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Abstract

Swiss rail is renowned for its ridership and quality, yet peak hours generate highly concentrated demand, placing pressure on the system and causing passenger discomfort. Peak pricing is an effective but underexplored demand management tool for Swiss rail. Since the policy aim is redistributing passengers rather than suppressing trips or shifting modes, departure-time choice is of central interest. This study uses data from a Swiss Stated Preference experiment to estimate a departure-time shift choice model, specified as a Multinomial Logit with terms for peak surcharge, schedule delay early and late, transfers, and crowding. Preliminary results show a general preference for departing at the peak period, captured through an off-peak dummy variable as well as significance of sociodemographic interaction terms, such as household size with cost sensitivity and more. Following steps involve integration of choice model results into SBB's agent-based model by adding disutility terms in the model's utility function with the estimated parameters differentiated across sociodemographic subgroups. Several peak pricing scenarios will then be tested in simulation. Beyond informing SBB and Swiss transport policy, the study aims to provide a methodological example of how rail peak pricing can be simulated in MATSim using choice modelling results.

Keywords

Peak pricing; Departure-time choice; Discrete choice modelling; Agent-based simulation; Public transport demand management; Schedule Delay; MATSim

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1 Introduction

While public transport operates throughout most of the day, passenger demand is highly concentrated during peak hours. In Switzerland, approximately half of all daily rail passengers travel during the morning and evening rush hours (SBB Statistics Portal, n.d.). This concentration causes crowding, increases the risk of delays, and places pressure on operators to accommodate peak demand (Hale and Charles, 2009). Meeting this demand requires large investments in infrastructure and rolling stock, even though this additional capacity is mainly used for a limited number of hours each day (Hale and Charles, 2009).

An alternative to capacity expansion is to redistribute demand away from the peak through time-of-day pricing, such as peak surcharges or off-peak discounts. In this way, operators can create financial incentives for travellers to shift their departure times (Hale and Charles, 2009; Liu and Charles, 2013; Thommen and Hintermann, 2023). Empirical evidence confirms that such methods can be effective, with peak reductions observed, for example, in Melbourne and the Netherlands (Currie, 2010; Peer *et al.*, 2016).

However, price alone does not determine departure-time choice. Travellers face scheduling constraints due to work, intra-household interactions, and daily routines, limiting flexibility (Thommen and Hintermann, 2023; Hale and Charles, 2009). In addition, crowding affects perceived comfort and safety influencing departure-time choice as well (Hale and Charles, 2009).

Currently, Switzerland does not apply time-of-day pricing, and a large share of passengers hold subscriptions which provide either unlimited or discounted travel (Huber *et al.*, 2021). Within this context, this paper explores the potential effects of introducing time-of-day pricing, more specifically, peak surcharges, in Swiss rail. This is done by estimating passenger preferences using choice modelling and integrating these into an activity-based simulation to assess network-wide effects. While price sensitivities have been studied, there is limited research for Switzerland that jointly examines departure-time choice and peak spreading at the network level.

2 Literature Review

The Swiss Context and Empirical Gap: Switzerland's high rail ridership makes peak demand concentration a particularly significant issue. Time-of-day pricing is a popular policy response, implemented by many cities around the world, but before it can be brought to public or political consideration, sufficient empirical evidence on passenger behaviour is needed. While SBB already employs a capable simulation model for demand responses at a national scale (Scherr *et al.*, 2020), it currently lacks empirically grounded behavioural parameters for how Swiss rail passengers respond to time-of-day fare changes. Existing Swiss studies have explored similar topics, such as behavioural responses to road transport peak pricing (Vrtic *et al.*, 2007, 2011) or price sensitivities regarding long-distance off-peak discount tickets (Huber *et al.*, 2021; Thommen and Hintermann, 2023). The most relevant research for Swiss public transport peak fares can be found in the 2021 MTMC Stated Preference report (Gayda *et al.*, 2024), which remains the latest available dataset, though findings from the 2025 wave - which also included peak pricing and departure-time choice - are expected to be published in the near future. However, in the 2021 report the public transport peak surcharge coefficient could not be robustly estimated, and other parameters showed unexpected signs and insignificance. This highlights a distinct gap for locally-based, policy-specific behavioural parameters.

