Public-Transportation Credits: The Potential of Three-Part Tariffs in Public Transportation (Short Paper)

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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 200,000 PTC invitees and 911 actual PTC buyers, we use the dispach of invitations as an instrumental variable. While observing substantial revenue increases, 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 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.

Keywords

randomized field experiment; public transportation; price elasticity; revenue management; three-part tariff; Halbtax PLUS; Half Fare Travelcard PLUS

Suggested Citation

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1 Introduction

In this short paper for 23rd Swiss Transport Research Conference (STRC), we we outline the findings presented in Sticher and Blättler (2024), where we explore the concept of three-part tariffs in public transportation and analyze the revenue implications of a corresponding novel pricing model in Switzerland. This model, launched in December 2023 by the association of public-transportation companies "Alliance SwissPass" (hereinafter referred to as "public-transportation providers"). The pricing model is marketed under the name "Halbtax PLUS" ("Half Fare Travelcard PLUS").[1] However, we opt to refer to it as a "public-transportation credits" (PTCs), thereby emphasizing its function from a customer's perspective.

Our definition of a PTC can be summarized in a single sentence: A customer purchases a non-transferable allowance of value V_{PTC} at a price $P_{\mathrm{PTC}} < V_{\mathrm{PTC}}$, and V_{PTD} can be spend on a wide selection of public-transportation tickets during one year. With its fixed-price component, the allowance, and the (standard) fare upon completion of the allowance, the PTC aligns with the concept of a three-part tariff as defined in Lambrecht *et al.* (2007).

Before the introducing of PTCs, public-transportation providers in Switzerland mandated the Swiss Federal Railways (SBB) to run a corresponding pilot study from December 2021 to March 2023 (SBB, 2021), which we were allowed to evaluate.[2]

PTCs may aim at a variety of goals: As they de-facto discount ticket prices, they may support public transportation's modal share, which is in turn an important basis for political support. To be economically feasible (enough), however, sales must be boosted quite substantially. Specifically, the usual assumption of a short-term price elasticity of -0.3, would leave public-transportation providers with a trade off between passenger-count goals and revenue goals.

In our paper, we show both theoretically and empirically that PTCs have the potential to overcome this trade off. To do so, we take into account that cross-price elasticities play a major role in Switzerland's public-transportation pricing. The reason for this becomes apparent once we regard the Swiss ticketing landscape with respect to its—implicit and explicit—quantity discounts: At the end of 2023, 0.447 million people in Switzerland were in possession of a "GA Travelcard" (GA), a season ticket which covers most of public

[1] See https://www.sbb.ch/en/tickets-offers/travelcards/half-fare-travelcard-plus.html.

[2] One of the authors was head of strategic pricing at the SBB until June 2022 and conceptualized the PTC. Access to the anonymized data from the entire pilot study conducted by the public-transportation companies was granted to him.

transportation in Switzerland. A further 3.147 inhabitants had a "Half Fare Travelcard" (HF) which generally allows to buy tickets at half price (SBB, 2024). We deal with cross-price effects by regarding public transportation as a single good with a somewhat intricate pricing structure. We argue that the pricing model prior to the introduction of the PTCs is rather unfavorable to customers "in between" the HF and GA travelcards, potentially leading them to opt for the major outside option, car ownership. A price reduction in this segment, as achieved through the PTC, can therefore lead to above-average demand effects, potentially even suspending the revenue-quantity tradeoff.

Upon briefly discussing the relevant literature in Section 2, we present our theoretical argument in Section 3. We discuss our study design alongside our data in Section 4. In Section 5, we present the treatment effect we obtain by studying the pilot study as a randomized field experiment with 200,000 PTC invitees and 911 actual PTC buyers. As our instrument (invitations) turns out to be week, we complement our study with a machine-learning supported matching approach (in Section 6. In Section 7, we augment our analysis by estimating the demand for a market-launch version of the PTC. We conclude in Section 8 with a brief discussion of our assumptions and results.

2 Literature Review

Our paper adds to the literature in transportation economics, which discuss the relationship between fares, demand, and revenue. To explain a potential revenue gain resulting from the introduction of the PTC, we have to resort to (local) price elasticities ϵ with $|\epsilon| > 1$. Public-transportation demand in Europe is normally considered less elastic. As Holmgren (2007) shows in a meta analysis, long-run price elasticities may be as high as $|\epsilon| = 0.91$, but only as long as vehicle kilometers is considered endogenous. In Switzerland, a field experiment in urban areas revealed a short-run price elasticity of $|\epsilon| = 0.31$ (Axhausen *et al.*, 2021), in line with the often cited rule of thumb of $|\epsilon| = 0.3$. Only when ignoring cross-rice elasticities, e.g., by restricing the attention to off-peak train tickets, substantially higher elasticities are found (Thommen and Hintermann, 2023, see, e.g.).

