buying the HF. Consequently, in Figure 3.3.2, we replace $\bar{E}_{\mathrm{HF}}(x)$ (from Figure 3.3.1) with $\bar{E}_{\mathrm{HF+}}(x)$.

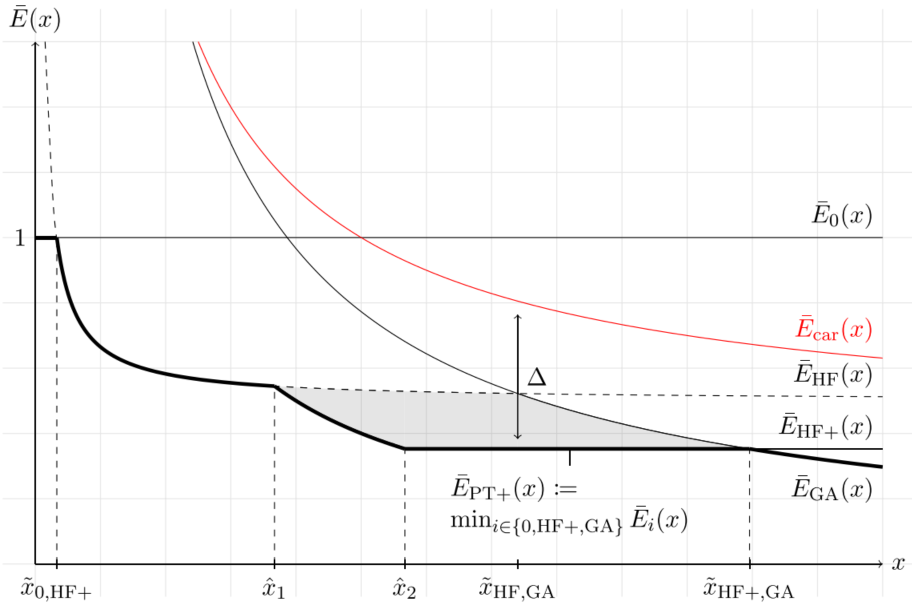


Figure 3.3.2: Average expenditures with public-transportation tickets (PTC included) and car ownership

Up to $x = \hat{x}_1$, which equals the (upfront) price of the PTC (CHF 2,000), $E_{\mathrm{HF}}(x) = E_{\mathrm{HF+}}(x)$, where the latter refers to the expenditure for both the HF and the PTC.[15] The average expenditure $\bar{E}_{\mathrm{HF+}}(x)$ decreases from $x = \hat{x}_1$

[14] For instance, if CHF 1,900 of the CHF 3,000 is spent, the refund amounts to CHF 100. If more than CHF 2,000 is spent, there is no refund. Accordingly, there is no arbitrage opportunity.

[15] Whether the HF and the PTC will be melted into a single product was yet undecided at the time of writing. The pros and cons depend on rather technical considerations, mainly regarding accounting issues. In the present discussion, we refer to the setting of the field study, where the two products were bought separately. There is no relevant distinction between the two cases as long as we assume a pro-rata reimbursement of the HF once the PTC is fully depleted, which we do in the following.

to $x = \hat{x}_2$, where $\hat{x}_2$ equals the allowance of the PTC (CHF 3,000). For $x \geq \hat{x}_2$, the average expenditure of using the PTC alongside the HF remains constant. This is the case because upon a premature depletion of the PTC, one may immediately buy a new one. $\tilde{x}_{\mathrm{HF,GA}}$ in Figure 3.3.1, the upper bound for values of x where the HF minimizes expenditure, gets replaced by $\tilde{x}_{\mathrm{HF+,GA}}$ in Figure 3.3.2. Obviously, $\tilde{x}_{\mathrm{HF+,GA}} > \tilde{x}_{\mathrm{HF,GA}}$, because more consumption is needed to make the GA worthwhile once the PTC becomes an option.[16]

To gauge public transportation's competitiveness vis-à-vis private transportation upon the introduction of the PTC, again pay attention to the lower envelope of the average-expenditure functions, $\bar{E}_{\mathrm{PT+}}(x) \min_{i\in\{0,\mathrm{HF+,GA}\}} \bar{E}_i(x)$. In Figure 3.3.2, the shaded area highlights the difference between $\bar{E}_{\mathrm{PT}}(x)$ and $\bar{E}_{\mathrm{PT+}}(x)$. Note that at $\tilde{x}_{\mathrm{HF,GA}}$, this difference reaches its peak. As we discussed in Section 3.1, it is plausible to assume that public transportation's price advantage is lowest at this point—at least before the introduction of the PTC. Hence, as indicated by the increase of Δ, we expect that the PTC-induced price reduction specifically targets an above-average elastic fragment of the customer pool.

Before delving into the design of our study, it is important to acknowledge that the preceding deliberations are somewhat abbreviated. In particular, when it comes to participating in a pilot study, the fixed component of car-related expenditure should be considered "sunk". Bear in mind, however, that, for $\tilde{x}_{\mathrm{HF,\,GA}}$ to be the maximum of $\bar{E}_{\mathrm{PT}}(x) - \bar{E}_{\mathrm{car}}(x)$ (see Figure 3.3.1), it is sufficient that the annual fixed component of $E_{\mathrm{car}}(x)$ exceeds the price of the HF, which is CHF 185 and below.[17] Notably, it is plausible that a portion of $\bar{E}_{\mathrm{car}}(x)$ is independent of x but still exhibits variability with regard to the time frame of the pilot study. Consider, for instance, parking season tickets at work and opportunity costs associated with family members lacking permanent access to the car.

[16] Consider a situation where only second-class tickets are considered. Then, for adults and as of 2023, the GA costs CHF 3,860, rendering $\bar{E}_{\mathrm{GA}}(x) = \mathrm{CHF}\,3{,}860/x$. With the PTC and the HF (with a fixed-price component of CHF 165 and a variable-price component of CHF $x/2$), for $x \geq \hat{x}_2$, the constant average expenditure equals $\bar{E}_{\mathrm{HF+}}(x) = (\mathrm{CHF}\,165 + \mathrm{CHF}\,2{,}000)/(2 \times 3{,}000) \simeq \mathrm{CHF}\,0.36$. By setting $\bar{E}_{\mathrm{HF+}}(\tilde{x}_{\mathrm{HF+,GA}}) = \bar{E}_{\mathrm{GA}}(\tilde{x}_{\mathrm{HF+,GA}})$, we obtain $\tilde{x}_{\mathrm{HF+,GA}} \simeq \mathrm{CHF}\,3{,}860/\mathrm{CHF}\,0.36 \simeq 10{,}697$. Recall that x refers to the corresponding expenses with *non-discounted* tickets (in CHF).

[17] Using the notation of Footnote 10, $\alpha_{\mathrm{HF}} < \alpha_{\mathrm{car}} < \alpha_{\mathrm{GA}}$ is sufficient for $\bar{E}_{\mathrm{PT}}(x) - \bar{E}_{\mathrm{car}}(x)$ to peak at $\tilde{x}_{\mathrm{HF,\,GA}}$.

3.4 Study Design

The main goal of our study is to identify the effect of the PTC on public-transportation revenue. To do so, we randomly assigned individuals to a treatment group and a control group. Subjects in the treatment group received a personalized promo code (linked to their email address), which allowed them to participate in the pilot study, that is, to purchase either a small or a large PTC on a dedicated section of the SBB webpage. The small PTC costed CHF 800 and provided an allowance of CHF 1,000, while the large PTC costed CHF 2,000 and provided an allowance of CHF 3,000 as a progressive quantity discount. Subjects in the control group were selected from the same customer pool (which we discuss in more detail in the following paragraph) as the subjects in the treatment group. The only structural difference between the treatment and control groups is that subjects in the control group did not receive a promo code for participating in the pilot study.[18]

In several respects, the pilot study differs from an actual implementation of the PTC. In the following, we briefly outline these differences, explain our countermeasures, and provide our conclusions on how these factors affect the interpretation of our results.

Accessibility To accurately measure the demand for the PTC and understand the behavior of buyers and non-buyers, it is crucial that all eligible public-transportation ticket buyers in Switzerland have an equal chance of being included in the treatment group. This requires contacting individuals and monitoring their usage of public transportation with and without the PTC. To facilitate this, we have to focus on customers in the SBB database who have a recorded email address.

Furthermore, since the PTC is a digital product (see below), we can obtain a complete picture of its usage. To minimize bias towards the treatment group, we need to be confident to also track most of the consumption of non-buyers and individuals of the control group. To achieve this, we stipulate "online affinity" as a requirement for customers without a season ticket. This means that ticket purchases made through digital distribution channels within the past 12 months are necessary for these customers to be considered for either the treatment or the control group.[19]

[18] Note that this assignment only applies to the randomized field experiment, discussed in Section 3.5. In the matching approach, which we discuss in Section 3.6, we construct a control group specifically for the buyers of the PTC.

[19] Note that there may still be customers who mix online and offline tickets. For example, an otherwise online-savvy customer may occasionally buy paper tickets for reimbursement purposes. We have to assume that there are no systematic differences between the treatment

Due to these restrictions, we stratify our sample according to socioeconomic indicators and type of ticket usage (see Table 3.8). As a result, we obtain representative pools for the treatment and control groups, which account for approximately 5.9 million customers of Swiss public transportation.[20] We implicitly assume that the introduction of the PTC has a negligible impact on people that do not use (and pay for) public transportation at all in the 12 months prior to the pilot study.

Data limitations In accordance with public-transportation providers, the pilot study is limited to a maximum of 600 PTC of each size. To account for market demand for both types of the PTC, the registration window, which opened in December 2021, closed after the first batch was exhausted in March 2022. At that point, 600 small-type PTCs and 311 large-type PTCs had been sold, resulting in a total of 911 PTCs. Up to this point, we had sent out 431,533 invitation emails to individuals in the treatment group.

Due to the large number of individuals who received a pilot-study invitation, it was not possible to track a year's worth of ticket sales for all of them. Specifically, for each PTC buyer, we monitor the consumption of 8 randomly selected non-buyers in the treatment group, and for each tracked individual in the treatment group, we track their twin in the control group.[21] This yields a total of $(893 \times (1 + 8)) \times 2 = 16,074$ observations.

Product features The PTC, as it will be introduced in late 2023, can be used for a wide variety of tickets, including route and zone tickets, day passes, as well as supersaver tickets, which offer a discount of up to 70% and are only available in advance. In contrast, existing season tickets—that themselves incorporate quantity discounts—cannot be purchased with the PTC. Additionally, the PTC cannot be used for non-personalized tickets: since they can be resold, their consideration would undermine the incentive scheme described in Section 3.3.

The technical implementation required to enforce the above restrictions is demanding in terms of resources. Implementing these restrictions for a pilot study is at odds with the principle of a "lean product development." Fortunately, Swiss public-transportation providers offer a solution called

and control groups in this respect, although offline tickets cannot be purchased with the PTC.

[20] We exclude children below the age of 18 and seniors above the age of 80 due to practical reasons. We also exclude residents of the Italian-speaking part of Switzerland, who constitute 6 percent of the Swiss population.

[21] We speak of "twins" when describing observations with identical values of the stratification variable (see Table 2).

"Automated Ticketing." This system relies on GPS-routed journeys tracked by smartphone applications. A central "price engine" combines route and zone tickets, as well as day passes, to determine a daily "best price" retrospectively (the following day). By limiting the use of the PTC to Automated Ticketing, we can eliminate the problem of non-personalized tickets and take advantage of an existing applicable ticket range.

However, by doing so, we forfeit two important features which the PTC will have at market launch: First, supersaver tickets are excluded. Second, people who do not want public-transportation providers to track their movement patterns—or dislike Automated Ticketing for other reasons, such as its impact on smartphone battery life—are less inclined to purchase the PTC in the pilot study as they will be with its final implementation.

We handle this issue in a twofold manner: On the one hand, we interpret our main results (in Sections 3.5 and 3.6) in terms of the treatment "introduction of a pilot-study PTC". On the other hand, we collect indicators for the eventual market demand by means of an online survey with non-buyers (from the treatment group). In Section 3.D, we show to what extent additional product features may raise the demand for this "market-launch PTC".

There are even more arguments (which we also discuss in Section 3.D) which let us assume that penetration of the market-launch PTC substantially exceeds the one of the pilot-study PTC. In some instances, however, we manage to control for altering product features preemptively in the study design. Notably, due to the short decision window of two weeks, we would expect that GA holders refrain from buying a PTC in the pilot study due to existing GA refund conditions. With the definitive launch, on the other hand, they can defer their purchase to the moment their GA expires, circumventing any financial loss. To take this into account, refund conditions were overwritten for the pilot study. Specifically, buyers of the PTC were allowed to refund their existing season tickets "pro rata temporis", which was also advertised in the invitation email. This way, at least the financial consequences for potential buyers who were not allowed to wait for the renewal date of their season ticket could be eliminated.

With the aforementioned considerations in mind, we can now approach the evaluation of the pilot study. As our main interest concerns the overall revenue impact from implementing the PTC, we gather the entirety of (personalized) sales across all sales channels. For instance, even customers who use the PTC might buy additional tickets (for touristic travel outside the area of validity), or they benefit from additionally purchasing a regional season ticket.

The observation period is observation-specific. For buyers (and their twins from the control group), the period starts on the first day of validity of the PTC and ends with the last day of validity, that is, 364 days later. For non-buyers (and their twins), we proxy equivalent dates by the (elapsed) purchase deadline. Thus, observations started between December 2020 and March 2021 and ended between December 2022 and March 2022. Owed to the yearlong individual observation periods—and as we assume that there are no interaction effects between season and PTC lifecycle—we do not have to control for seasonality.

To compute total revenue, we add up individual expenditures for tickets. In the case of (mostly season-) tickets with validity periods starting or ending outside the observation period, we compute the share of the validity period as a fraction of the observation period and truncate expenditures accordingly.

Regarding the PTC, recall from Section 3.3 that a remaining allowance is refunded up to the price of the PTC. Using $E_{\text{PTC-T}}$ for ticket expenses met with the PTC, P_{PTC} for the price of the PTC and V_{PTC} for its value (size of the allowance), we compute PTC-related expenditures as:

$$E_{\text{PTC}} = \begin{cases} \sum E_{\text{PTC-T}}, & \text{if } \sum E_{\text{PTC-T}} \leq P_{\text{PTC}}, \\ P_{\text{PTC}}, & \text{if } P_{\text{PTC}} < \sum E_{\text{PTC-T}} \leq V_{\text{PTC}}, \\ \frac{365}{T} \times P_{\text{PTC}} & \text{if } \sum E_{\text{PTC-T}} > V_{\text{PTC}}. \end{cases} \tag{3.4.1}$$

In the final case of equation 3.4.1, T refers to the number of days it takes to deplete the PTC. Instead of separately adding up ticket expenditures after this point in time, we act as if such a buyer would immediately buy another PTC of the same size. Even though this was not possible in the course of the pilot study, it would be the sensible thing to do. Note that equation (3.4.1) is in line with Figure 3.3.2 in Section 3.3. Specifically, the immediate renewal of the PTC corresponds to the constant average expenditure $\bar{E}_{\text{HF}+}$ between $\hat{x}_2$ and $\tilde{x}_{\text{HF+,GA}}$.

3.5 Randomized Field Experiment

In our field experiment, 431,533 randomly selected public-transportation customers received a mail invitation to participate in the pilot study. 893 of these individuals used the attached promo code, purchased the PTC, and completed the pilot study. This indicates that the majority of customers did not comply with the random assignment and chose not to participate in the pilot study. Therefore, while the mail invitation was randomized, the purchase choice may be confounded. To assess the revenue impact of the PTC based on the dispatch of invitations, we must account for imperfect compliance.

Therefore, following Angrist and Imbens (1995), Angrist, Imbens, and Rubin (1996) and Huber and Wüthrich (2019), we identify the effect based on an instrumental variable approach. We define a binary treatment $D \in \{0, 1\}$, which takes the value 1 when purchasing the PTC and the value 0 when not purchasing the PTC and a binary instrument $Z \in \{0, 1\}$, which takes the value 1 when receiving a mail invitation and the value 0 when not receiving a mail. Additionally, let Y denote our outcome of interest "expenditure". Based on the potential outcome framework (see, for instance, Rubin, 1974) we refer to $D(z)$ as the potential treatment state that would occur if the instrument Z was exogenously set to value z and refer to $Y(z, d)$ the potential outcome when setting Z and D to $z, d \in \{0, 1\}$.

A variable Z is an instrumental variable for the causal effect of D on Y if it is randomly assigned, the exclusion restriction and the monotonicity assumption hold and its average effect on D is nonzero. Based on Angrist, Imbens, and Rubin (1996) and Huber and Wüthrich (2019), we discuss these assumptions in the following:

Assumption 1: Random Assignment
Assumption 1 states that the instrument assignment is as good as random. That is, the instrumental variable is independent of the potential treatments $D(z)$ as well as the potential outcomes $Y(z, d)$. In our case, this assumption is satisfied by design as the mail invitations were sent out randomly.

Assumption 2: Exclusion Restriction
Assumption 2 implies that any effect of Z on Y must be via an effect of Z on D. That is, the instrumental variable must not have a direct effect on Y other than through D. Due to this assumption, we can define the potential outcome $Y(z, d)$ as a function of the treatment D alone: $Y(d)$.

Assumption 3: Monotonicity
Assumption 3 states that the potential treatment state of any individual

does not decrease in the instrumental variable. In our case, assumption 3 is satisfied by construction as no one can purchase the PTC without having received the mail invitation.

Assumption 4: Nonzero Average Causal Effect of Z on D
Assumption 4 requires an average causal effect of Z on D not equal to zero.