Discrete Choice Modelling: To derive these missing parameters, researchers commonly rely on Stated Preference (SP) data combined with Discrete Choice Modelling (DCM). DCM is grounded in Random Utility Maximisation (RUM) theory, which models individual decision-making by assuming a decision-maker chooses the alternative that maximises their utility (Ben-Akiva *et al.*, 1997). For departure-time choice specifically, a core theoretical component is schedule delay, which introduces disutility terms for departing earlier (Schedule Delay Early, SDE) or later (Schedule Delay Late, SDL) than preferred. The literature reveals several key behavioural insights regarding these parameters: schedule delay penalties are often asymmetric (Vrtic *et al.*, 2007; Peer *et al.*, 2016), peak surcharges are generally found to be more effective at shifting demand than off-peak discounts (Liu and Charles, 2013), and trip purpose heavily influences flexibility (Weesie *et al.*, 2009; van den Berg *et al.*, 2009). Regarding model formulation, Multinomial Logit (MNL) is widely utilised as a baseline specification. A shift-based model, where alternatives are defined relative to a respondent's preferred departure time, is appropriate when individual scheduling preferences are accessible (Fox *et al.*, 2015), as is the case with the dataset and agent-based simulation of this study.

Network-Wide Simulation: While discrete choice models provide individual-level behavioural parameters, evaluating system-wide policy impacts requires embedding these responses within a network-level framework. Traditional four-step models treat time-of-day distributions as fixed inputs and rely on aggregate flows, making them incapable of capturing individual heterogeneous responses to pricing policies (Raney and Nagel, 2006). Agent-based models (ABMs), such as MATSim, address this by simulating the interactions between individual agents and the transport network. In these models, each agent attempts to maximise the utility of their activities and travel, reaching a stable state through iterative replanning. Previous studies have successfully utilised MATSim to evaluate the equity effects of road pricing (Meyer de Freitas *et al.*, 2016) and citywide congestion charges (He *et al.*, 2021). Furthermore, research has demonstrated the feasibility of embedding DCM-estimated behavioural parameters into MATSim's utility function to represent preference heterogeneity (Müller *et al.*, 2022). However, while SIMBA MOBi incorporates robust parameters for mode and destination choice and has been applied to peak pricing scenarios, its utility function lacks several detailed departure-time and peak pricing components that are important for accurately capturing departure-time shifts.

Literature gap: Overall, three literature gaps emerge. First, there is no robust departure-time choice model with peak pricing sensitivity for Swiss rail passengers. Second, simulation models lack the behavioural components needed to capture the detailed schedule-shift effects of such policies. Third, to the authors' knowledge, there is no end-to-end study linking choice modelling with network-level simulation for public transport peak pricing. This study addresses these gaps by estimating a departure-time choice model and integrating the results into SIMBA MOBi to evaluate system-wide effects.

3 Methodology

The methodology follows a two-stage approach: first, estimating a departure-time choice model using stated preference data; and second, integrating the estimated behavioural parameters into an activity-based simulation to evaluate network-wide effects.

3.1 Dataset

The study uses the departure-time choice experiment (SP4) from the Swiss stated preference survey 2021 (Weis *et al.*, 2021; Gayda *et al.*, 2024). The stated preference scenarios are anchored to each respondent's own reference trip from the Swiss Mobility and Transport Microcensus (MTMC) 2021, a nationally representative revealed preference survey (Swiss Federal Statistical Office (FSO) and Federal Office for Spatial Development (ARE), 2023). This provides an RP-SP dataset. The public transport (PT) morning subsample of the departure-time choice experiment (SP4) used in this study contains 180 respondents and 1,076 observations after quality related exclusions. A larger sample for departure time choice is expected from the 2025 wave of the survey, which will be considered for implementation once data becomes available.

A key advantage of the SP4 dataset is the availability of preferred arrival times (PAT), allowing the construction of schedule delay variables. This enables a shift-based modelling approach, where alternatives are defined relative to an individual's preferred departure time. Where the PAT is not given, the reference trip arrival time is used as a proxy.