When limiting attention on individual submarkets and segments, higher price elasticities become more common: Kholodov *et al.* (2021) find that demand for trains is relatively elastic ($|\epsilon| = 0.90$), even more so when considering long-distance journeys in particular. Similarly, Wardman (2022) finds that rail trips taken for leisure purposes are highly elastic.

Somewhat comparable to our result is the unusual finding of Liu *et al.* (2019), who report overall revenue gains from a price reduction in Australia.

The conceptual idea behind PTCs is based on economic literature outside the transportation field. Authors such as Lambrecht *et al.* (2007) and Fibich *et al.* (2017) introduce three-part tariffs as specific type of non-linear pricing. They demonstrate that, under the broad assumption of customer heterogeneity, multiple three-part tariff plans should be chosen to enhance revenue.[3]

Empirically, three-part tariffs are mainly studied in domains such as telecommunications: Ascarza *et al.* (2012) observe that the inclusion of allowances can lead to consumption increases beyond those expected from relaxed budget constraints, resulting in higher revenues. Conversely, Malone *et al.* (2014) find that customers under three-part-tariff tend to reduce their usage in comparison to unlimited plans (the telecom equivalents of the GA). Behavioral effects and/or imperfect information may also be an important factor: Nevo *et al.* (2016) show that allowance usage changes as a function of the remaining days in the billing cycle.

In transportation economics, evidence on three-part tariffs is rare (Caiati *et al.* (2020), who find that customers generally prefer three-part tariffs over two-part tariffs regarding e-car rentals, is an exception.) There are various studies on mobility budgets (Zijlstra and Vanoutrive, 2018; Millonig *et al.*, 2022), which can be considered special cases of three-part tariffs with the fixed-price component being zero. However, this literature focuses on corporate sustainability and HR management. Regarding transportation economics, we consider our research as a pioneering effort.