Based on Angrist, Imbens, and Rubin (1996) and closely following Huber and Wüthrich (2019) we define four treatment compliance types by the joint potential treatment states under $z = 1$ and $z = 0$. The first type, the compliers purchase the PTC when receiving a mail invitation and do not purchase the PTC when not receiving the mail invitation $(D(1) = 1, D(0) = 0)$. The second type, the never takers do not purchase a PTC regardless whether they received a mail invitation or not $(D(1) = 0, D(0) = 0)$. The third type, the always takers purchase the PTC regardless whether the received a mail invitation $(D(1) = 1, D(0) = 1)$ and the fourth type, the defiers react counter-intuitively by not purchasing the PTC when receiving a mail invitation and purchasing a PTC when not receiving a mail invitation $(D(1) = 0, D(0) = 1)$. Since no one can purchase the PTC without the mail invitation, always takers and defiers do not exist in our pilot study with so-called one-sided noncompliance.

With the instrumental variable approach the local average treatment effect on compliers can be calculated. That is the average effect for individuals whose treatment status is influenced by changing the value of Z or in other words, by marginally making the product more attractive (Angrist and Imbens, 1995).

As we only have a subsample available—that is 16,074 observations—of customers being part of the experiment, we cannot rely on conventional instrumental variable approaches to estimate the treatment effect. However, we observe the mean outcome when $D = 1$ for compliers and can derive the mean outcome when $D = 0$ for compliers. The difference of those mean outcomes is then the average treatment effect on compliers.

In our pilot study we have no always takers and defiers, hence $Z = 0$ implies $D = 0$:

$$E[Y|Z = 0] = E[Y|D = 0, Z = 0]. \tag{3.5.1}$$

$E[Y|D = 0, Z = 0]$ contains the mean potential outcomes under non-treatment of the compliers and the never takers:

$$E[Y|Z = 0] = Pr(compliers) \times E[Y(0)|compliers] + Pr(never\ takers) \times E[Y(0)|never\ takers]. \tag{3.5.2}$$

$Pr(compliers)$ and $Pr(never\ takers)$ are the shares of compliers and never takers. As there exist no defiers, the never takers' mean outcome can be identified by $E[Y|D = 0, Z = 1]$. We can therefore substitute $E[Y(0)|nevertakers]$ by $E[Y|D = 0, Z = 1]$ in equation (3.5.2) and solve the equation for the mean outcome when $D = 0$ for compliers:

$$E[Y(0)|compliers] = (E[Y|Z = 0] - Pr(never\,takers) \times E[Y|D = 0, Z = 1])/Pr(compliers). \tag{3.5.3}$$

Since always takers and defiers do not exist, $Pr(never\,takers) = Pr(D = 0|Z = 1)$ and $Pr(compliers) = Pr(D = 1|Z = 1)$ and hence the mean outcome when $D = 0$ for compliers can be calculated with the following equation:

$$E[Y(0)|compliers] = (E[Y|Z = 0] - Pr(D = 0|Z = 1) \times E[Y|D = 0, Z = 1])/Pr(D = 1|Z = 1). \tag{3.5.4}$$

Finally, the local average treatment effect on compliers is then the difference between the mean outcome when $D = 1$ and the mean outcome when $D = 0$:

$$E[Y|D = 1, Z = 1] - E[Y(0)|compliers]. \tag{3.5.5}$$

For the estimated effect we calculate a 95% bootstrap confidence interval. This involves randomly drawing subjects with replacement from our subsample 2000 times and then estimating the effect in every bootstrap sample.

Since our sample largely consists of never takers, resulting in minimal variation in the treatment D between the treatment and control groups, our instrument is weak and may explain only a small portion of the variation in Y. This leads to potentially very noisy estimates. To reduce this noise, we only consider the part of Y that is not explained by previous expenditures. In other words, we regress Y on the expenditure of the year before the pilot study and calculate the point estimate with the resulting residuals.[22]

Using this approach, we estimate a average treatment effect of CHF 1,787.3. However, this point estimate is statistically insignificant. The 95% bootstrap confidence interval ranges from CHF -7,315.7 to CHF 10,576.0.[23] As expected due to weak correlation between the instrument "mail invitation" and the PTC purchases, our instrument is too weak to draw conclusive inferences regarding the impact of the PTC on expenditure and revenue.

[22] In Appendix 3.A, as robustness checks, we estimate the effect, when not regressing on previous expenditures and when including all covariates from Table 3.1.

[23] In the published version of this chapter, see Sticher and Blättler (2024), we consider customers that left their emails unopened as having not received the instrument, which relies on the strong assumption that the instrument remains as good as random when defining it based on opening (rather than on the randomly assigned reception of) the e-mail.

3.6 Selection on observables

To complement our analysis of the experiment's findings, we incorporate a selection on observables approach. Instead of relying solely on the random invitation as an identifying factor, we match the 893 study participants with similar customers in the control group based on observable characteristics. That is, we aim to compare customers with similar characteristics but different treatment states.

Compared to the randomized field experiment of Section 3.5, we have to assume conditional independence, implying that we have observed and accounted for all variables that jointly influence both Y and D.[24] Fortunately, as outlined in Table 3.1, we have access to a comprehensive dataset that allows us to not only control for personal characteristics but also consumption patterns in the year prior to the pilot study. Table 3.2 presents the descriptive statistics of our control variables for the treatment group and control group. Unfortunately, we cannot observe and control for changes in life circumstances, such as moving place of residence or work, which might also influence both Y and D (for detailed discussion, see Section 3.7). It is important to note that all control variables refer to information collected before the start of the pilot study, ensuring that they are not influenced by the treatment in a way that is related to the outcome (i.e., exogeneity of confounders). To balance the treatment and control group, we employ the causal forest, as described by Athey and Wager (2019), due to its functional flexibility in capturing non-linear dependencies. We utilize the *grf* package developed by Tibshirani, Athey, Friedberg, Hadad, Hirshberg, Miner, Sverdrup, Wager, Wright, and Tibshirani (2018) and the *lmtest* package developed by Hothorn, Zeileis, Farebrother, Cummins, Millo, Mitchell, and Zeileis (2015) in the statistical software *R*.

In addition to the conditional independence and the exogeneity assumption, common support has to be fulfilled. This assumption states that the probability of buying a PTC must fall strictly between 0 and 1, indicating that the treatment assignment mechanism is not deterministic (see, e.g., Huber, 2023). Figure 3.6.1 and Table 3.3 present the conditional treatment probabilities—also called propensity scores—with a notable number of customers having propensity scores close to zero. To account for that,

[24] In our case of panel data, the use of the conditional-independence approach instead of the difference-in-differences approach is suggested by Imbens and Wooldridge (2009). However, we apply the difference-in-differences approach as a robustness check in Appendix 3.A

Variable	**Description**
Expenditures (total)	Sum of expenditures on season tickets and single tickets
Expenditures (single tickets)	Sum of expenditures on single tickets
Ticket type	Stratification variable (see Table 3.8)
Spread	Maximum value of a expenditures on single tickets minus minimum value of expenditures on single tickets
Spread (months)	Maximum monthly sum of expenditures minus minimum monthly sum of expenditures
CV	Coefficient of variation (standard deviation divided by mean) of expenditures on single-tickets
CV (months)	Coefficient of variation of monthly sum of expenditures
Trips	Number of single-ticket purchases
Trips (first class)	Number of first-class single-ticket purchases
Age	0–99
Gender	Male/female

Table 3.1: Description of control variables

we calculate the overlap-weighted average treatment effect, recommended by Li, Morgan, and Zaslavsky (2018). This estimand is particularly suitable when the propensity scores are close to zero or one, as it does not involve dividing by estimated propensity scores (Tibshirani, Athey, Friedberg, Hadad, Hirshberg, Miner, Sverdrup, Wager, Wright, and Tibshirani, 2018). Instead, it uses the product of the propensities to be in the treatment and control group. Therefore, we estimate the average treatment effects for the population with sufficient overlap between the treatment and control group. That is the effect on customers with a combination of covariate values occuring sufficiently in both the treatment and control group. However, by focusing on the overlap population, there is a loss of external validity of the effect on the population with no sufficient overlap. Note that the average treatment effect on the overall population and on the treated population are estimated as robustness checks in Appendix 3.A.

Variable	**PTC Buyers**	**Control group**
Ticket type (GA, first class = 1)	0.02 (0.13)	0.01 (0.09)
Ticket type (GA, second class = 1)	0.10 (0.30)	0.09 (0.28)
Ticket type (HF = 1)	0.72 (0.45)	0.50 (0.50)
Ticket type (HF + other season ticket = 1)	0.12 (0.33)	0.11 (0.31)
Ticket type (other season ticket = 1)	0.01 (0.12)	0.14 (0.35)
Ticket type (non-discounted tickets = 1)	0.03 (0.16)	0.15 (0.35)
Age	46.98 (13.78)	43.90 (16.18)
Gender (female=1)	0.43 (0.50)	0.54 (0.50)
Region (German=1)	0.79 (0.41)	0.75 (0.43)
Previous Expenditure (total)	1,585.24 (1213.67)	834.57 (1,028.88)
Previous Expenditure (single tickets)	614.93 (613.51)	169.77 (323.19)
Spread	37.15 (27.88)	16.59 (23.65)
Spread (months)	188.87 (125.16)	75.26 (88.23)
CV	0.63 (0.38)	0.36 (0.42)
CV (months)	0.66 (0.43)	0.54 (0.62)
Trips	44.66 (46.40)	14.26 (28.21)
Trips (first class)	4.59 (14.38)	1.09 (6.26)
Expenditure (Outcome)	1,860.11 (1091.42)	955.27 (884.57)

Table 3.2: Means (standard deviations) of buyers and control group

Propensity scores	Number of observations	
	PTC Buyers	Control group
0.006-0.100	179	5,949
0.101-0.200	182	1,180
0.201-0.300	185	515
0.301-0.400	143	224
0.401-0.500	126	131
0.500-0.633	78	38
Total	893	8,037

Table 3.3: Observations in certain propensity score ranges

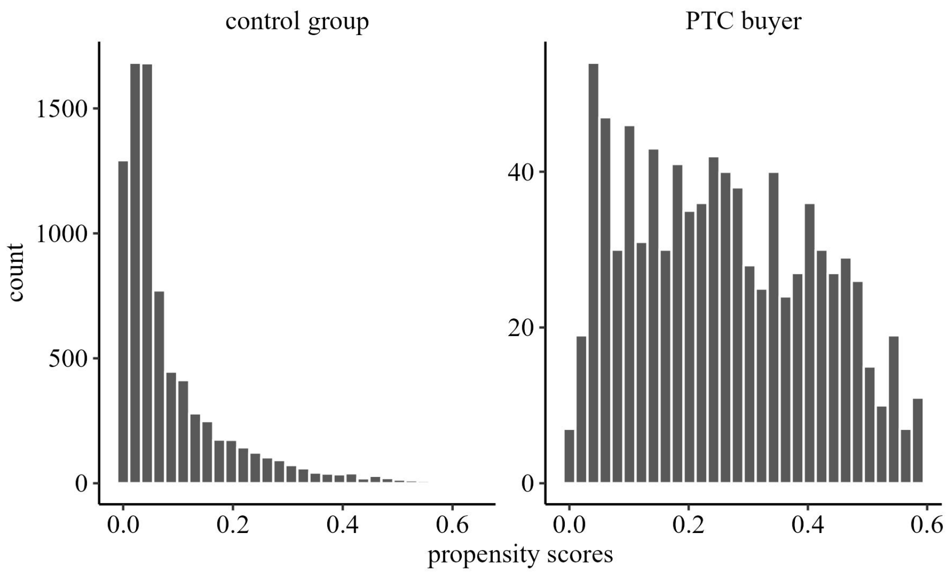


Figure 3.6.1: Distribution of propensity scores

We obtain an average treatment effect for the population with sufficient overlap of CHF 179.7 per PTC. The 95% confidence interval ranges from CHF 115.0 to CHF 244.4, signifying a statistically significant point estimate. We benchmark our estimated effect using linear regression. As the regression table 3.7 in Appendix 3.B shows, the OLS treatment effect amount to CHF 202.2, being significant at the 1% level.

In Table 3.4, we summarize our results. Note that, despite not explicitly leveraging the randomization of the invitations in the selection on observables approach, the interpretation remains similar to the randomized experiment. That is, as long as purchasing the PTC is as good as random conditional on the control variables. However, the various approaches target different populations. While we estimate the overlap-weighted average treatment effect for the total population in this section, we estimate the local average treatment effect on compliers in Section 3.5. As we have one-sided noncompliance in our experiment, the local average treatment effect on compliers coincides with the average treatment effect on the treated (Huber and Wüthrich, 2019). The latter we estimate in Section 3.A .

	Randomized field experiment	Causal forest	Linear regression
Treatment effect	1787.3	179.7	202.2
Standard error	4389.23*	33.02	21.92
p-value	0.690*	0.000	0.000
Number of observations	16,074	8,930	8,930

* *Values computed with bootstrapping ($N = 2,000$).*

Table 3.4: Effect of PTC on expenditure

3.7 Discussion and Conclusion

In our study, we first presented theoretical arguments for the application of three-part tariffs in public transportation as a means to simultaneously increase demand and revenue. By considering the price–quantity structure and competitive environment, we demonstrated that introducing a product between two-part tariffs (the HF) and season tickets (the GA) can effectively address particularly elastic demand.

Empirically, we supported this hypothesis by analyzing the pilot-study for the PTC, a three-part tariff set to be introduced in Switzerland in December 2023. Employing a randomized field-experiment approach, our findings yielded point estimates aligned with the revenue-enhancing argument. However, these estimates are not statistically significant, potentially due to a "weak instrument" issue arising from the low participation rate among invitees who received an e-mail offer to participate in the pilot study.

To enhance the statistical power of our analysis, we applied the conditional-independence assumption (CIA) and constructed a comparison group by matching PTC buyers with individuals from the control group based on observable characteristics. While the resulting revenue increase of CHF 179.7 is highly significant, the CIA is crucial: For instance, it may well be the case that some customers self-select into the treatment group based on their (unobservable) prospects. Consider changes in life circumstances which we cannot observe. For instance, if moving to a new residence leads to an increase in both the willingness to pay for public transportation and the likelihood to purchase a PTC, the CIA may be compromised, potentially leading to an overestimation of the treatment effect. Since the pilot study was conducted during the Covid-19 recovery (with the baseline data from the midst of the pandemic), life circumstances underwent changes for nearly everyone, making the possibility of such a violation non-negligible. However, to a certain extent, our comprehensive data set also allows us to control for the responses to the pandemic: As Table 3.1 shows, we included predictors such as the variation coefficient and the spread of expenditure between months in the year preceding the pilot study. Since during the baseline year there were also months with barely any Covid restrictions in Switzerland, the reaction to the Covid-19 recovery is not entirely unaccounted for.

Finally, we endeavored to predict market demand for the PTC upon its official launch. To achieve this, we had to rely—at least partially—on self-reported purchase intentions of non-buyers in the pilot study. Given the circumstance that the market-launch PTC will differ from its pilot-study counterpart, our point estimate of approximately 200,000 demanded PTCs per year has to be taken with a grain of salt (for the calculation, see Appendix

3.D).

To address all the uncertainties mentioned above, closely monitoring customer behavior in the initial years following the PTC's launch and making necessary adjustments to both the analytical and empirical models, as well as the PTC itself, will be crucial.

Beginning with the analytical model, there is potential to expand the nascent research on three-part tariffs with competitive elements (in our case: competition between modes). Formally endogenizing modal choice could also facilitate a comparison of prices set by public-transportation providers with first-best prices from a utilitarian standpoint. Presently, our results only suggest an augmented combined rent in the public-transportation market due to the implementation of the PTC, as customers' loosened budget constraints coincide with providers' higher contribution margins. To make statements on societal welfare, however, a consideration of various factors would be needed, ranging from congestions and emissions to crowding issues and the public financing of infrastructure. Notably, unlike traditional season tickets and recently increasingly experimented-with (almost) fare-free transportation, the PTC is neither particularly well-suited for commuters nor does it encourage excessive demand. Assuming that induced additional (leisure) trips are more likely to occur in underutilized vessels, at least our abstraction from (step-fixed) costs seems justifiable.

Transitioning to recommendations for additional empirical research, first note that our study contributes to the pricing-elasticity literature by framing the demand for public transportation as a function of the specific price structure. Although the quantitative measurement of elasticities is impeded in our case by the absence of universal consumption data (as opposed to expenditure data), we can derive qualitative conclusions regarding 'local' elasticities.[25] We advocate for capitalizing on the growing accessibility of consumption data to obtain more nuanced insights into price elasticities.

Regarding the product itself, further differentiation is welcome as far as compatible with customer ease of use. This could involve offering additional discounts for different customer groups or introducing additional allowance packages, such as the scheduled "intermediate" PTC. As for future steps and potential adoption by other countries, we suggest staying on the exploratory path involving tests, pilot studies and a gradual market launch.

[25] Note that while public-transportation providers measure passenger kilometers through frequency surveys, these data are only available at an aggregate level. Computing elasticities concerning specific pricing measures (as opposed to general price adjustments) would require micro-level data or, at least, distributional information.

Appendices

3.A Robustness checks

3.A.1 Randomized field experiment

In section 3.5, we use the random dispatch of invitations to participate in the pilot study as an instrumental variable to analyze the effect of the PTC on expenditure. Table 3.5 shows that all estimated effects—without and with covariates included—are insignificant. Unfortunately, the instrument is too weak and the variance too high to draw conclusive inferences regarding the impact of the PTC on expenditure with this approach.