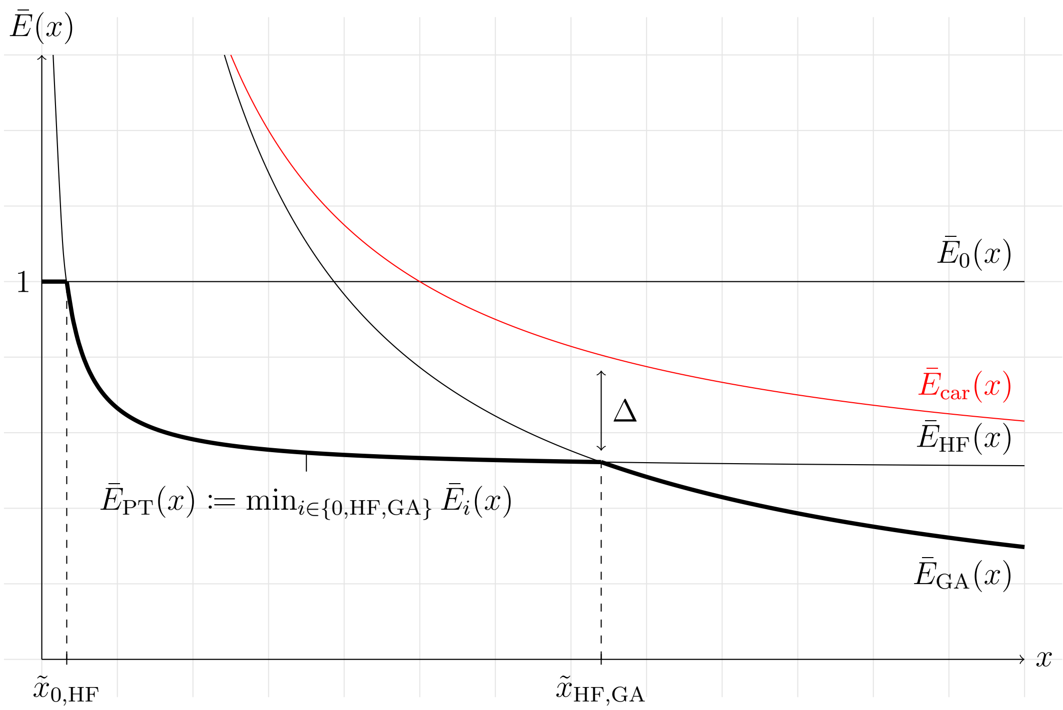
3 Product Design

In Figure 1, we depict a simplified overview of average expenditures with the main public-transportation tickets in Switzerland prior to the introduction of the PTC. x denotes the annual expenditure if it is incurred with non-discounted tickets. Therefore, $\bar{E}_0(x)$, the average expenditure regarding non-discounted tickets is constantly 1. The average expenditure with the HF, $\bar{E}_{\mathrm{HF}}(x)$, and the average expenditure with the GA, $\bar{E}_{\mathrm{GA}}(x)$,

[3]Note that both the GA (as a one-part tariff) and the HF (as a two-part tariff) are special cases of the three-part tariff.

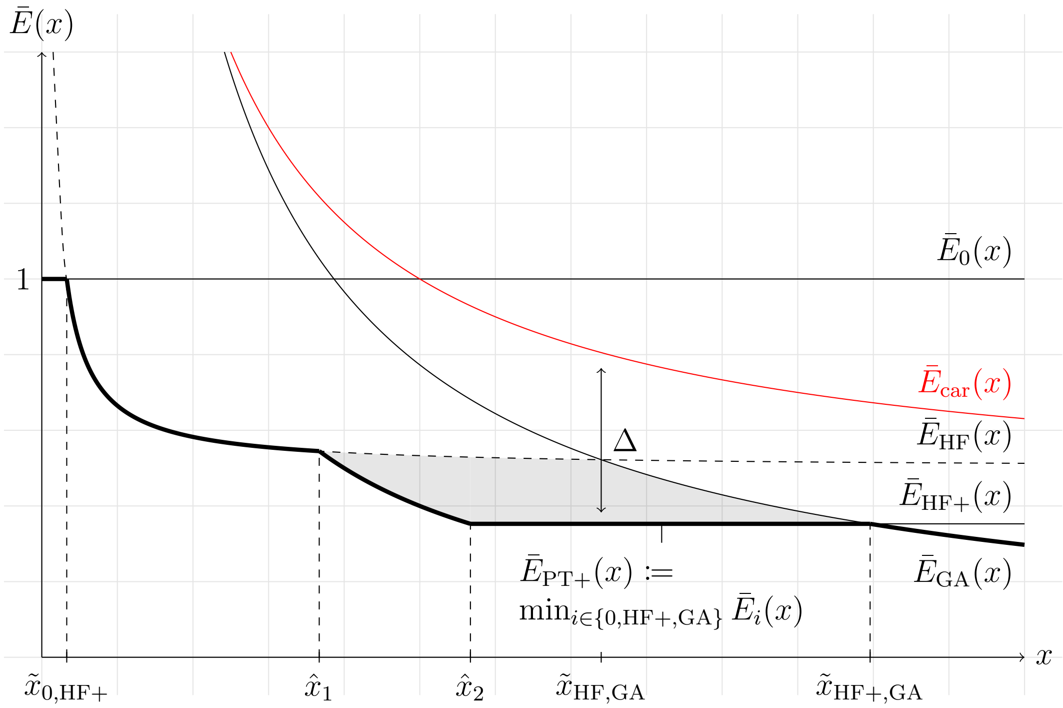
exhibit the typical progression for two-part tariffs and season tickets. As we show in Sticher and Blättler (2024), under general assumptions, public transportation is least competitive with the outside option at the intersection of $\bar{E}$HF(x) and $\bar{E}$GA(x) ("car"), represented by $\tilde{x}$HF,GA.

Figure 1: Average expenditures with public-transportation tickets and car ownership (Source: Sticher and Blättler, 2024)



In Figure 2, we supplement Figure 1 by incorporating the PTC. Because of the PTC's generous reimbursement conditions, acquiring a PTC alongside the HF weakly dominates purchasing only the HF. Hence, we denote the average expenditure with the combination of HF and PTC as $\bar{E}_{\mathrm{HF}+}(x)$. To again assess public transportation's competitiveness vis-à-vis private transportation, we consider the lower envelope of the average-expenditure functions, $\bar{E}_{\mathrm{PT}+}(x) \coloneqq \min_{i\in\{0,\mathrm{HF}+,\mathrm{GA}\}} \bar{E}_i(x)$. In Figure 2, the greyed area highlights the differences of customer expenditures before and after the introduction of the PTC, which reaches its peak at $\tilde{x}_{\mathrm{HF},\mathrm{GA}}$. As this is the value for x where public transportation's price advantage was lowest before the introduction of the PTC, it is save to assume that a rather elastic customer segment is attracted by the new offer.

Figure 2: Average expenditures with public-transportation tickets (PTC included) and car ownership (Source: Sticher and Blättler, 2024)



4 Study Design and Data

To examine the impact of the PTC on revenue, we randomly assigned individuals to either a treatment group or a control group. Participants in the treatment group were invited to join the pilot study and given the option to purchase either a "small" or a "large" PTC. The cost of these PTCs was CHF 800 and CHF 2,000, respectively, with corresponding allowances of CHF 1,000 and CHF 3,000, provided as a progressive quantity discount.[4]

Registration opened in December 2021, with a limit of 600 PTCs of each size. By March 2022, when 600 small and 311 large PTCs had been sold, recruitment ceased due to differing market demand for the two types. According to SBB, approximately 200,000 invitation emails had been opened at this point, resulting in a participation rate of only 0.45%. Employing stratification techniques described in detail in Sticher and Blättler (2024), we gathered data from 16,074 customers, including all pilot study participants, capturing their consumption during and one full year prior to the pilot study. In the full-paper version of this article, we elaborate on how the pilot study diverges from the actual implementation of the PTC concerning accessibility, data constraints, and product

[4]Note that in Section 3, we simplify by focusing on a single PTC. Additionally, in the matching approach discussed in Section 5, we specifically construct a control group for PTC buyers.

features, and how we account for these differences by slightly narrowing our population, as well as by computing and interpreting our treatment effects.

Due to 18 dropouts during the pilot study, our final dataset consists of 592 costumers of the small PTC, alongside 301 customers of the large PTC. In Table 1, we summarize the season-ticket ownership type as well as some socioeconomic indicators of these customers.

Table 1: Descriptive statistic of buyers (Source: Sticher and Blättler, 2024)

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

During the pilot study, PTC buyers spent on average CHF 1,860.10 on public transportation in total. Non-buyers in the treatment group and control group spent CHF 948.75 and CHF 955.25, respectively.

Obviously, due to self selection, we cannot simply compare yearly expenditures to determine the revenue impact of the PTC.[5] Individuals with high propensities to consume public transportation are arguably also more prone to purchase a PTC. Therefore, in the following two sections, we present strategies to construct more valid comparison groups for the PTC buyers.

[5] In the year prior to the pilot study, PTC buyers spent 1,585.25, whereas non-buyers in the treatment group and control group spent CHF 823.70 and CHF 834.55, respectively. Also note that the year prior to the pilot study was heavily impacted by Covid-19.

5 Randomized Field Experiment

As only 893 out of approximately 200,000 randomly selected customers participated in the pilot study (and completed it), it is highly conceivable that systematically differ from subjects of control group not only regarding observed but also unobserved characteristics. To account for imperfect compliance (Imbens and Rubin, 2015), we use $Z \in \{0, 1\}$ (which takes on the value 1 when an invitation to participate in the pilot study was sent to the customer) as an instrumental variable for our explanatory variable $D \in \{0, 1\}$ (which takes the value 1 when a customer purchases the PTC when given the opportunity). To identify the treatment effect, we need to derive the (counterfactual) expenditure $\mathbb{E}[E|D = 1, Z = 0]$ which we then compare with $\mathbb{E}[E|D = 1, Z = 1]$ (which we can measure). To do so, two assumptions must be met. First, D and Z must be statistically independent. Second, Z may not affect the expenditure E except through D. The first of these assumptions is met by design, the second very plausible at the very least. Applying these assumptions, we can write the $\mathbb{E}[E|D = 1, Z = 0]$ as

$$\frac{\mathbb{E}[E|Z = 0] - \mathbb{P}[D = 0, Z = 1] \times \mathbb{E}[E|Z = 1, D = 0]}{\mathbb{P}[D = 1, Z = 1]},$$

which allows us to compute an average treatment effect of CHF 925. However, as the 95% bootstrap confidence interval ranges from CHF -3,108 to CHF 4,815, this effect is clearly statistically insignificant. As expected, the correlation between the instrument "invitations" and the PTC purchases leads to the issue of a "weak instrument".