Included covariates	None	Previous expenditure (total)	All from Table 3.1
Treatment effect	-2351.0	1787.3	3583.4
Bootstrap CI*	[-19184.4;14633.6]	[-7315.7;10576.0]	[-4945.6;11837.4]
p-value	0.782	0.690	0.387
Number of observations	16,074	16,074	16,074

**2,000 bootstrap estimates were computed.*

Table 3.5: Effect of PTC on expenditure

3.A.2 Selection on observables

In Section 3.6, we define the PTC buyers as treatment group and customers not receiving an invitation to participate in the pilot study as control group. Based on a selection on observables approach, we use the causal forest and calculate the overlap-weighted average treatment effect, recommended by Li, Morgan, and Zaslavsky (2018). In the following, we perform robustness checks to challenge the main result and display the results in table 3.6.

Firstly, we check whether our result is sensitive to the choice of the control group. Instead of using the customers not receiving an invitation as control group, we define the non-buyers that received the invitation to participate in the pilot study but did not buy the PTC as control group in robustness check (1). The PTC buyers remain the treatment group. The estimated average effect of CHF 191.7 per PTC is similar to the results in Section 3.6. Conversely, in robustness check (2), we replace the PTC buyers and define the non-buyers as treatment group. In this setting, non-buyers are considered to be 'pseudo-treated' and the customers not receiving an invitation to participate in the pilot study are the control group. Note that neither the treatment group nor the control group receive any treatment, so that the robustness check serves as a placebo test. The estimated average effect of CHF 6.7 per PTC is close to zero and statistically insignificant. Hence, the robustness checks indicate that the potential bias in either control group is minimal and does not significantly affect the outcome.

Secondly, we compare the average treatment effect among different target samples (using the rhetoric of causal inference, this procedure is referred to as "moving the goalpost" (see, e.g., Crump, Hotz, Imbens, and Mitnik, 2006). The overlap-weighted average treatment effect shows the impact on the population where we have sufficient overlap between the treatment and control group. However, this average treatment effect may not be directly generalized to the overall population. In robustness check (3), we estimate the average treatment effect for the overall population, including observations with poor overlap.[26] The estimated average effect doubles to CHF 380.3 per PTC. However, this result should be interpreted with much caution, as the estimated propensity scores go close to zero and effects for observations with propensity scores close to zero may not be well identified and may therefore be biased. Additionally, we can estimate the average treatment effect among PTC buyers. The effect on those actually buying the PTC is particularly interesting for policy-makers. Therefore, in robustness check (4), we calculate this average treatment effect on the treated (ATET)[27]. The estimated average effect on the treated is CHF 152.4 CHF per PTC and hence, similar to the overlap-weighted treatment effect.

Thirdly, in robustness check (5), we use the difference-in-differences approach instead of the selection-on-observables approach.[28] Using the difference-in-differences method checks for differences between approaches. The difference-in-differences approach is—among others—based on the assumption that PTC buyers under nontreatment and nontreated customers in the control group follow a common trend (see, e.g., Snow, 1855, Card and Krueger, 1994). The method yields therefore the average treatment effect on the treated (ATET). For this estimation, we us the *wooldrigde* package in the statistical software R. The estimated average effect on the treated amounts to CHF 154.2 per PTC. The similarity between the average treatment effect on the treated in robustness check (4) and (5) suggests that the results are robust across methodological approaches. Also note that we benchmark our

[26]To be precise, we set in the statistical software R the `target.sample`-argument from `target.sample="overlap"` to `target.sample="all"`.

[27]To be precise, we set in the statistical software R the `target.sample`-argument from `target.sample="overlap"` to `target.sample="treated"`.

[28]We employ the difference-in-differences method without including covariates.

estimated effect using a linear regression approach in Section 3.6.

Overall, the estimated average effects with different control groups, target samples and methodological approaches strengthen the robustness of the main result. However, the robustness checks (as well as the main result) are based on crucial assumptions—conditional independence or common trend—whose fulfillment we cannot check empirically (for detailed discussion, see Section 3.7).

Check	1	2	3	4	5
Effect	191.7	6.7	380.3	152.4	154.2
Standard error	34.18	8.23	37.05	33.87	52.92
p-value	0.000	0.419	0.000	0.000	0.004
Number of observations	8,037	14,181	8,930	8,930	8,930

Table 3.6: Effect of PTC on expenditure (robustness checks 1 through 5)

3.B Linear Regression (Benchmark)

	Coefficient	**Standard error**	**t-value**	**p-value**
(Intercept)	428.17	62.51	6.85	0.00
Ticket type (GA, first class = 1)	1,572.42	94.51	16.64	0.00
Ticket type (GA, second class = 1)	733.26	62.47	11.74	0.00
Ticket type (HF + other season ticket = 1)	182.98	58.10	3.15	0.00
Ticket type (HF = 1)	-126.41	55.74	-2.27	0.02
Ticket type (other season ticket = 1)	-308.42	57.55	-5.36	0.00
Ticket type (other season ticket = 1)	72.92	57.58	1.27	0.21
Age	-1.51	0.39	-3.85	0.00
Gender (female=1)	-37.84	12.00	-3.15	0.00
Region (German = 1)	4.11	14.19	0.29	0.77
Previous Expenditure (total)	0.58	0.01	49.44	0.00
Previous Expenditure (single tickets)	0.20	0.05	4.34	0.00
Spread	0.89	0.57	1.58	0.12
Spread (months)	0.49	0.11	4.53	0.00
CV	13.76	29.62	0.46	0.64
CV (months)	89.60	12.45	7.19	0.00
Trips	1.58	0.45	3.52	0.00
Trips (first class)	4.65	0.87	5.35	0.00
Treatment effect	202.23	21.76	9.29	0.00

Table 3.7: Linear regression, as a benchmark for the matching approach described in Section 3.6

3.C Descriptive Statistics and Consumption Patterns

592 costumers of our final dataset bought the small PTC, whereas 301 customers bought the large PTC (cp. Section 3.3). At the outset of the pilot study, 84.1 percent of the PTC buyers owned an HF and 11.8 percent a GA. 1.5 percent of the PTC buyers held one or more other travel cards, and 2.6 percent traveled with non-discounted tickets. In the control group, 60.1 percent of the customers owned a HF, 9.5 percent a GA. 15.2 percent possessed other travel cards and 14.5 percent traveled with non-discounted tickets. We summarize the season-ticket ownership type as well as some socioeconomic indicators of PTC buyers in Table 3.8.

Variable	**Values**	**Number of observations**
Season-ticket ownership type	GA	106
	HF	751
	Other season tickets	13
	Non-discounted tickets	23
Age group	18–49 years	525
	49+ years	368
Region	German	708
	French	184
	Other	1

Table 3.8: Descriptive statistic of buyers (stratification variable)

During the pilot study, the PTC buyers (of both types) spent on average CHF 1,860.10, including expenditures on the PTC as well as on other tickets. Non-buyers in the treatment group spent on average CHF 948.75, costumers in the control group CHF 955.25.

However, already prior to the pilot study, PTC buyers spent more on public transportation than customers in the control group. While PTC buyers spent on average CHF 1,585.25 during the year prior to the field experiment, non-buyers in the treatment group spent on average CHF 823.70, costumers in the control group CHF 834.55.[29]

Obviously, we cannot simply compare yearly expenditures of the buyers in the treatment group with customers of the control group to determine the

[29] Recall that the year prior to the pilot study marked the midst of the Covid-19 pandemic.

revenue impact of the PTC. This is because individuals with high propensities to consume public transportation arguably self-select into the buyer group.[30] In Sections 3.5 and 3.6, we identify strategies to construct more apt comparison groups for the PTC buyers.

However, the data on PTC expenditures provides evidence that suggests a consumption-boosting impact of the PTC. Figure 3.C.1 illustrates the daily PTC expenditures during the pilot study. In the left-hand panel, we show the daily means for all PTC buyers ($N = 893$).

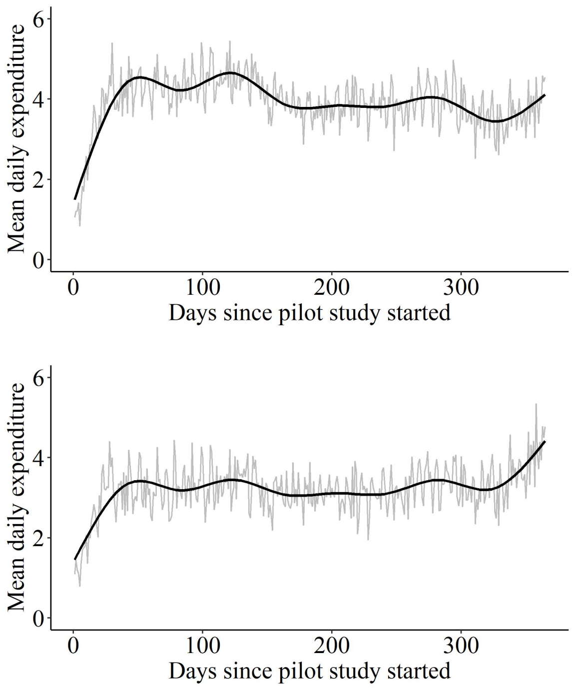


Figure 3.C.1: Temporal consumption patterns of all PTC buyers (left-hand panel) and the reduced sample (right-hand panel)

These values exhibit the highest levels during the first four months of the pilot study. This may be explained by the fact that we cannot observe further PTC expenditures from buyers whose allowances have been fully depleted.

To address this, in the right-hand panel of Figure 3.C.1, we narrow down our sample to customers who have not spent more than 11/12 of their allowance during the first 11 months of the pilot study. In this reduced sample ($N = 493$), we observe an increase in the mean daily expenditure towards the end of the pilot study. Specifically, while the average daily PTC expenditure

[30]For a comparison of the buyer group and the control group, see Table 3.2 in Section 3.6.

from weeks 3 through 50 is CHF 3.24, this value rises by 31% to CHF 4.25 during the last two weeks.

This observed "catch-up effect" suggests that the PTC stimulates consumption.[31] However, it is evident that this consumption stimulus is limited, as we observe many PTC buyers who do not fully take advantage of their "free" tickets: In Figure 3.C.2, we group PTC buyers based on the relation between their expenditures and the PTC price and allowance.

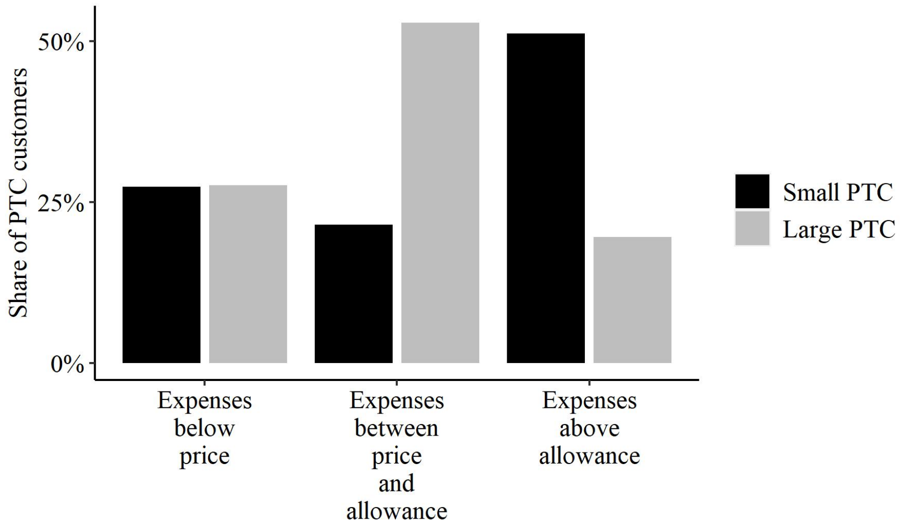


Figure 3.C.2: Temporal consumption patterns of all PTC buyers (left-hand panel) and the reduced sample (right-hand panel)

Notably, we observe that many purchasers of the large PTC do not exhaust their allowance fully. This behavior aligns with a scenario of highly inelastic public-transportation demand: The large PTC becomes the rational choice with an anticipated PTC consumption of more than only CHF 2,200.[32] Consequently, we expect a considerable proportion of "large PTC" buyers whose anticipated consumption level falls between the price (CHF 2,000) and the allowance (CHF 3,000).

However, on a scenario without the PTC, these customers might have

[31] Note the sharp initial increase in PTC expenditures in both panels of Figure 3.C.1. This pattern can be explained by the fact that PTC buyers initially continued to use their previous season tickets during the early days of the pilot study. There are various scenarios that render this behavior economically beneficial, even with the generous refund conditions explained in Section 3.4.

[32] With an expected consumption of between CHF 800 and CHF 2,200, the small PTC (including a "bonus" of CHF 200) becomes more favorable.

spent less than CHF 2,000 on public transportation. Hence, even if they do not strongly react to zero-marginal cost tickets during the pilot study, these customers might well exhibit high price elasticities at initial purchase of the PTC.

To thoroughly disentangle these partially contradicting effects, it is best to globally compare a situation with the PTC to counterfactual scenarios without it. This comparison is precisely what we undertake in the two sections 3.5 and 3.6.

3.D Market Potential

In Section 3.4, we mentioned that the participation rate only applies to the "pilot-study PTC" but is highly likely to underestimate demand for the PTC after market launch. The PTC's appeal will extend beyond the above-mentioned inclusion of supersaver tickets.[33] It will offer enhanced accessability through various sales channels, not limited to Automated Ticketing. Furthermore, additional improvements will be implemented, such as the introduction of an "intermediate" PTC and discounted prices for young individuals. Importantly, potential customers will have the opportunity to purchase the PTC outside of a test environment, eliminating the requirement of participating in market research. This will allow for more time to deliberate, better understanding of the product, and exposure to promotions and word-of-mouth advertising, among other factors.

To evaluate the market potential, the public-transportation providers conducted an online survey specifically targeting members of the treatment group who opted not to purchase the PTC. Within this survey, a total of 273 participants provided reasons for their decisions and revealed which altered product features would persuade them to buy the PTC. Based on these and other criteria,[34] in conjunction with the planned design of the final PTC, the public-transportation providers reached the conclusion that approximately 6.3% of non-buyers from the pilot study are likely to change their minds upon the official launch of the product.

Using the same algorithm as the public-transportation providers, we are able to replicate this finding (see Table 3.9). However, as an attempt to

[33] Note that the inclusion of supersaver tickets not only affects demand, but also the yield. In the following, we ignore this circumstance based on the public-transportation providers' statement that supersaver tickets are (at least) revenue-neutral as compared to regular tickets.

[34] Other criteria included the perceived attractiveness of the PTC and the level of understanding of the product.

correct for self-reporting and self-selection biases, we propose two correcting measures.

	Proportion (N)	**Proportion, weighted*** (N)
At least one affirmative response to ”I would buy a PTC if the following were true” (actual improvements from pilot study**)	61.2% (167)	65.0% (177.2)
”Use by several people” explicitly not mentioned as ”I would buy a PTC if the following were true”	60.8% (166)	59.5% (162.3)
Not having refrained from the pilot study because of not understanding the PTC	93.4% (255)	93.1% (254.1)
PTC rated as attractive (at least 6 out of 7 points)	31.1% (85)	35.3% (96.3)
Not having refrained from the pilot study because of ”too small” or ”too large” PTCs	52.0% (142)	44.5% (121.3)
Conditions cumulatively met	4.8% (13)	6.3% (17.3)

* *Weighting according to the stratification variable listed in Table 3.1.*
** *Improvements: PTC can be purchased not only online; PTC is not registered to Automated Ticketing; PTC can be used for supersaver tickets; PTC at other sizes available; PTC can be used for other ticket types such as first-class upgrades; positive testimonials available.*

Table 3.9: Stated preferences (market potential)

First, we match the individual respondents' stated preferences with the propensity score, as described in Section 3.6. The propensity score, which summarizes the likelihood of buying a PTC, can be matched with the contact data of 218 out of the 273 respondents. We compare the distribution of these 218 values with those of all non-buyers from the treatment group (a total of 7,144 available records), enabling us to calibrate the sample once again. Specifically, we compute weights by comparing population ratios (regarding all non-buyers) with sample ratios (regarding survey respondents).[35] This allows us to recognize that self-selection occurred to a considerable extent. The lowest bin (representing those least likely to buy a PTC) consists of only 7 individuals surveyed, while each of the top 3 bins (representing those most likely to buy a PTC) includes 35 to 37 respondents.

[35] Following Sturges' rule (number of bins = $\lceil 1 + \log_2(N) \rceil$), we compute these ratios for 9 equally populated intervals.

Second, we argue that stated preferences of potential PTC customers are only credible when supported by corresponding consumption patterns. Specifically, we require their propensity scores to be within the interval of the top 95% of actual PTC buyers. By combining this requirement with the post-stratification weights from the previous steps, we conclude that only 45.4% of the respondents possess propensity scores that align with those of PTC buyers. Taking this into account alongside their self-reported willingness to buy, we determine that 2.92% of non-buyers are ultimately likely to purchase the market-launch PTC. According to SBB, of the 431,533 mails sent roughly 200,000 mails were opened. Unopened mails may have been sent to recipients' junk folders and if not, at most the e-mail header was visible. In the latter case, we believe that even after reading the e-mail header "Travel more flexibly—take part in the pilot study", it cannot be assumed that recipients were adequately informed about the PTC. Therefore, based on opened emails, a market potential for the "pilot-study PTC" of 0.45% can be calculated. Adding the 2.92% of non-buyers who are ultimately likely to purchase the market-launch PTC to the actual buyers, the estimated market demand becomes $[0.45\% + (1 - 0.45\%) \times 2.92\%] \times 5.9\,\text{m.} \approx 198{,}000$ customers.