6 Matching

To gain statistical power, we match the 893 study participants with similar customers in the control group based on observable characteristics. However, to do so, we need to assume conditional independence. Fortunately, as shown in Table A.1 in Appendix A, our comprehensive dataset allows us to control not only for socioeconomic indicators but also consumption patterns from the previous year.

Using conditional treatment probabilities, referred to as propensity scores, we can balance the control group such that it structurally resembles the treatment group, as we exemplify in Table A.2 in Appendix A. We also illustrate the distribution of propensity scores of PTC buyers and the control group in Figure A.1 in Appendix A.

To implement the proponsity-score matching, we employ the *causal forest*, as described by Athey and Wager (2019), due to its functional flexibility in capturing non-linear dependencies. In the statistical software *R*, we use the *grf* package for developed by Tibshirani *et al.* (2018). Specifically, we calculate the overlap-weighted average treatment effect, recommended by Li *et al.* (2018), which is particularly suitable when the propensity scores of one group are close to zero.

Our resulting average treatment effect is CHF 179.7. More importantly, this point effect is statistically highly significant, with the 95% confidence interval ranging from CHF 115.0 to CHF 244.4.[6]

7 Market Potential

As the "market-launch PTC" differs from the "pilot-study PTC" in several aspects (inclusion of supersaver tickets, enhanced accessibility through various sales channels, purchase outside of test environment), the participation rate of 0.45% is likely to underestimate the demand for the PTC. To analyze market potential, we were granted access to an online survey of the public-transportation providers, specifically targeted at subjects from the treatment group who opted not to purchase the PTC. Under market-launch conditions, 6.3% of the 273 respondents self-reported that they will purchase a PTC.

To adjust for selection and self-reporting biases, we match these indications with actual consumption data from the respondents. By calibrating the distribution of survey respondents' propensity scores according to those of the non-buyers, we ex-post stratify the sample distribution. By further only considering stated purchase intentions when the individual respondent's propensity score is located within the top 95% propensity-score interval of actual PTC buyers, we take into account the "credibility" of these statements. As these two modifications reduce the fraction of would-be buyers to 2.92%, our point estimate for the market demand is $0.0045 + (1 - 0.0045) \times 0.0292) \times 5.9\text{m.} \simeq 198,000$. The 95% bootstrap interval reaches from 63,230 to 479,060 customers. (See also Figure A.2 in Appendix A.)

[6]As a benchmark, we also use linear regression (see Table A.3 in Appendix A). The OLS treatment effect amounts to CHF 202.2, being significant at the 1% level.

8 Discussion and Conclusion

In our study, we first demonstrated theoretically that introducing a product between two-part tariffs (the HF) and season tickets (the GA) has the potential to address particularly elastic demand.

Employing a randomized field-experiment approach, we encountered limitations due to a weak instrument, preventing us from establishing statistically significant supportive evidence. However, the point estimate is consistent with our theoretical framework. By applying the conditional-independence assumption (CIA) and constructing a control group through propensity-score matching, we observed a statistically significant revenue increase of CHF 179.7 per PTC buyer. The CIA is crucial: It does not allow for customers self-selecting into the treatment group based on unobservable prospects. Consider the fact that life circumstances underwent changes during the Covid-19 recovery (where our baseline data stems from). If such changes affect both the willingness to pay for public transportation in general as well as the likelihood to purchase a PTC, the CIA may be violated. Fortunately, our comprehensive dataset allowed us to account for responses to varying degrees of Covid restrictions by including predictors such as the variation coefficient and the spread between months.

Regarding demand predictions, we had to rely on ”ad-hoc” assumptions due to differences between the market-launch PTC and its pilot-study counterpart. Thus, our point estimate of 198,000 demanded PTCs per year requires a cautious interpretation. Another data deficit pertains to the absence of passenger kilometers (for season-ticket holders). Capitalizing on the increasing accessibility of consumption data could aid in computing specific elasticities and providing more nuanced insights into modal-split implications.

Close monitoring of customer behavior in the initial years following the PTC's launch in December 2023 will be crucial. Provider revenue is not the sole consideration. Societal implications, such as impacts on traffic congestion, emissions, and public infrastructure financing, should also be considered. Note, however, that unlike traditional season tickets and recently experimented-with fare-free transportation, the PTC is not tailored for daily commuters nor does it incentivize excessive demand.

Regarding the PTC itself, we advocate for further testing of differentiations such as the scheduled ”intermediate” PTC and youth discounts. Additionally, we recommend maintaining an exploratory approach, allowing for adjustments when theoretical predictions miss their marks.