Some reservations remain, however. First, the prediction of 2.92% of non-buyers expected to convert into buyers is based on a small sample size of only 218 interviews, resulting in a mere 7 individuals (unweighted) who are likely to change their minds. As a result, the forecast carries a high level of uncertainty. To emphasize this point, we performed a bootstrap analysis using 5,000 samples of the 218 survey respondents (with replacement). Figure 3.D.1 illustrates the density of the resulting distribution, which exhibits a clear positive skew. The corresponding 95% bootstrap confidence interval spans from 63,230 to 479,060 customers.

Second, it is worth mentioning that the propensity scores rely on the observed covariates and unobserved characteristics might also influence the response behavior such that the self-selection problem cannot be fully resolved.

The third caveat pertains to revenue-related conclusions. We refrain from extrapolating the findings of Sections 3.5 and 3.6 to the market expansion from the pilot-study PTC to the market-launch PTC. This extrapolation could only be justified if the improved product features would solely impact the demand for the PTC but not the behavior of buyers. However, it cannot be precluded that the latter will be influenced as well.

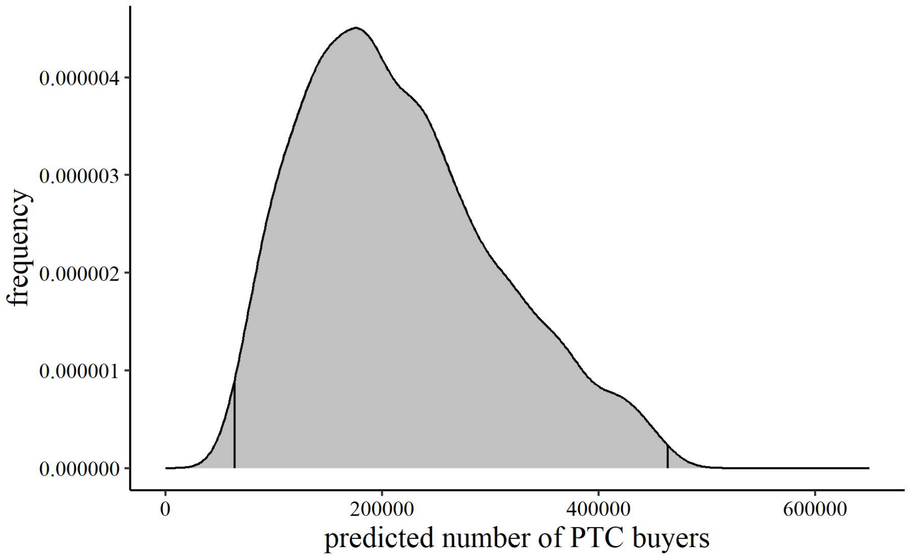


Figure 3.D.1: Probability distribution of the demand for the market-launch PTC (vertical lines indicate the 95% confidence interval)

Chapter 4

Free public transport to the tourism destination

A causal analysis of tourists' travel mode choice

joint with **Hannes Wallimann** and **Widar von Arx***

Abstract

In this paper, we assess the impact of a fare-free public transport policy for overnight guests on travel mode choice to a Swiss tourism destination. The policy directly targets domestic transport to and from a destination, the substantial contributor to the CO_2 emissions of overnight trips. Based on a survey sample, we identify the effect with the help of the random element that the information on the offer from a hotelier to the guest varies in day-to-day business. We estimate a shift from private cars to public transport due to the policy of, on average, 14.8 and 11.6 percentage points, depending on the application of propensity score matching and causal forest. This knowledge is relevant for policy-makers to design future public transport policies for tourists. Overall, our paper exemplifies how such an effect of natural experiments in the transport and tourism industry can be properly identified.

*Chapter 4 is based on a working paper. It is published as Blättler, Wallimann, and von Arx (2024). We are grateful to the SBB Research Fund for financial support.

4.1 Introduction

Tourism's global carbon footprint accounts for about 8% of global greenhouse gas emissions (Lenzen, Sun, Faturay, Ting, Geschke, and Malik, 2018). Transportation contributes 72% substantially to the global CO_2 emissions of overnight tourism (Peeters and Dubois, 2010). Whereas in international travels, most CO_2 emissions stem from air travel, emissions from private car trips gain importance in domestic overnight stays. Even though private car usage emits more CO_2 per passenger kilometre than public transport, Peeters and Dubois (2010) estimate that 90% of domestic trips in developed countries are made by car. Since a shift towards public transport helps decrease CO_2 emissions, there exists a wide range of studies discussing the mode shift from private cars towards public transport (Redman, Friman, Gärling, and Hartig, 2013). In the context of tourism, policies that effectively incentivize leisure travelers to use public transport instead of private cars (or airplanes) are at the forefront of the thinking of researchers and policy-makers (Le-Klähn and Hall, 2015).

However, besides its tremendous impact on the environment, there is limited information on such natural experiment estimates, where policies directly target the arrival and departure of overnight tourists—which differ from other travelers, e.g., by traveling with more luggage. With the prospect of considerably reducing CO_2 emissions, a Swiss tourism destination launched an innovative offer, where overnight guests who stay for at least three nights can order a free public transport ticket (for the whole Swiss public transport network) for their arrival and departure—reducing the monetary cost for sustainable arrivals and departures to zero. Adding to studies investigating fare-free policies (see, e.g., Cats, Susilo, and Reimal, 2017, Kębłowski, 2020, Štraub, Kębłowski, and Maciejewska, 2023, Lu, Mahajan, Lyu, and Antoniou, 2024), this paper analyzes the effect of a free arrival and departure offer on the travel mode choice of the specific group of overnight tourists. Whereas research papers present various estimates of the effects of price changes in public transport due to natural experiments (see, e.g., Kholodov, Jenelius, Cats, van Oort, Mouter, Cebecauer, and Vermeulen, 2021, Wallimann, Blättler, and von Arx, 2023), studies identifying the effects of natural policy experiments on overnight travelers are rare. Studying the effect on this specific group is valuable as leisure travelers are typically more price-sensitive than those commuting and traveling for work (see, e.g., Huber, Meier, and Wallimann, 2022). The travel mode choices between same-day (see, e.g, Rodriguez, Martinez-Roget, and Gonzalez-Murias, 2018) and overnight tourists may differ. Thus, focusing on the group of overnight tourists is important as tourism is growing and the arrival is often coupled with long distances—inevitably associated with increasing CO_2 emissions (Gössling and Higham, 2021). Therefore, innovative transportation policies tailored for overnight tourists must be discussed and evaluated.

In our case, the free arrival and departure offer to and from the destination is only valid when guests actively order the public transport ticket before arrival. Our causal analysis takes advantage of the random element that the information on the offer from the hotelier to the guest varies in day-to-day business. Therefore, we can split the guests with regard to the information status into two groups, i.e., informed and non-informed guests. Using matching methods (i.e., causal forest (Athey, Tibshirani, and Wager, 2019) and propensity score matching (Rosenbaum and Rubin, 1983)) and based on the so-called "selection-on-observable assumption", we answer the research question on the causal effect of the free arrival and departure offer on mode shift from private car to public transport among overnight guests. Finally, the thing to notice is that to identify our theoretical mechanism of interest—i.e., the causal effect of the free arrival and departure offer on mode shift from private car to public transportation—we estimate the effect (only) among guests, not being aware of the offer during the booking process.

We obtain average treatment effects (ATE) of 0.116 and 0.148, both being statistically significant at conventional levels, when applying the causal forest and propensity score matching, respectively. That means when a guest gets informed by the hotelier, the probability that the guest travels by public transportation (instead of a car) increases by 11.6 or 14.8 percentage points (depending on the statistical method). We benchmark our estimates in several robustness checks, e.g., by using guests in surrounding regions without such an offer as a control group. These investigations show that the effect remains significantly positive. To sum up, we provide the first empirical evidence that a free arrival and departure offer for overnight tourists can effectively shift trips to the destination from private car to public transportation.

The remainder of the paper is organized as follows. Section 4.2 discusses the relevant literature. Section 4.3 contains the background of the offer in Switzerland and data steaming from a unique survey in the region of interest. In Section 4.4, we describe how we identify the causal effects. Section 4.5 outlines descriptive statistics. In Section 4.6, we show the estimated effects of the free arrival and departure offer on mode shift. Section 4.7 discusses the results in the practical and political context. Finally, Section 4.8 concludes.

4.2 Literature review

Our study relates to the literature on fare-free policies, the most drastic possible price reduction, as we generate new insights for researchers and policy-makers by analyzing a free public transport policy for the customer segment of overnight guests. The thing to notice is that fare-free public transportation can be implemented twofold: Full fare-free public transport and partial fare-free public transport (Kębłowski, 2020). The latter subsumes temporary (short period of time), spatially (only one or two routes), and socially (a specific group) limited fare-free policies (Kębłowski, 2020). An example is the paper of Cats, Susilo, and Reimal (2017), concluding that full fare-free public transport in Tallinn (Estonia) led to a demand increase (i.e., number of trips) of 14%, while in the rest of the country during the period of investigation, the mode share of public transport decreased. On the other hand, analyzed offers of free public transport exist for a specific customer segment. Based on a case of students from Brussels (Belgium), De Witte, Macharis, Lannoy, Polain, Steenberghen, and Van de Walle (2006) show an increase in public transport usage among students benefiting from the offer. Rotaris and Danielis (2014) conclude, based on a case of the University of Trieste (Italy), that fully subsidizing buses would raise bus share from 53% to 61-81%. Shin (2021) estimates there was a 16% increase in subway use by citizens aged 65 and above after a fare-free policy was introduced for this age group in Seoul. Recently, Štraub, Kębłowski, and Maciejewska (2023) investigate 93 municipalities engaged in fare-free programs and show, for instance, that these programs are more likely to emerge in localities with stable and increasing populations and relatively high levels of public expenditure. Recently, Rozynek (2024) investigated the effect of the temporary, nearly fare-free public transport with the help of qualitative interviews and found that low-income people's mobility and social participation benefits from affordable public transport. However, in contrast to these studies, we focus on the effect of social-limited fare-free public transport on the travel mode choices of tourists with overnight stays.

Moreover, the thing to notice is that studies using quasi-experimental approaches (such as the so-called selection-on-observables assumption as in our study) to investigate the effect on policies on guests' travel mode choices are rare, where there exist estimates of the effects of price changes in public transport due to natural experiments (see, e.g., Hoang-Tung, Kato, Huy, Le Binh, and Duy, 2021, Kholodov, Jenelius, Cats, van Oort, Mouter, Cebecauer, and Vermeulen, 2021, Wallimann, Blättler, and von Arx, 2023). Recently, closely related to our study, Andersson, Björklund, Warner, Lättman, and Adell (2023) investigate the effect of a free public transport card intervention on mode shift using a quasi-experimental setting. As in our paper, the latter study examines the influence of measures on a travel mode shift and not rarely an increase in the number of travelers on public transport (as, e.g., Wallimann, Blättler, and von Arx, 2023). However, again, we differ in that we do this for a specific segment—the overnight guests.

The mean of transport of overnight tourism is mainly analyzed for long-distance travels. Thrane (2015) shows that distance matters for the travel mode choice, as the probability of choosing air transportation over private and public transportation increases significantly with longer routes. The results suggest a turning point at around 400 km at which tourists shift from using private cars or public transportation to using air transportation. Koo, Wu, and Dwyer (2010) show that (low) airfares matter for tourists to switch from cars to airplanes. Compared to this literature, our paper focuses mainly on shorter domestic trips, for which private cars and public transportation are the major counterparts. Pellegrini and Scagnolari (2021) examine the travel mode choice to reach the destination for domestic trips in Switzerland and highlight that the trip-related decisions such as length of stay, mean of transport, and accommodation type correlate. Masiero and Zoltan (2013), also investigating Swiss tourism, find that travel mode choice and movement patterns during holidays are interlinked. Additionally, another stream of literature related to the underlying study focuses on the mobility behavior at the destination rather than the travel mode choice to reach a destination. For instance, Bursa, Mailer, and Axhausen (2022a) and Bursa, Mailer, and Axhausen (2022b) suggest that, inter alia, travel time, group composition, trip purpose, weather, and information about the destination are associated with the mode choice for activities within a destination. Zamparini and Vergori (2021) add that besides the mobility habits at home, the transport mode to reach a destination relates to the mobility behavior within a destination.

Moreover, when discussing determinants of tourists' travel mode choices, the influence of public transport supply is crucial. For instance, Gronau and Kagermeier (2007) argue that the destination's target groups should have a proneness towards public transport, such that public transport policies can be effective. However, if this prerequisite is given, quality improvement has the potential to shift towards public transport. Therefore, Le-Klähn and Hall (2015) state that tourists rather use public transport in urban areas more than in remote areas since urban transport systems are typically of higher quality. Pagliara, Mauriello, and Garofalo (2017) find that improvements in connectivity and accessibility in public transportation in Italy increase demand for the destination. The complementary study of Boto-García and Pérez (2023) observes that public transport improvements in Spain increased the share of arrivals in the low season, indicating a modal shift. However, Bursa, Mailer, and Axhausen (2022b) argue that price interventions neither for public transportation nor private cars induce a substantial shift to public transportation. Therefore, Orsi and Geneletti (2014) summarize that effective policies should cautiously combine public transport policies and car-use regulations. Finally, Romao and Bi (2021) point out that public transport services can increase the overall trip satisfaction of tourists.

In a broader picture, our paper has implications for tourism destination management under the low-carbon imperative (see, e.g., Gössling and Higham, 2021). On the one hand, a switch from private car to public transport reduces the tourists' CO_2 emissions. On the other hand, with the offer at hand exclusively valid for guests that stay at least three nights, particular guests are targeted that generate (per arrival) below-average environmental impact, which might lead to a more sustainable tourist mix in the destination (Oklevik, Gössling, Hall, Jacobsen, Grøtte, and McCabe, 2020). Besides that, the offer might have positive economic spillover effects on accommodation businesses. For instance, Wallimann (2022) shows that drastic price reductions of skiing passes positively affected the number of overnight stays in a Swiss destination.

4.3 Background and survey

Our study focuses on Switzerland, a country in the middle of Europe where tourism generates 16.8 billion Swiss francs gross value added (Swiss Tourism Federation, 2023) and contributes about 3% to Swiss GDP (regiosuisse – Netzwerkstelle Regionalentwicklung, 2023). Approximately 4% of the Swiss export revenue stems from tourism, and about 3.8% of all employees in Switzerland work in the tourism industry (Swiss Tourism Federation, 2023). The Swiss resident population undertook 16.3 million trips with one or more overnight stays, of which 9.1 million were within Switzerland (Swiss Tourism Federation, 2023). The public transport system in Switzerland, due to the high level of system integration with frequent services, comprehensive fare integration, and synchronized timetables, is of high quality of service (see, e.g., Thao, von Arx, and Frölicher, 2020). However, of those Swiss residents with overnight stays traveling within Switzerland, 57.1% travel by car to their destination in Switzerland, compared to (only) 31.9% traveling by train according to Switzerland Tourism (2017).

Our area of interest is the Swiss canton Appenzell Innerrhoden, a small, rural canton located in the East Alpine region of Switzerland. With 16,000 inhabitants, it is the least populous canton in Switzerland.[1] The canton is well known for its main town, Appenzell, and the surrounding nature and

[1] Officially, it is a so-called half-canton, not being relevant for our study.

mountains, as well as its cultural heritage. Hence, tourism contributes 12.8% to the cantonal GDP, and a considerable share of 16.8% of inhabitants work in tourist-related businesses (Schwehr, Rütter-Fischbacher, Hoff, Nathani, and Hellmüller, 2019). The main town is accessible by train at a half-hour frequency from the Swiss cities of Herisau and St.Gallen. Most smaller towns are also accessible by these train lines, with no or one changeover in Appenzell.

The free arrival and departure offer was launched by the destination marketing organization (henceforth also referred to as DMO) in 2020. Since then, overnight guests who stay for at least three nights in the canton of Appenzell Innerrhoden can order a free public transport ticket (for the whole Swiss public transport network) for their arrival and departure. During the pilot phase from 2020 to 2022, the offer was co-financed by the New Regional Policy, which aims to reduce regional disparities by financially supporting innovative projects and initiatives in rural regions (Verein Appenzellerland Tourismus AI , 2021). The seed capital provided in the framework of the New Regional Policy is paid by the federal government and the respective canton in equal parts.[2] Since 2023, the DMO has independently financed and promoted the offer. The accommodation businesses do not have to make a direct contribution.

Appenzell Innerrhoden has also established a "guest card" for a couple of decades that permits guests who stay at least three nights in an accommodation to use 20 attractions and public transport within the destination free of charge.[3] While public transport free of charge within the destination during the stay is implemented in various Swiss (and German-speaking) tourism destinations (see, e.g., Gronau (2017)), public transport free of charge for the arrival and departure to and from the destination on top of it—our policy of interest—is novel.[4] However, in contrast to the free arrival and departure offer, the accommodation businesses co-finance the guest card (Verein Appenzellerland Tourismus AI , 2023). In our study period, the free arrival and departure offer was used by 2,373 overnight guests, and 12,886 guest cards were distributed.

To gather the relevant data, we conducted an online survey between May and October 2023 based on the software Unipark. Our leading partner in carrying out the survey was the Appenzell Innerrhoden DMO. In cooperation

[2]See https://regiosuisse.ch/en/new-regional-policy-nrp (accessed on October 18, 2023).

[3]See https://www.appenzell.ch/de/unterkunft/appenzeller-ferienkarte.html (accessed on October 18, 2023). The card is valid for a maximum of seven nights. Guests who stay longer than seven nights receive a new Appenzell guest card free of charge.

[4]As far as we know, besides the offer in Appenzell Innerrhoden, there exist only a few smaller-scale free arrival and departure offers in Switzerland. They are either limited to certain hotels (e.g., Glarnerland) or specific activities (e.g., Nature Parks).

with the DMO, we addressed 4,333 guests owning a guest card by mail. Guests were directed to the online survey via a link. Additionally, we attached the link to the free arrival and departure offer, and the hotels distributed flyers with a QR-code to the online survey among their overnight guests.[5] 1,871 guests that stayed at least three nights in Appenzell Innerrhoden completed the survey.

Retrieved from the literature (see Section 4.2), we asked questions about the travel mode choice and all factors influencing this decision. After collecting the data about the mode choice and the explanatory variables, we also questioned the overnight guests about the free arrival and departure offer. For our analysis, it is fundamental to determine whether and when they received the information about the free arrival and departure offer in this part. That is because this knowledge allows us to identify the effect of the policy on travel mode choice, which we explain in the forthcoming section in greater detail.

4.4 Identification and estimation

4.4.1 Definition of causal effects

Our causal analysis is based on the potential outcome framework (see, for instance, Rubin, 1974): The causal effect of a treatment is the difference between the outcomes of individuals to a certain point in time exposed and not exposed to a treatment initiated at an earlier stage. At time t_1, the hotelier may (guest "A" in Figure 4.4.1) or may not (guest "B" in Figure 4.4.1) inform these guests. Therefore, we take advantage of the fact that the information from the hotelier to the guest varies due to everyday stress and duties.[6] Hence, we define D as a binary treatment indicator, whether the accommodation informs the guest about the offer ($D = 1$, i.e., guest "A" in Figure 4.4.1) or the accommodation does not inform the guest ($D = 0$, i.e., guest "B" in Figure 4.4.1). In t_2, we either observe potential outcome $Y(1)$ or $Y(0)$, whereas the observable outcome Y is "travel mode choice"—$Y = 1$ and $Y = 0$ indicate public transport and no public transport usage, respectively (depicted with the two chevron arrows to the accommodation in Figure 4.4.1).[7] Using the rhetoric of causal inference, we can uncover the average causal effect—also known as average treatment effect (ATE)—of the information that one could

[5]The flyers made it possible also to reach guests staying in the surrounding tourism destination Appenzell Ausserrhoden and Toggenburg.

[6]This random element was recognized in exchange with the DMO and validated in informal discussions with 13 hoteliers.

[7]Note that negligible 1% of the guests travel with the bike to the destination.

arrive and departure with public transport free of charge on the outcome travel mode choice at time t_2. The ATE denoted by Δ corresponds to the difference in the average potential outcomes $Y(1)$ and $Y(0)$ in the population of interest:

$$\Delta = E[Y(1)] - E[Y(0)]. \tag{4.4.1}$$

To ensure the identification of the effect, we only look at those guests who were not aware of the free arrival and departure offer at time t_0 of the booking process. On the other hand, guest "C" is already informed about the offer when booking the holidays (e.g., because of marketing). As these such guests (represented by "C") who use public transportation may differ in terms of unobservable characteristics from guests who were not aware of the free arrival and departure offer at the time of the booking process (represented by "A" and "B"), we, for our causal analysis, ignore them.

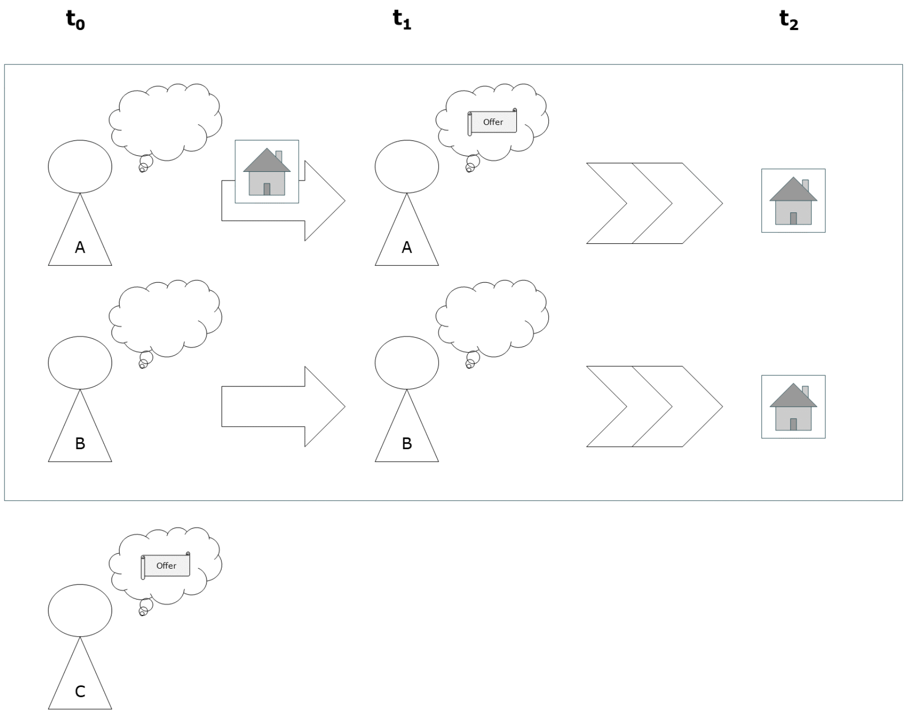


Figure 4.4.1: Information status of guests at three time stages

As with many empirical applications, our analysis relies on observational (nonrandomized) data. Therefore, we uncover the treatment effect with the "selection-on-observable assumption". The idea is to compare the outcomes of individuals exposed and not exposed to the treatment that are similar in terms of covariates—characteristics that jointly influence both the decision to receive treatment and the outcome of interest (see, e.g., Huber, 2023). Therefore, we assume that by controlling for observed characteristics, the treatment is as good as if it were randomly assigned among those treated and non-treated subjects (as in an experiment). Put differently, we can avoid that the treatment effect is mixed up with any impact of differences in covariates and interpret differences in the outcomes to be exclusively caused by differences in the treatment.

The directed acyclic graph (DAG) in Figure 4.4.2 illustrates the causal framework of our identification strategy.[8] Our entire set of observed characteristics X can be subsumed under accommodation-specific characteristics A, trip-related characteristics T, mobility tools M, and socio-demographic characteristics S. For the accommodation-specific characteristics (A), we include a hotel-specific ratio of informed vs. uninformed guests per accommodation to account for the probability that a guest is informed by the different hoteliers as well as two dummy variables for the accommodation type and the accessibility by train (see for the latter two variables, e.g., Pagliara, Mauriello, and Garofalo, 2017, Pellegrini and Scagnolari, 2021). Further, we add the relevant trip-related characteristics (T) travel party composition, travel purpose, length of stay, distance with the private car from home to the accommodation, travel time difference between car and public transport, and Swiss residence (see, e.g., Rodriguez, Martinez-Roget, and Gonzalez-Murias, 2018). Moreover, as mobility tool ownership (M) influences the travel behavior (see, e.g., Thao and Ohnmacht, 2020), we consider the covariates accounting for car and public transport season ticket ownership. Finally, we also control for socio-demographic characteristics S as age, income, and gender (see, e.g., Rodriguez, Martinez-Roget, and Gonzalez-Murias, 2018, Thao and Ohnmacht, 2020).

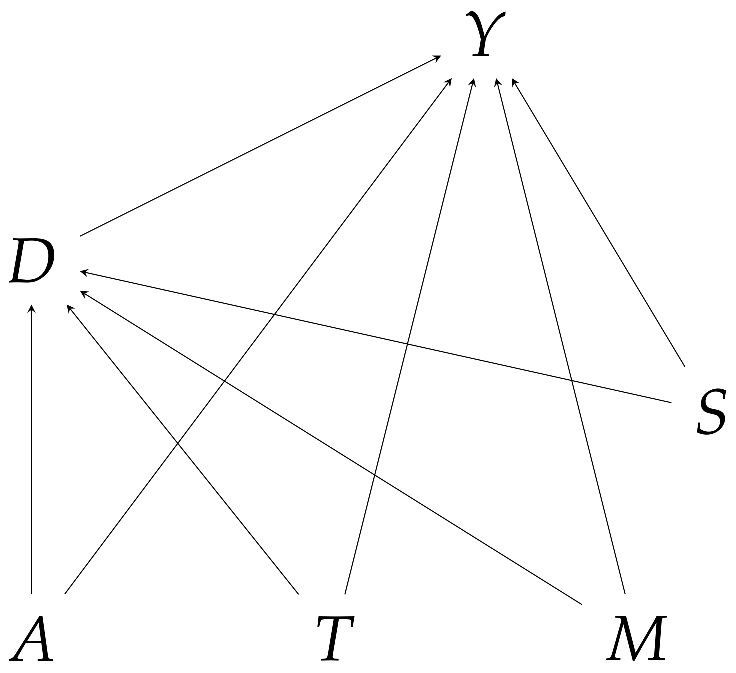
To ensure the identification of the effect, we drop two particular subgroups that cannot, or only to a limited extent, gain benefit from the free arrival and departure offer. On the one hand, we ignore guests with a GA Travelcard. This season ticket allows the unlimited use of public transport Swiss-wide and therefore yields the same benefit as the offer of interest in this paper. On the other hand, we omit guests with an arrival journey to the destination that is longer than 400 km. From this threshold, air transportation becomes relevant (Thrane (2015)).[9] The thing to notice is that our subset of observations now

[8]Figure 4.4.2 is a simplified version of the DAG as there might also be causal associations between the observed characteristics X. For example, socio-demographic characteristics S might influence mobility tools M and that might affect accommodation-specific characteristics A.

[9]The most distant city in Switzerland, Geneva, is less than 400 km away (by car and public

differs from the typical average treatment effect estimand ATE over the full population.

Figure 4.4.2: Causal framework



4.4.2 Identifying assumptions

Identifying the potential outcomes under treatment and non-treatment relies on assumptions how the real world works. Therefore, our estimations of the effect of the free travel offer also rely on assumptions.

Assumption 1 (conditional independence assumption):
Assumption 1 (also called selection on observables) is satisfied when the potential outcomes $(Y(1),Y(0))$ are conditionally independent of the treatment (D) when controlling for covariates (X), formally

$$\{Y(1),Y(0)\} \perp\!\!\!\perp D|X. \tag{4.4.2}$$

This assumption holds, when all covariates that jointly influence potential outcomes and treatment are observed and controlled for. This implies that

transport) from the canton of Appenzell Innerrhoden.

the treatment is as good as randomly assigned among treated and non-treated overnight guests with the same characteristics. Due to our rich set of observed characteristics X that we derived from the literature—subsumed under accommodation-specific characteristics A, trip-related characteristics T, mobility tools M, and socio-demographic characteristics S—, it is realistic that the conditional independence assumption is fulfilled.

Assumption 2 (common support):
Assumption 2 states that the conditional treatment probability is larger than zero and smaller than one such that (D) is not deterministic in X, formally:

$$0 < p(X) < 1, \tag{4.4.3}$$

where $p(X) = Pr(D = 1|X)$ is the conditional treatment probability—also called the propensity score. In other words, when comparing the treatment and control groups, there must be substantial overlap in the distribution of the observed covariates. An example in our case is that for every value of car ownership (i.e., "Yes" and "No"), there must be subjects receiving and not receiving the information about free arrival and departure offer.

Assumption 3 (exogeneity):
Assumption 3 stipulates that X is not a function of D and therefore does not contain characteristics that are affected by the treatment, formally:

$$X(1) = X(0) = X. \tag{4.4.4}$$

It is worth mentioning that we only have guests in our sample who had already planned a stay of three or more nights at time t_0 of the booking process. Guests who had planned a stay of less than three nights at time t_0 of the booking process are not part of our sample, regardless of whether they received the information at time t_1 or not and, regardless whether they adjusted their length of stay (as the offer can only be ordered for a stay of at least three nights) or not.

Additionally, we check in Section 4.6.2 whether our results are influenced by the vast number of guest card owners in our sample as guest card ownership might be affected by our treatment.

Assumption 4 (identifiability of treatment status at t_1):
By Assumption 4, we assume we know whether a person was informed by the hotel $(D = 1)$ or not $(D = 0)$. Assumption 4 is satisfied in the absence of misreporting regarding this information.

Following Huber (2023) to show how our assumptions permit identifying the average treatment effect (ATE), let us use $\mu_d(x) = E[Y|D = d, X = x]$ to denote the expected conditional mean outcome given the binary treatment D (i.e., "information status") which is either 0 ("not informed") or 1 ("informed"), and the observed covariates X (including accommodation-specific characteristics A, trip-related characteristics T, mobility tools M, and socio-demographic characteristics S). $\mu_1(x) - \mu_0(x)$ identifies the causal effect among individuals which share the same values x of the observed covariates X. We denote the average effect under the condition that subjects share the same covariate values X = x as conditional average treatment effect (CATE):

$$\Delta_x = E[Y(1)|X = x] - E[Y(0)|X = x] = \mu_1(x) - \mu_0(x). \tag{4.4.5}$$

Averaging CATEs among all values of x which the covariates X take in the population permits to identify the average treatment effect (ATE):

$$\Delta = E[\mu_1(X) - \mu_0(X)]. \tag{4.4.6}$$

4.4.3 Estimation based on propensity score matching and causal forest

In our study, we use matching methods to derive our average treatment effect estimands. To make treatment and control groups comparable, matching methods create a set of weights for each observation. To estimate the treatment's effect, we can calculate a weighted mean of the outcomes. As matching variables, we use accommodation-specific characteristics A, trip-related characteristics T, mobility tools M, and socio-demographic characteristics S (see also Figure 4.4.2). Statistically speaking, matching is the process of closing back doors between the treatment variable D and the outcome variable Y (see, e.g., Huntington-Klein, 2021).

Rosenbaum and Rubin (1983) demonstrate that conditioning on the propensity score $p(X)$ balances the distribution of the covariates X across the treatment group and control group such that potential outcomes are conditionally independent of the treatment: $\mathrm{X} \perp\!\!\!\perp \mathrm{D}|\mathrm{p(X)}$. In Figure 4.A.1 in Appendix 4.A, we see that the propensity score can be interpreted as a function of our covariates X through which any effect of X on D operates. Therefore, we can identify the ATE when controlling for the propensity score $p(X)$ as:

$$\Delta_x = E[\mu_1(p(x)) - \mu_0(p(x))]. \tag{4.4.7}$$

To achieve the effect through propensity score matching, we use logit regression to estimate the propensity scores. To account for the estimation based on propensity score, we calculate and display bootstrap-based standard errors (see, e.g., Huber, 2023).

We also apply the causal forest approach of Wager and Athey (2018) and Athey, Tibshirani, and Wager (2019); see also Huber, Meier, and Wallimann (2022) for the first application of causal machine learning in the public transportation literature. The causal forest approach estimates propensity scores and ATEs using random forest. Causal forest is especially useful in the presence of irrelevant covariates. Also, the causal forest has the nice properties to estimate effect heterogeneity, the CATEs. Both strengths enable us to analyze the case more flexibly.

To estimate the causal effects of the free arrival and departure offer with propensity score matching and causal forest, we use *Matching* and *grf* packages in the statistical software R.

4.5 Descriptive analysis

For our estimation, it remains a sample with 843 observations. 189 observations have missing values, from which 157 have only one covariate missing. Descriptive statistics suggests that these covariates are missing at random (see Table 4.5 in Appendix 4.B), and hence, we decide to drop the observations with missing values. However, we impute the missing values in a robustness check and re-estimate the effect (see Section 4.6.3).

In Table 4.1, we present descriptive statistics of our set of matching variables (X) and the outcome variable (Y) by the binary indicator D taking the value $D = 1$ for informed guests. Different hoteliers prioritize the guest information in their day-to-day business and accordingly make guests more or less aware of the offer during the booking process. Therefore, we observe in Table 4.1 that the hotel-specific ratio of informed vs. uninformed guests varies between treatment ($D = 1$) and control group ($D = 0$).

Naturally, the hotel-specific ratio of informed guests is higher in the treatment group than in the control group, as this variable reflects the varying probability of hoteliers informing their guests (note that for this variable, we consider all holiday flats as a hotel).[10] Also, uninformed guests stay on average more in holiday flats than in hotels. Hotel guest information upon arrival might be more professional and standardized than that of holiday flats. Moreover, guests in the treatment group rather stay in accommodations accessible by train, whereas more guests in the control groups stay in accommodations only accessible by bus. This is possible because hotels that are directly accessible

[10] Note that the ratios of the individual hotels correlate strongly with the statements of the hoteliers about their frequency of informing guests during the informal discussions.

by train might expect a higher benefit from promoting the offer. As expected, the accommodation-specific variables A vary, reflecting the varying frequency of each hotelier informing their overnight guests during the booking process.

Most guests do not travel with their families, whereas the guest's primary holiday purpose is nature or hiking in both groups, with both proportions being slightly higher in the control group. Other trip-related variables (T), such as the length of stay, swiss residence, travel distance in km by car, and travel time difference between car and public transport usage are comparable for both groups. The two latter we accessed on Google Maps knowing the anonymized destination and origin (postal code) of guests.[11]

Furthermore, more guests in the treatment group than in the control group own a Half Fare Travelcard (implying a price reduction of 50% for public transport tickets in Switzerland). This difference can be interpreted as guests with a Half Fare Travelcard being more prone to use public transport and, therefore, rather ask the hotelier for public transport offers during the booking process. However, as a thing to notice, this does not directly imply that more people with a Half Fare Travelcard actually use the offer as our treatment is the information about the offer and not the offer itself. Secondly, the treatment and control groups are similar in car ownership, with the share of people owning a car is high in our sample.