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A Supplementary Tables and Figures

Table A.1: Description of control variables (Source: Sticher and Blättler, 2024)

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 1)
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 A.2: Means (standard deviations) of buyers and control group (Source: Sticher and Blättler, 2024)

Variable	**Buyers**	**Control group (unbalanced)**	**Control group (balanced)**
Ticket type (GA, first class = 1)	0.02 (0.13)	0.01 (0.09)	0.02 (0.13)
Ticket type (GA, second class = 1)	0.10 (0.30)	0.09 (0.28)	0.11 (0.32)
Ticket type (HF = 1)	0.72 (0.45)	0.50 (0.50)	0.65 (0.48)
Ticket type (HF + other season ticket = 1)	0.12 (0.33)	0.11 (0.31)	0.12 (0.33)
Ticket type (other season ticket = 1)	0.01 (0.12)	0.14 (0.35)	0.05 (0.23)
Ticket type (non-discounted tickets = 1)	0.03 (0.16)	0.15 (0.35)	0.04 (0.20)
Age	46.98 (13.78)	43.90 (16.18)	44.61 (14.63)
Gender (female=1)	0.43 (0.50)	0.54 (0.50)	0.51 (0.50)
Region (German=1)	0.79 (0.41)	0.75 (0.43)	0.75 (0.43)
Previous Expenditure (total)	1,585.24 (1213.67)	834.57 (1,028.88)	1,475.78 (1,180.66)
Previous Expenditure (single tickets)	614.93 (613.51)	169.77 (323.19)	577.80 (603.42)
Spread	37.15 (27.88)	16.59 (23.65)	36.34 (29.52)
Spread (months)	188.87 (125.16)	75.26 (88.23)	176.17 (123.05)
CV	0.63 (0.38)	0.36 (0.42)	0.62 (0.40)
CV (months)	0.66 (0.43)	0.54 (0.62)	0.66 (0.46)
Trips	44.66 (46.40)	14.26 (28.21)	43.34 (47.66)
Trips (first class)	4.59 (14.38)	1.09 (6.26)	4.75 (14.07)
Expenditure (Outcome)	1,860.11 (1091.42)	955.27 (884.57)	

Figure A.1: Distribution of propensity scores (Source: Sticher and Blättler, 2024)

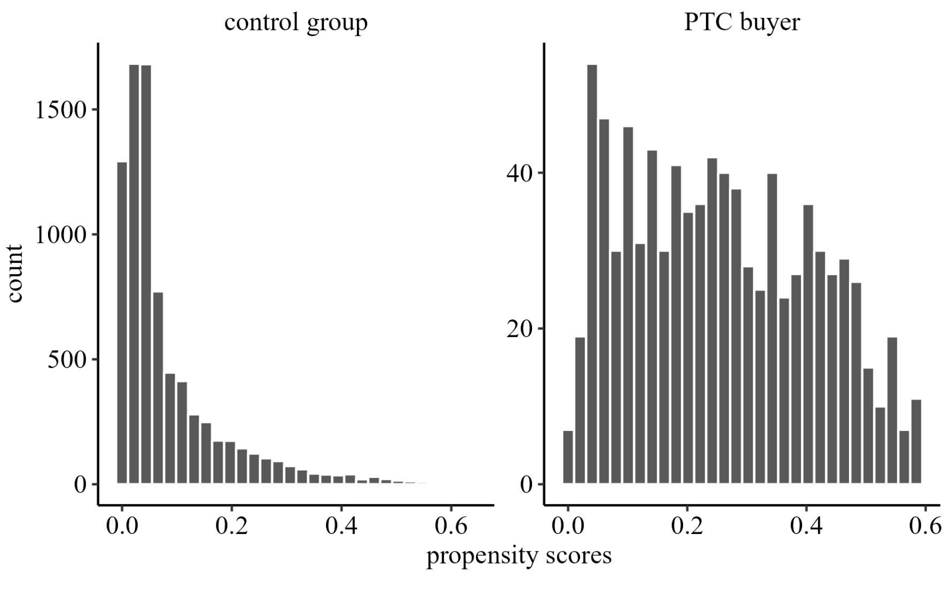

Table A.3: Linear regression, as a benchmark for the matching approach described in Section 6 (Source: Sticher and Blättler, 2024)

	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

Figure A.2: Probability distribution of the demand for the market-launch PTC, with the vertical lines indicating the 95% confidence interval (Source: Sticher and Blättler, 2024)