Finally, guests in the treatment group are significantly older than in the control group. It is plausible that older people interact more intensively with the hotelier, and consequently, are rather informed. Gender, and income status (i.e., represented by a guest's household owning more than 12,000 Swiss francs) are similarly spread among treatment and control groups.

Our outcome variable states whether a guest uses public transportation for the journey. Looking again at Table 4.1, we see that 44% of the informed guests used a means of mass transportation, while, on the other hand, only 22% of the non-informed guests traveled by public transportation. Moreover, among the treated guests, 41% used the free arrival and departure offer to travel to the accommodation.

[11] See https://console.cloud.google.com/google/maps-apis, accessed on November 11, 2023.

Table 4.1: Mean and standard deviation by information status

	Informed guests ($D = 1$)	**Uninformed guests** ($D = 0$)
Hotel-specific ratio of informed guests	0.61 (0.29)	0.41 (0.27)
Holiday flat	0.19 (0.39)	0.25 (0.43)
Train accessibility	0.91 (0.29)	0.83 (0.38)
Alone	0.12 (0.33)	0.11 (0.32)
Family	0.19 (0.40)	0.25 (0.43)
Purpose nature	0.63 (0.48)	0.71 (0.46)
Length of stay	4.75 (2.11)	4.39 (1.85)
Distance car	164.80 (74.98)	169.73 (79.65)
Travel time difference	89.59 (23.47)	92.62 (23.59)
Swiss residence	0.92 (0.27)	0.89 (0.32)
Car ownership	0.84 (0.37)	0.85 (0.36)
Half Fare Travelcard	0.82 (0.39)	0.71 (0.46)
Age	60.73 (13.93)	55.87 (14.66)
Women	0.56 (0.50)	0.52 (0.50)
High income	0.10 (0.29)	0.09 (0.31)
Public transport	0.44 (0.50)	0.22 (0.41)
Free arrival-departure offer	0.41 (0.49)	0.00 (0.00)
Observations	530	124

Note: The sample contains guests who stay more than two nights in Appenzell Innerrhoden.

4.6 Results

4.6.1 Common support and match quality

Using matching methods, we assume that there are appropriate control observations to match with. According to Assumption 2, common support, there must be substantial overlap in the distribution of matching variables when comparing the treatment and control observations. Using statistical parlance, we must not be able to deterministically observe the treatment (i.e., information) status of an individual based on its covariates. Using the propensity score, we are obligated to observe a substantial overlap of the propensity score's $p(X)$ distribution, and none of the propensity scores should be zero or one.

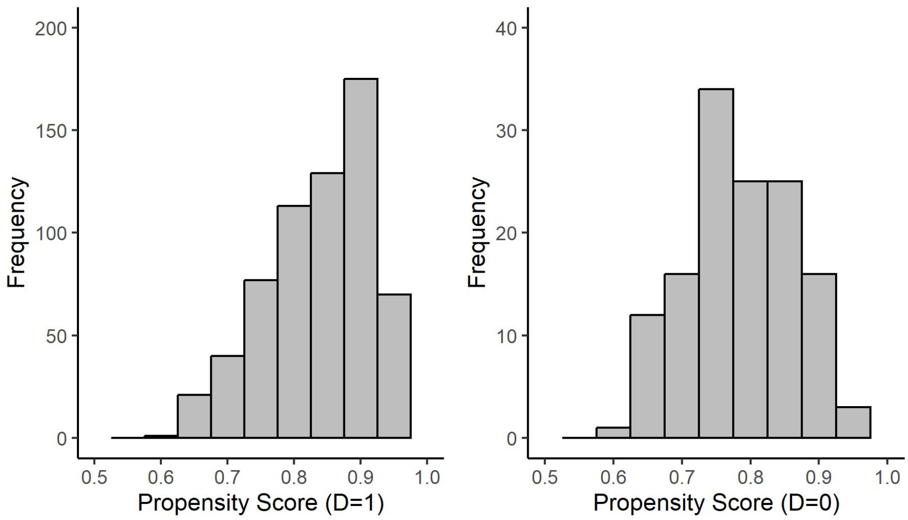


Figure 4.6.1: Propensity scores of treatment and control group

Looking at Figure 4.6.1, depicting the propensity scores of the causal forest estimation, we observe a decent overlap in our sample: All observations across treatment and control groups have (at least a few) observations in the respective other group that have comparable propensity scores. Furthermore, the propensity scores are quite similar across treatment and control groups due to the random element in our research design. Therefore, assuming that we have no major differences in unobserved characteristics is reasonable. However, we also face some observations with relatively high propensity scores, i.e., scores close to one. Therefore, as a robustness check, we re-estimate the effect when trimming the propensity score (see Section 4.6.3).

The idea of matching methods is to compare the outcomes of informed and non-informed (about the free arrival and departure offer) individuals that are similar in terms of covariates, i.e., treatment and control groups are balanced. Table 4.2 presents the mean values of pre-selected variables that differ between treatment and control groups before propensity score matching, i.e., raw data. We see that there exist differences at the 5% significance level before matching for the variables hotel-specific ratio of informed guests, train accessibility, and Half Fare Travelcard by looking at the p-values for a t-test, testing if the means are different in the treated and control groups. However, after matching, there are no meaningfully large (significant) differences in the means for the variables presented in Table 4.2. Therefore, we conclude that treatment and control groups are balanced.

Table 4.2: Balance table before and after matching

	Before Matching	**After Matching**
Hotel-specific ratio of informed guests		
Mean Treatment	0.612	0.576
Mean Control	0.407	0.575
Std. Mean Diff	70.793	0.558
t-test p-value	<0.001	0.825
Train accessibility		
Mean Treatment	0.908	0.899
Mean Control	0.831	0.901
Std. Mean Diff	26.524	-0.761
t-test p-value	0.035	0.878
Half Fare Travelcard		
Mean Treatment	0.819	0.790
Mean Control	0.710	0.821
Std. Mean Diff	28.325	-7.705
t-test p-value	0.015	0.110
Age		
Mean Treatment	60.726	59.666
Mean Control	55.871	60.265
Std. Mean Diff	34.866	-4.197
t-test p-value	<0.001	0.381

4.6.2 The effect of the free public transport offer

Table 4.3 shows the estimates of the free arrival and departure offer on travel mode choice, namely the main result of our analysis. When applying the causal forest, we obtain an average treatment effect (ATE) of 0.116, indicating that the information about the free arrival and departure offer, on average, increases the number of guests using public transportation by 11.6 percentage points. Considering the estimate of the propensity score matching, we arrive at an average treatment effect of 0.148, suggesting that the information increases the number of mode shifts towards public transportation by 14.8 percentage points. Both estimates are significant at the 5% level (with the estimate of the causal forest being significant at the 1% level). Hence, our estimates point to a positive average treatment effect of the free arrival and departure offer on travel mode choice.

Table 4.3: Effects on mode shift

	Causal forest	**Propensity score matching**
Effect	0.116	0.148
Standard error	0.043	0.065
p-value	<0.001	0.023
Number of observations	654	

Considering the heterogeneity of the effects estimated by the causal forest in greater detail, Figure 4.6.2 depicts the distribution of the conditional average treatment effects (CATEs). In conclusion, the CATEs are almost exclusively positive among different guest groups.

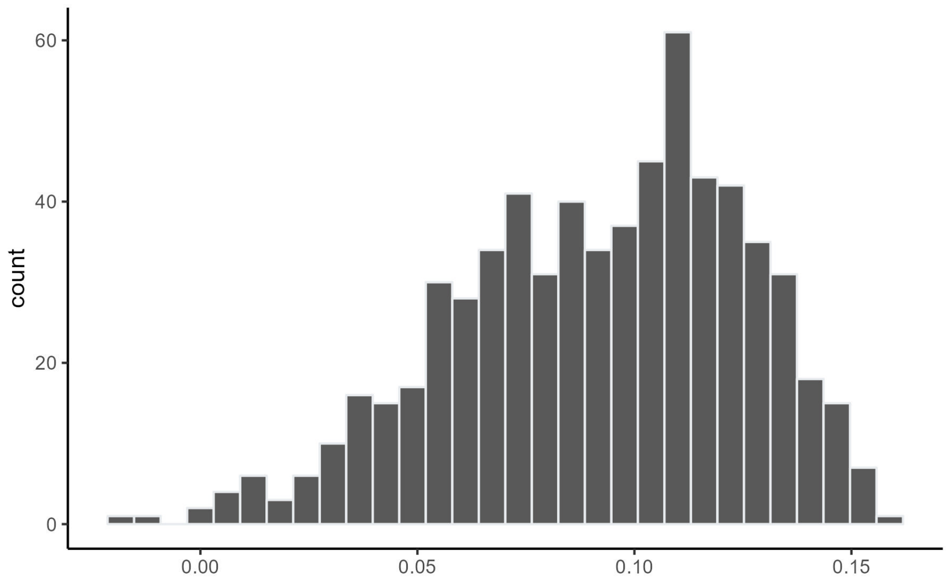


Figure 4.6.2: Histogram of CATEs

Finally, we check whether guest card owners—the vast majority in our sample—differ from the overall population, we model the tree structure of the causal forest based on the original sample as well as on the subsample of all guest card owners. For both models, we then estimate the CATEs for all observations. If our sample conditioning on X is as good as randomly assigned, then the CATEs of the two tree structures should be similar. In Figure 4.6.3, we display the difference between the two estimated CATEs for each observation. The differences between the CATEs are minimal; however, they are significant and positive. Concluding, if we have a selection problem due to the sampling process, it is tiny and influences our results to a negligible extent. The thing to notice is that the causal framework (see Figure 4.4.1) also controls for the relevant covariates that jointly influence the ownership of the guest card.

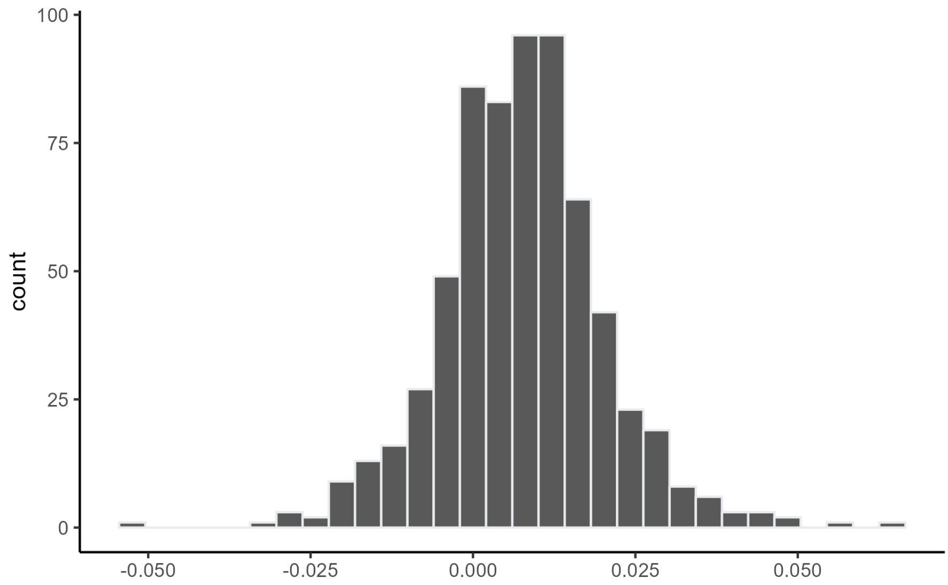


Figure 4.6.3: Differences between the CATEs

4.6.3 Robustness Checks

We conduct robustness checks to investigate the sensitivity of our main results.

As a first check, we challenge our results in a sense that we assume to have comparable propensity scores. This check stems from the fact that some observations with relatively high propensity scores are close to one. To do so, we i) change the target sample of the causal forest using the weighting scheme of Li, Morgan, and Zaslavsky (2018), in which each unit's weight is proportional to the probability of that unit being assigned to the opposite group. The thing to notice is that we now observe an average treatment effect for the overlap population (ATO).[12] Moreover, using propensity score matching, we ii) apply the trimming rule of Dehejia and Wahba (1999) and omit all treatment group observations with a propensity score higher than the highest value among the control group.[13]

[12] To be precise, we set in the statistical software `R` the `target.sample`-argument from `target.sample="all"` to `target.sample="overlap"`.

[13] Therefore, we change the `CommonSupport`-command to `TRUE` in the statistical software `R`.

Looking at Table 4.4, we see that, again, both estimates are positive and significant. The value of the propensity score matching is almost the same and only 0.7 percentage points higher. Also, the estimate of the causal forest is comparable to our original result (i.e., 2.5 percentage points lower).

Table 4.4: Effects on mode shift

Check	1	2	3
Causal Forest			
Effect	0.091	0.119	0.205
Standard error	0.039	0.041	0.044
p-value	0.020	0.003	0.000
Propensity score matching			
Effect	0.155	0.134	0.301
Standard error	0.057	0.067	0.101
p-value	0.009	0.018	0.003
Number of observations	654	843	583

Notes: Check 1 focuses more on the observations with comparable propensity scores. Check 2 includes observations with missing values by imputing the values. Check 3 uses overnight guests from neighboring cantons as control group.

Second, we impute the missing data of covariates using multiple imputation to account for the uncertainty implemented by the MICE algorithm as described by Van Buuren and Groothuis-Oudshoorn (2011) and Van Buuren (2018).[14] So, we can include the 189 observations that have missing variables, from which 157 observations have only one covariate missing. The estimates are very similar to the main results, amounting to 0.134 for the propensity score matching and 0.119 for the causal forest matching. Therefore, we conclude that covariate missings are missings at random.

Third, we replace our control group of uninformed guests with tourists who stay more than three nights in the cantons of Appenzell Ausserrhoden and Toggenburg. In Appendix 4.B, we present the descriptive statistics for this robustness check. The thing to notice is that the control group becomes (too) small as we could not contact these guests by email (and thus, it might be that this control group is only in a limited sense comparable to the treated group). However, the impact of the treatment on demand shift is remarkable and amounts, depending on the algorithm, 0.205 and 0.301.

As we set out to learn something about free arrival and departure offers in general, our robustness checks further indicate that these have a meaningful causal effect on the choice of means of transport.

[14] We apply the `mice`-command of the package `mice` in the statistical software `R`.

4.7 Discussion

We estimate a treatment effect of 11.6 and 14.8 percentage points. These estimates of the fare-free arrival and departure policy for overnight guests are comparable to the effects of the fare-free policy in Tallinn (14%) and the fare-free subway policy for citizens aged 65 or above in Seoul (16%), see Cats, Susilo, and Reimal (2017) and Shin (2021). Assuming that only overnight guests who ordered a free departure-arrival ticket changed their behavior due to the information provided by the hotelier (41.3 percent in the treatment group), we can calculate that 28.1% (11.6/41.3) respective 35.8% (14.8/41.3) of the overnight guests using the free arrival and departure offer would not arrived public transport in the absence of the free arrival and departure offer.

Ecologically of great relevance, we can again estimate the mode shifts influence on CO_2 emissions based on assumptions. Put simply, we assign a CO_2 value to the average routing distances per means of transport. Following, e.g., Ohnmacht, Z'Rotz, and Dang (2020), we base our values on the so-called "mobitool factors"[15] to assess the environmental impacts of different means of transport per person-kilometer. The CO_2 values include direct operation, vehicle maintenance, indirect CO_2 emissions caused by energy provision, vehicle manufacture, and the CO_2 emissions used for the infrastructure (track/road). The CO_2 values per person-kilometre for car (fleet average) and public transport (average public transport) amount to 186.4 and 12.4 gram CO_2 per person-kilometre, respectively. Therefore, using these two CO_2 values per distance and an average travel distance per means of transportation using Google Maps data (i.e., 165.8 for car and 187.7 for public transport), we can calculate an equivalent that reflects the CO_2 savings of the guests shifting transport mean. The savings amount to 57.2 kilograms CO_2 for every person traveling with public transport instead of a private car (for the calculation, see Appendix 4.C). The Swiss mean of domestic CO_2 emission (equivalence) for transportation amounts to about 1.62 tons per person and year (see for Swiss CO_2 emissions and population Bundesamt für Umwelt BAFU, 2023, Bundesamt für Statistik BFS, 2023). Concluding, the usage of the offer (to and from the destination) reduces the yearly domestic CO_2 transportation emissions in Switzerland by 3.6%. The share of domestic leisure travels would, therefore, be higher and the share of total transport, including international (air) travel, lower.

Our results are, according to our robustness checks, valid for similar settings in which the targeted guest segments have a proneness towards public

[15] See https://www.mobitool.ch/de/tools/mobitool-faktoren-v3-0-25.html (accessed on October 24, 2023).

transport, and the quality of public transport services is high. Conversely, the external validity is limited for target guest groups with higher constraints (e.g., skiing tourism with more luggage to transport) and with a lack of quality in public transport services (e.g., international travels across poorly connected subnetworks Grolle, Donners, Annema, Duinkerken, and Cats, 2024). Hence, future studies (in other settings or with more statistical power) should investigate whether there is significant effect heterogeneity with respect to trip-related constraints (see, e.g., Huber, Meier, and Wallimann, 2022). These insights on effect heterogeneity may then also support the elaboration of an optimal financial scheme policy for integrated products of public transport and accommodation.

4.8 Conclusion

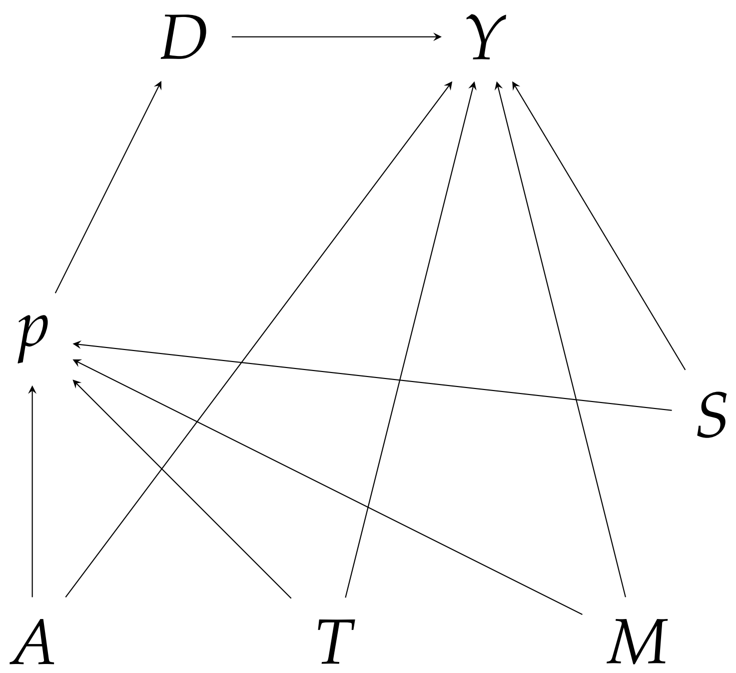
We assessed the causal effect of a free arrival and departure offer for overnight guests of a Swiss tourism destination. Based on the so-called "selection on observable" assumption, we take advantage of the random element that the information on the offer from a hotelier to a guest varies in day-to-day business. Using the causal forest and propensity score matching, we found that public transportation usage increases by 11.6 and 14.8 percentage points, depending on the method. The results also stand up to robustness checks, indicating that the average effect lies between 9.1 and 15.5 percentage points.

Our paper is the first to provide empirical evidence for researchers and policy-makers on how such a free arrival and departure offer influences the (domestic) guests' transport mode choice in Switzerland. Our estimands are essential for designing future comparable offers in light of CO_2 reductions, as a shift towards public transport helps decrease CO_2 emissions. To this end, our empirical approach may also be applied to comparable natural experiments of the transport and tourism industry in Switzerland or other countries.

Appendices

4.A Causal framework including the propensity score

Figure 4.A.1: Causal framework including the propensity score (denoted by p)



4.B Descriptive statistics robustness checks

Table 4.5: Descriptive statistics robustness check 2: Data imputation

	Informed guests ($D = 1$)	**Uninformed guests** ($D = 0$)
Hotel-specific ratio of informed guests	0.61 (0.29)	0.41 (0.27)
Holiday flat	0.18 (0.39)	0.28 (0.45)
Train accessibility	0.91 (0.28)	0.85 (0.36)
Alone	0.13 (0.34)	0.10 (0.30)
Family	0.20 (0.40)	0.25 (0.43)
Purpose nature	0.62 (0.49)	0.72 (0.45)
Length of stay	4.71 (2.08)	4.38 (1.83)
Distance car	163.47 (75.93)	163.64 (79.95)
Travel time difference	89.74 (23.53)	92.26 (23.43)
Swiss residence	0.91 (0.29)	0.87 (0.34)
Car ownership	0.86 (0.35)	0.83 (0.37)
Half Fare Travelcard	0.80 (0.40)	0.69 (0.46)
Age	61.30 (13.84)	56.15 (14.47)
Women	0.56 (0.50)	0.53 (0.50)
High income	0.09 (0.28)	0.09 (0.29)
Public transport	0.41 (0.49)	0.22 (0.42)
Free arrival-departure offer	0.39 (0.49)	0.00 (0.00)
Observations	687	156

Notes: The sample contains guests who stay more than two nights in Appenzell Innerrhoden.

Table 4.6: Descriptive statistics robustness check 3: Appenzell Ausserrhoden and Toggenburg

	Informed guests	**Control group**
Holiday flat	0.19 (0.39)	0.38 (0.49)
Train accessibility	0.91 (0.29)	0.66 (0.48)
Alone	0.12 (0.33)	0.09 (0.30)
Family	0.19 (0.40)	0.38 (0.49)
Purpose nature	0.63 (0.48)	0.81 (0.39)
Length of stay	4.75 (2.11)	5.30 (2.36)
Distance car	164.80 (74.98)	169.73 (79.65)
Travel time difference	89.59 (23.47)	92.62 (23.59)
Swiss residence	0.92 (0.27)	0.89 (0.32)
Car ownership	0.84 (0.37)	0.79 (0.41)
Half Fare Travelcard	0.81 (0.39)	0.74 (0.45)
Age	60.73 (13.93)	52.62 (13.26)
Women	0.56 (0.50)	0.45 (0.50)
High income	0.09 (0.29)	0.11 (0.32)
Public transport	0.44 (0.50)	0.25 (0.43)
Free arrival-departure offer	0.41 (0.49)	0.00 (0.00)
Observations	530	53

Notes: The sample contains guests who stay more than two nights in Appenzell Innerrhoden (treatment group), Appenzell Ausserrhoden, and Toggenburg (both control group).

4.C Calculation of the CO_2 emissions

Savings for a person using public transport instead of private car to and from a destination:

$$2 * \frac{165.8 * 186.4 - 187.7 * 12.4}{1000} = 57.2 \text{ kilogram } CO_2 \qquad (4.C.1)$$

Bibliography

ABADIE, A. (2021): "Using synthetic controls: Feasibility, data requirements, and methodological aspects," *Journal of Economic Literature*, 59(2), 391–425.

ABADIE, A., A. DIAMOND, AND J. HAINMUELLER (2010): "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program," *Journal of the American statistical Association*, 105(490), 493–505.

ABADIE, A., AND J. GARDEAZABAL (2003): "The economic costs of conflict: A case study of the Basque Country," *American economic review*, 93(1), 113–132.

ALLIANCE SWISSPASS (2022): "Informationen über Tarif- und Sortimentsanpassungen für öV-Reisende," https://www.allianceswisspass.ch/de/tarife-vorschriften/tarifmassnahmen, Accessed: 2023-01-24.

ALONSO-GONZÁLEZ, M. J., T. LIU, O. CATS, N. VAN OORT, AND S. HOOGENDOORN (2018): "The potential of demand-responsive transport as a complement to public transport: An assessment framework and an empirical evaluation," *Transportation Research Record*, 2672(8), 879–889.

ANDERSSON, J., G. BJÖRKLUND, H. W. WARNER, K. LÄTTMAN, AND E. ADELL (2023): "The complexity of changes in modal choice: A quasi-experimental study," *Transportation Research Part F: Traffic Psychology and Behaviour*, 96, 36–47.

ANGRIST, J., AND G. IMBENS (1995): "Identification and estimation of local average treatment effects," .

ANGRIST, J. D., G. W. IMBENS, AND D. B. RUBIN (1996): "Identification of causal effects using instrumental variables," *Journal of the American statistical Association*, 91(434), 444–455.

Arkhangelsky, D., S. Athey, D. A. Hirshberg, G. W. Imbens, and S. Wager (2019): “Synthetic difference in differences,” *NBER Working Papers*.

Ascarza, E., A. Lambrecht, and N. Vilcassim (2012): “When talk is “free”: The effect of tariff structure on usage under two-and three-part tariffs,” *Journal of Marketing Research*, 49(6), 882–899.

Athey, S., and G. W. Imbens (2017): “The state of applied econometrics: Causality and policy evaluation,” *Journal of Economic Perspectives*, 31(2), 3–32.

——— (2019): “Machine learning methods that economists should know about,” *Annual Review of Economics*, 11, 685–725.

Athey, S., J. Tibshirani, and S. Wager (2019): “Generalized random forests,” *Annals of Statistics*, 47, 1148–1178.

Athey, S., and S. Wager (2019): “Estimating treatment effects with causal forests: An application,” *Observational Studies*, 5(2), 37–51.

Avermann, N., and J. Schlüter (2019): “Determinants of customer satisfaction with a true door-to-door DRT service in rural Germany,” *Research in Transportation Business & Management*, 32, 100420.

Axhausen, K., and P. Fröhlich (2012): “Übersicht zu Stated Preference-Studien in der Schweiz und Abschätzungen von Gesamtelastizitäten,” report from the Federal Office for Spatial Development.

Axhausen, K. W., J. Molloy, C. Tchervenkov, F. Becker, B. Hintermann, B. Schoeman, T. Götschi, A. Castro Fernández, and U. Tomic (2021): “Empirical analysis of mobility behavior in the presence of Pigovian transport pricing,” Discussion paper, ETH Zurich.

Axhausen, K. W., J. Molloy, C. Tchervenkov, F. Becker, B. Hintermann, B. Schoeman, T. Götschi, A. Castro Fernández, and U. Tomic (2021): “Empirical analysis of mobility behavior in the presence of Pigovian transport pricing,” Discussion paper, ETH Zurich.

Batty, P., R. Palacin, and A. González-Gil (2015): “Challenges and opportunities in developing urban modal shift,” *Travel Behaviour and Society*, 2(2), 109–123.

BFS (2022): "Kilometerkosten des motorisierten Verkehrs," https://www.bfs.admin.ch/bfs/de/home/statistiken/mobilitaet-verkehr/kosten-finanzierung.assetdetail.23684170.html., Accessed: 2023-02-06.

BFS (2022): "Ständige Wohnbevölkerung nach Alter, Geschlecht und Staatsangehörigkeitskategorie, 2010–2021," https://www.bfs.admin.ch/bfs/de/home/statistiken/bevoelkerung/stand-entwicklung/alter-zivilstand-staatsangehoerigkeit.assetdetail.23064701.html, Accessed: 2023-02-03.

BLÄTTLER, K., H. WALLIMANN, AND W. VON ARX (2024): "Free public transport to the destination: A causal analysis of tourists' travel mode choice," *arXiv preprint arXiv:2401.14945*.

BOTO-GARCÍA, D., AND L. PÉREZ (2023): "The effect of high-speed rail connectivity and accessibility on tourism seasonality," *Journal of Transport Geography*, 107, 103546.

BRECHAN, I. (2017): "Effect of price reduction and increased service frequency on public transport travel," *Journal of Public Transportation*, 20(1), 139–156.

BREIMAN, L. (2001): "Random forests," *Machine learning*, 45, 5–32.

BRESSON, G., J. DARGAY, J.-L. MADRE, AND A. PIROTTE (2003): "The main determinants of the demand for public transport: a comparative analysis of England and France using shrinkage estimators," *Transportation Research Part A: Policy and Practice*, 37(7), 605–627.

——— (2004): "Economic and structural determinants of the demand for public transport: an analysis on a panel of French urban areas using shrinkage estimators," *Transportation Research Part A: Policy and Practice*, 38(4), 269–285.

BROWN, A. (2019): "Redefining car access: Ride-hail travel and use in Los Angeles," *Journal of the American Planning Association*, 85(2), 83–95.

BUEHLER, R., AND A. HAMRE (2015): "The multimodal majority? Driving, walking, cycling, and public transportation use among American adults," *Transportation*, 42, 1081–1101.

BUEHLER, R., J. PUCHER, AND A. ALTSHULER (2017): "Vienna's path to sustainable transport," *International Journal of Sustainable Transportation*, 11(4), 257–271.

Bundesamt für Statistik BFS (2023): "Die Bevölkerung der Schweiz im Jahr 2022," Discussion paper.

Bundesamt für Umwelt BAFU (2023): "Emissionen von Treibhausgasen nach CO2-Gesetz und Übereinkommen von Paris," Discussion paper.

Bursa, B., M. Mailer, and K. W. Axhausen (2022a): "Intra-destination travel behavior of alpine tourists: a literature review on choice determinants and the survey work," *Transportation*, 49(5), 1465–1516.

——— (2022b): "Travel behavior on vacation: transport mode choice of tourists at destinations," *Transportation Research Part A: Policy and Practice*, 166, 234–261.

Caiati, V., S. Rasouli, and H. Timmermans (2020): "Bundling, pricing schemes and extra features preferences for mobility as a service: Sequential portfolio choice experiment," *Transportation Research Part A: Policy and Practice*, 131, 123–148.

Canzler, W., and A. Knie (1998): *Möglichkeitsräume: Grundrisse einer modernen Mobilitäts-und Verkehrspolitik*. Böhlau Verlag Wien.

Carbajo, J. C. (1988): "The economics of travel passes: non-uniform pricing in transport," *Journal of Transport Economics and Policy*, pp. 153–173.

Card, D., and A. Krueger (1994): "Minimum wages and employment: A case study of the fast food industry in New Jersey and Pennsylvania," *The American Economic Review*, 84(4), 772–739.

Cats, O., Y. O. Susilo, and T. Reimal (2017): "The prospects of fare-free public transport: evidence from Tallinn," *Transportation*, 44(5), 1083–1104.

Citec Ingénieurs SA (2021): "Perspektiven zur Erhöhung des Modalsplit des öffentlichen Verkehrs – Mehr Agilität für die Zukunft," report.

Coutinho, F. M., N. van Oort, Z. Christoforou, M. J. Alonso-González, O. Cats, and S. Hoogendoorn (2020): "Impacts of replacing a fixed public transport line by a demand responsive transport system: Case study of a rural area in Amsterdam," *Research in Transportation Economics*, 83, 100910.

Crump, R. K., V. J. Hotz, G. Imbens, and O. Mitnik (2006): "Moving the goalposts: Addressing limited overlap in the estimation of average treatment effects by changing the estimand," *NBER Working Paper*.

Currie, G., and N. Fournier (2020): “Why most DRT/Micro-Transits fail–What the survivors tell us about progress,” *Research in Transportation Economics*, 83, 100895.

Dai, J., Z. Liu, and R. Li (2021): “Improving the subway attraction for the post-COVID-19 era: The role of fare-free public transport policy,” *Transport Policy*, 103, 21–30.

Daniels, R., and C. Mulley (2012): “Flexible transport services: Overcoming barriers to implementation in low-density urban areas,” *Urban Policy and Research*, 30(1), 59–76.

Davison, L., M. Enoch, T. Ryley, M. Quddus, and C. Wang (2012): “Identifying potential market niches for Demand Responsive Transport,” *Research in Transportation Business & Management*, 3, 50–61.

De Jong, W., J. Vogels, K. van Wijk, and O. Cazemier (2011): “The key factors for providing successful public transport in low-density areas in The Netherlands,” *Research in Transportation Business & Management*, 2, 65–73.

De Witte, A., C. Macharis, P. Lannoy, C. Polain, T. Steenberghen, and S. Van de Walle (2006): “The impact of “free” public transport: The case of Brussels,” *Transportation Research Part A: Policy and Practice*, 40(8), 671–689.

Dehejia, R. H., and S. Wahba (1999): “Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs,” *Journal of the American statistical Association*, 94(448), 1053–1062.

Diana, M., L. Quadrifoglio, and C. Pronello (2007): “Emissions of demand responsive services as an alternative to conventional transit systems,” *Transportation Research Part D: Transport and Environment*, 12(3), 183–188.

Doerr, L., F. Dorn, S. Gaebler, and N. Potrafke (2020): “How new airport infrastructure promotes tourism: evidence from a synthetic control approach in German regions,” *Regional Studies*, 54(10), 1402–1412.

Fibich, G., R. Klein, O. Koenigsberg, and E. Muller (2017): “Optimal three-part tariff plans,” *Operations Research*, 65(5), 1177–1189.

FitzRoy, F., and I. Smith (1999): “Season tickets and the demand for public transport,” *Kyklos*, 52(2), 219–238.

FSO, ARE (2012): "Mobilität in der Schweiz: Ergebnisse des Mikrozensus Mobilität und Verkehr 2010," report from the Federal Statistical Office and Federal Office for Spatial Development.

Gehrke, S. R., M. P. Huff, and T. G. Reardon (2021): "Social and trip-level predictors of pooled ride-hailing service adoption in the Greater Boston region," *Case Studies on Transport Policy*, 9(3), 1026–1034.

Gkritza, K., M. G. Karlaftis, and F. L. Mannering (2011): "Estimating multimodal transit ridership with a varying fare structure," *Transportation Research Part A: Policy and Practice*, 45(2), 148–160.

Gössling, S., and J. Higham (2021): "The low-carbon imperative: Destination management under urgent climate change," *Journal of Travel Research*, 60(6), 1167–1179.

Grolle, J., B. Donners, J. A. Annema, M. Duinkerken, and O. Cats (2024): "Service design and frequency setting for the European high-speed rail network," *Transportation Research Part A: Policy and Practice*, 179, 103906.

Gronau, W. (2017): "Encouraging behavioural change towards sustainable tourism: a German approach to free public transport for tourists," *Journal of sustainable Tourism*, 25(2), 265–275.

Gronau, W., and A. Kagermeier (2007): "Key factors for successful leisure and tourism public transport provision," *Journal of Transport Geography*, 15(2), 127–135.

Guidon, S., D. J. Reck, and K. Axhausen (2020): "Expanding a (n)(electric) bicycle-sharing system to a new city: Prediction of demand with spatial regression and random forests," *Journal of Transport Geography*, 84, 102692.

Hainmueller, J., and A. Diamond (2015): "Package Synth," *R Package Version 1.1-5.*

Hoang-Tung, N., H. Kato, T. T. Huy, P. Le Binh, and L. Duy (2021): "Impacts of the introduction of bus rapid transit on travel behaviors of commuters in Hanoi, Vietnam: A quasi-experimental approach," *Case Studies on Transport Policy*, 9(1), 95–102.

Holmgren, J. (2007): "Meta-analysis of public transport demand," *Transportation Research Part A: Policy and Practice*, 41(10), 1021–1035.

Hörcher, D., and A. Tirachini (2021): "A review of public transport economics," *Economics of Transportation*, 25, 100196.

Hothorn, T., A. Zeileis, R. W. Farebrother, C. Cummins, G. Millo, D. Mitchell, and M. A. Zeileis (2015): "Package 'lmtest'," *Testing linear regression models. https://cran. r-project. org/web/packages/lmtest/lmtest. pdf. Accessed*, 6.

Huber, M. (2023): *Causal Analysis: Impact Evaluation and Causal Machine Learning with Applications in R.* MIT Press.

Huber, M., J. Meier, and H. Wallimann (2022): "Business analytics meets artificial intelligence: Assessing the demand effects of discounts on Swiss train tickets," *Transportation Research Part B: Methodological*, 163, 22–39.

Huber, M., and K. Wüthrich (2019): "Local average and quantile treatment effects under endogeneity: A review," *Journal of Econometric Methods*, 8(1), 20170007.

Huntington-Klein, N. (2021): *The effect: An introduction to research design and causality.* Chapman and Hall/CRC.

Imbens, G. W., and J. M. Wooldridge (2009): "Recent developments in the econometrics of program evaluation," *Journal of economic literature*, 47(1), 5–86.

Imhof, S., and K. Blättler (2023): "Assessing spatial characteristics to predict DRT demand in rural Switzerland," *Research in Transportation Economics*, 99, 101301.

Imhof, S., J. Frölicher, and W. von Arx (2020): "Shared Autonomous Vehicles in rural public transportation systems," *Research in transportation economics*, 83, 100925.

Jain, S., N. Ronald, R. Thompson, and S. Winter (2017): "Predicting susceptibility to use demand responsive transport using demographic and trip characteristics of the population," *Travel Behaviour and Society*, 6, 44–56.

James, G., D. Witten, T. Hastie, R. Tibshirani, et al. (2013): *An introduction to statistical learning*, vol. 112. Springer.

Kębłowski, W. (2020): "Why (not) abolish fares? Exploring the global geography of fare-free public transport," *Transportation*, 47(6), 2807–2835.

Kholodov, Y., E. Jenelius, O. Cats, N. van Oort, N. Mouter, M. Cebecauer, and A. Vermeulen (2021): "Public transport fare elasticities from smartcard data: Evidence from a natural experiment," *Transport Policy*, 105, 35–43.

Kilani, M., S. Proost, and S. Van der Loo (2014): "Road pricing and public transport pricing reform in Paris: complements or substitutes?," *Economics of Transportation*, 3(2), 175–187.

Koo, T. T., C.-L. Wu, and L. Dwyer (2010): "Transport and regional dispersal of tourists: Is travel modal substitution a source of conflict between low-fare air services and regional dispersal?," *Journal of Travel Research*, 49(1), 106–120.

Kuhnimhof, T., R. Buehler, M. Wirtz, and D. Kalinowska (2012): "Travel trends among young adults in Germany: increasing multimodality and declining car use for men," *Journal of Transport Geography*, 24, 443–450.

Lambrecht, A., K. Seim, and B. Skiera (2007): "Does uncertainty matter? Consumer behavior under three-part tariffs," *Marketing Science*, 26(5), 698–710.

Langen, H., and M. Huber (2023): "How causal machine learning can leverage marketing strategies: Assessing and improving the performance of a coupon campaign," *Plos one*, 18(1), e0278937.

Le-Klähn, D.-T., and C. M. Hall (2015): "Tourist use of public transport at destinations–a review," *Current Issues in Tourism*, 18(8), 785–803.

Lee, M.-T., and C.-F. Yeh (2019): "Causal effects between bus revenue vehicle-kilometers and bus ridership," *Transportation Research Part A: Policy and Practice*, 130, 54–64.

Lenzen, M., Y.-Y. Sun, F. Faturay, Y.-P. Ting, A. Geschke, and A. Malik (2018): "The carbon footprint of global tourism," *Nature climate change*, 8(6), 522–528.

Li, F., K. L. Morgan, and A. M. Zaslavsky (2018): "Balancing covariates via propensity score weighting," *Journal of the American Statistical Association*, 113(521), 390–400.

Li, W., Z. Pu, Y. Li, and X. J. Ban (2019): "Characterization of ridesplitting based on observed data: A case study of Chengdu, China," *Transportation Research Part C: Emerging Technologies*, 100, 330–353.

Litman, T. (2004): “Transit price elasticities and cross-elasticities,” *Journal of Public Transportation*, 7(2), 37–58.

Liu, Y., S. Wang, and B. Xie (2019): “Evaluating the effects of public transport fare policy change together with built and non-built environment features on ridership: The case in South East Queensland, Australia,” *Transport Policy*, 76, 78–89.

Lu, Q.-L., V. Mahajan, C. Lyu, and C. Antoniou (2024): “Analyzing the impact of fare-free public transport policies on crowding patterns at stations using crowdsensing data,” *Transportation Research Part A: Policy and Practice*, 179, 103944.

Malone, J. B., J. L. Turner, and J. W. Williams (2014): “Do three-part tariffs improve efficiency in residential broadband networks?,” *Telecommunications Policy*, 38(11), 1035–1045.

Masiero, L., and J. Zoltan (2013): “Tourists intra-destination visits and transport mode: A bivariate probit model,” *Annals of Tourism Research*, 43, 529–546.

Matas, A., J.-L. Raymond, and A. Ruiz (2020): “Economic and distributional effects of different fare schemes: Evidence from the Metropolitan Region of Barcelona,” *Transportation Research Part A: Policy and Practice*, 138, 1–14.

Millonig, A., C. Rudloff, G. Richter, F. Lorenz, and S. Peer (2022): “Fair mobility budgets: A concept for achieving climate neutrality and transport equity,” *Transportation Research Part D: Transport and Environment*, 103, 103165.

Molin, E., P. Mokhtarian, and M. Kroesen (2016): “Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers,” *Transportation Research Part A: Policy and Practice*, 83, 14–29.

Mounce, R., M. Beecroft, and J. D. Nelson (2020): “On the role of frameworks and smart mobility in addressing the rural mobility problem,” *Research in transportation economics*, 83, 100956.

Mulley, C., J. Nelson, R. Teal, S. Wright, and R. Daniels (2012): “Barriers to implementing flexible transport services: An international comparison of the experiences in Australia, Europe and USA,” *Research in Transportation Business & Management*, 3, 3–11.

National Academies of Sciences, E., Medicine, et al. (2019): "Microtransit or general public demand–response transit services: state of the practice," .

Nevo, A., J. L. Turner, and J. W. Williams (2016): "Usage-based pricing and demand for residential broadband," *Econometrica*, 84(2), 411–443.

Nykiforuk, C. I., N. M. Glenn, I. Hosler, H. Craig, D. Reynard, B. Molner, J. Candlish, and S. Lowe (2021): "Understanding urban accessibility: A community-engaged pilot study of entrance features," *Social Science & Medicine*, 273, 113775.

Ohnmacht, T., J. Z'Rotz, and L. Dang (2020): "Relationships between coworking spaces and CO2 emissions in work-related commuting: first empirical insights for the case of Switzerland with regard to urban-rural differences," *Environmental Research Communications*, 2(12), 125004.

Oklevik, O., S. Gössling, C. M. Hall, J. K. S. Jacobsen, I. P. Grøtte, and S. McCabe (2020): "Overtourism, optimisation, and destination performance indicators: A case study of activities in Fjord Norway," in *Tourism and Degrowth*, pp. 60–80. Routledge.

Orsi, F., and D. Geneletti (2014): "Assessing the effects of access policies on travel mode choices in an Alpine tourist destination," *Journal of Transport Geography*, 39, 21–35.

Pagliara, F., F. Mauriello, and A. Garofalo (2017): "Exploring the interdependences between High Speed Rail systems and tourism: Some evidence from Italy," *Transportation Research Part A: Policy and Practice*, 106, 300–308.

Parry, I. W., and K. A. Small (2009): "Should urban transit subsidies be reduced?," *American Economic Review*, 99(3), 700–724.

Peeters, P., and G. Dubois (2010): "Tourism travel under climate change mitigation constraints," *Journal of Transport Geography*, 18(3), 447–457.

Pellegrini, A., and S. Scagnolari (2021): "The relationship between length of stay and land transportation mode in the tourism sector: A discrete–continuous framework applied to Swiss data," *Tourism Economics*, 27(1), 243–259.

Percoco, M. (2015): “Heterogeneity in the reaction of traffic flows to road pricing: a synthetic control approach applied to Milan,” *Transportation*, 42(6), 1063–1079.

Rantzien, V. H. a., and A. Rude (2014): “Peak-load pricing in public transport: a case study of Stockholm,” *Journal of Transport Literature*, 8(1), 52–94.

Redman, L., M. Friman, T. Gärling, and T. Hartig (2013): “Quality attributes of public transport that attract car users: A research review,” *Transport policy*, 25, 119–127.

regiosuisse – Netzwerkstelle Regionalentwicklung (2023): “regiosuisse Monitoring,” Discussion paper.

Rodriguez, X. A., F. Martinez-Roget, and P. Gonzalez-Murias (2018): “Length of stay: Evidence from Santiago de Compostela,” *Annals of Tourism Research*, 68, 9–19.

Romao, J., and Y. Bi (2021): “Determinants of collective transport mode choice and its impacts on trip satisfaction in urban tourism,” *Journal of Transport Geography*, 94, 103094.

Ronald, N., R. Thompson, J. Haasz, and S. Winter (2013): “Determining the viability of a demand-responsive transport system under varying demand scenarios,” in *Proceedings of the sixth ACM SIGSPATIAL international workshop on computational transportation science*, pp. 7–12.

Rosenbaum, P. R., and D. B. Rubin (1983): “The central role of the propensity score in observational studies for causal effects,” *Biometrika*, 70(1), 41–55.

Rotaris, L., and R. Danielis (2014): “The impact of transportation demand management policies on commuting to college facilities: A case study at the University of Trieste, Italy,” *Transportation Research Part A: Policy and Practice*, 67, 127–140.

Rozynek, C. (2024): “Imagine the financial barrier to public transport use disappears. The impact of the 9-Euro-Ticket on the mobility and social participation of low-income households with children,” *Transport Policy*.

Rubin, D. B. (1974): “Estimating causal effects of treatments in randomized and nonrandomized studies.,” *Journal of educational Psychology*, 66(5), 688.

SBB (2021): "Markttest ÖV-Guthaben," `https://www.sbb.ch/de/kampagne/markttest-oev-guthaben.html`, Accessed: 2023-01-24.

——— (2022): "Die SBB in Zahlen und Fakten," `https://reporting.sbb.ch/`, Accessed: 2023-01-27.

Scheiner, J., K. Chatterjee, and E. Heinen (2016): "Key events and multimodality: A life course approach," *Transportation Research Part A: Policy and Practice*, 91, 148–165.

Schulz, T., M. Böhm, H. Gewald, and H. Krcmar (2021): "Smart mobility–an analysis of potential customers' preference structures," *electronic markets*, 31, 105–124.

Schwehr, T., U. Rütter-Fischbacher, O. Hoff, C. Nathani, and P. Hellmüller (2019): "Die Wertschöpfung des Tourismus im Kanton Appenzell Innerrhoden 2017," Discussion paper.

Scott, R. A. (2010): *Demand responsive passenger transport in low-demand situations*, no. 425.

Sharmeen, F., and H. Meurs (2019): "The governance of demand-responsive transit systems—A multi-level perspective," *The Governance of Smart Transportation Systems: Towards New Organizational Structures for the Development of Shared, Automated, Electric and Integrated Mobility*, pp. 207–227.

Shin, E. J. (2021): "Exploring the causal impact of transit fare exemptions on older adults' travel behavior: Evidence from the Seoul metropolitan area," *Transportation Research Part A: Policy and Practice*, 149, 319–338.

Silva, B. C. (2020): "Package SCtools: Extensions to the synthetic controls analyses," *R Package Version 0.3.1*.

Snow, J. (1855): *On the mode of communication of cholera*. John Churchill.

Sörensen, L., A. Bossert, J.-P. Jokinen, and J. Schlüter (2021): "How much flexibility does rural public transport need?–Implications from a fully flexible DRT system," *Transport Policy*, 100, 5–20.

SRF (2022): "Zugfahren mit neuem Bezahlmodell ab Fahrplanwechsel 2023," `https://www.srf.ch/news/schweiz/abo-mit-guthaben-zugfahren-mit-neuem-bezahlmodell-ab-fahrplanwechsel-2023`, Accessed: 2023-01-26.

Sticher, S., and K. Blättler (2024): "Public-Transportation Credits: The potential of three-part tariffs in public transportation," *Transportation Research Part A: Policy and Practice*, 182, 104022.

Štraub, D., W. Kębłowski, and M. Maciejewska (2023): "From Bełchatów to Żory: Charting Poland's geography of fare-free public transport programmes," *Journal of Transport Geography*, 111, 103650.

Swiss Tourism Federation (2023): "Swiss Tourism in figures - Structure and industry data 2022," Discussion paper.

Switzerland Tourism (2017): "Tourism Monitor Switzerland 2017," Discussion paper.

Thao, V. T., S. Imhof, and W. von Arx (2021): "Integration of ridesharing with public transport in rural Switzerland: Practice and outcomes," *Transportation Research Interdisciplinary Perspectives*, 10, 100340.

——— (2023): "Demand responsive transport: New insights from peri-urban experiences," *Travel Behaviour and Society*, 31, 141–150.

Thao, V. T., and T. Ohnmacht (2020): "The impact of the built environment on travel behavior: The Swiss experience based on two National Travel Surveys," *Research in Transportation Business & Management*, 36, 100386.

Thao, V. T., W. von Arx, and J. Frölicher (2020): "Swiss cooperation in the travel and tourism sector: long-term relationships and superior performance," *Journal of Travel Research*, 59(6), 1044–1060.

Thommen, C., and B. Hintermann (2023): "Price versus Commitment: Managing the demand for off-peak train tickets in a field experiment," *Transportation Research Part A: Policy and Practice*, 174, 103691.

Thrane, C. (2015): "Examining tourists' long-distance transportation mode choices using a Multinomial Logit regression model," *Tourism Management Perspectives*, 15, 115–121.

Tibshirani, J., S. Athey, R. Friedberg, V. Hadad, D. Hirshberg, L. Miner, E. Sverdrup, S. Wager, M. Wright, and M. J. Tibshirani (2018): "Package 'grf'," .

TPG (2013): "Rapport annuel de gestion 2012," report.

——— (2016): "Rapport annuel de gestion 2015," report.

Tveter, E., M. Welde, and J. Odeck (2017): "Do fixed links affect settlement patterns: a synthetic control approach," *Research in Transportation Economics*, 63, 59–72.

Unireso (2016): "Rapport de Gestion 2015," report.

Van Buuren, S. (2018): *Flexible imputation of missing data*. CRC press.

Van Buuren, S., and K. Groothuis-Oudshoorn (2011): "mice: Multivariate imputation by chained equations in R," *Journal of statistical software*, 45, 1–67.

Verband öffentlicher Verkehr (2020): "Fakten und Argumente: Zum öffentlichen Verkehr der Schweiz," report.

Verein Appenzellerland Tourismus AI (2021): "Geschäftsbericht 2020," Discussion paper.

——— (2023): "Geschäftsbericht 2022," Discussion paper.

Vitale Brovarone, E. (2022): "Accessibility and mobility in peripheral areas: a national place-based policy," *European Planning Studies*, 30(8), 1444–1463.

Wager, S., and S. Athey (2018): "Estimation and inference of heterogeneous treatment effects using random forests," *Journal of the American Statistical Association*, 113(523), 1228–1242.

Wallimann, H. (2022): "A complementary product of a nearby ski lift company," *Tourism Economics*, 28(2), 418–434.

Wallimann, H., K. Blättler, and W. von Arx (2023): "Do price reductions attract customers in urban public transport? A synthetic control approach," *Transportation Research Part A: Policy and Practice*, 173, 103700.

Wardman, M. (2022): "Meta-analysis of price elasticities of travel demand in great britain: Update and extension," *Transportation Research Part A: Policy and Practice*, 158, 1–18.

Wardman, M., J. Toner, N. Fearnley, S. Flügel, and M. Killi (2018): "Review and meta-analysis of inter-modal cross-elasticity evidence," *Transportation Research Part A: Policy and Practice*, 118, 662–681.

WECKSTRÖM, C., M. N. MLADENOVIĆ, W. ULLAH, J. D. NELSON, M. GIVONI, AND S. BUSSMAN (2018): "User perspectives on emerging mobility services: Ex post analysis of Kutsuplus pilot," *Research in transportation business & management*, 27, 84–97.

WEIS, C., M. VRTIC, K. AXHAUSEN, AND M. BALAC (2016): "Sp-befragung 2015 zum Verkehrsverhalten," report from the Federal Office for Spatial Development.

XIN, M., A. SHALABY, S. FENG, AND H. ZHAO (2021): "Impacts of COVID-19 on urban rail transit ridership using the Synthetic Control Method," *Transport Policy*, 111, 1–16.

ZAMPARINI, L., AND A. S. VERGORI (2021): "Sustainable mobility at tourist destinations: The relevance of habits and the role of policies," *Journal of Transport Geography*, 93, 103088.

ZIJLSTRA, T., AND T. VANOUTRIVE (2018): "The employee mobility budget: Aligning sustainable transportation with human resource management?," *Transportation Research Part D: Transport and Environment*, 61, 383–396.

ZWICK, F., AND K. W. AXHAUSEN (2022): "Ride-pooling demand prediction: A spatiotemporal assessment in Germany," *Journal of Transport Geography*, 100, 103307.