3.2 Choice Model Estimation:

The departure-time choice set follows the experimental design where respondents choose between three alternatives: the respondent's current public transport trip at approximately their reference departure time (Alternative 1), the same mode at an earlier or later departure time (Alternative 2), and a car alternative at approximately the reference departure time (Alternative 3). While in the ARE Research Report (Gayda *et al.*, 2024) departure time choice is estimated within a broader joint mode and departure time choice model, including both car and public transport (PT) users, the present study focuses exclusively on morning PT users and treats departure time choice as the primary modelling objective. This allows a more targeted specification for peak pricing policy evaluation and for transfer into the simulation framework that the joint mode and departure time choice model did not pursue.

The choice model specification followed a stepwise procedure. Each model was formulated as a shift-based Multinomial Logit (MNL), estimated on a panel of six choice tasks per respondent using the panel likelihood trajectory. Model selection at each stage was based on final log-likelihood, ρ^2, $\bar{\rho}^2$, AIC, BIC, and parameter significance.

For PT alternatives, the utility function includes travel time, monetary cost, schedule delay early and late, number of transfers, crowding, and a time-of-day dummy indicating arrival period; for the car alternative, it includes travel time, fuel cost, toll, schedule delay early and late, and the same time-of-day dummy. Parameters shared across modes were consolidated where supported by Wald tests. Sociodemographic and trip-level interaction terms were then tested systematically against the four core parameters - cost sensitivity, SDE, SDL, and the time-of-day dummy - across all available respondent characteristics, with significant terms retained in a combined specification.

3.3 Agent-Based Model Integration

To assess system-wide impacts, the estimated behavioural parameters are integrated into SIMBA MOBi, the national activity-based transport model developed by SBB (Scherr *et al.*, 2020). By embedding empirically estimated behavioural parameters into SIMBA MOBi, the model can be used to simulate peak pricing scenarios and evaluate their effects on departure-time distribution and modal split at the national level.

SIMBA MOBi model context: SIMBA MOBi is built on the MATSim framework and represents travel demand through a synthetic population of agents, each performing daily activity schedules. In the model, agents iteratively adjust their activity plans, including departure times, routes, and modes, based on a utility function. This allows the simulation to capture interactions between individual behaviour and network conditions, such as congestion and crowding.

SIMBA MOBi incorporates behavioural responses for several choice dimensions, such as mode, destination, and activity patterns. However, it currently lacks a behaviourally grounded representation of departure-time choice and peak pricing sensitivity. In particular, the utility function does not include key components required for peak pricing analysis, such as schedule delay or peak surcharge terms, which is the contribution made by this study.

SIMBA MOBi integration: The second stage of the methodology consists of integrating the estimated behavioural parameters into SIMBA MOBi. This is achieved by introducing additional disutility terms into the model's utility function such as peak surcharge, schedule delay early and late and timing preference. The parameters from choice modelling results are implemented within the replanning step of the simulation. To scale them to fit with existing parameters, it is proposed to convert parameters into Willingness-to-pay space based on cost sensitivity. The model will be set to allow temporal replanning of maximum ± 1 hour (instead of the current ± 30 minute limit) to allow meaningful shift in daily schedule. To reflect heterogeneity, parameters are differentiated across subpopulations based on sociodemographic characteristics.

Following model integration, a baseline scenario will be run with no peak charge to validate and calibrate the parameter integration. Furthermore, multiple peak pricing scenarios will be simulated. The scenarios vary in the amount of the surcharge and application structure (timing and links). The resulting outputs include changes in departure-time distribution, peak demand levels, modal split, passenger kms and revenue.

4 Results

First, the base attribute parameters were examined (Table 4 in the Appendix). Base ticket cost was insignificant ($p = 0.2476$) and could not be consolidated with other monetary parameters via Wald tests, thus, supporting its exclusion. This is behaviourally plausible given that base fare did not vary between PT alternatives and that a large share of the sample holds Half-fare or GA subscriptions, which significantly reduce ticket costs, making it largely irrelevant. Furthermore, exclusion also allows a generic cost parameter that supports appropriate scaling of parameters for the MATSim utility function using the Willingness-to-pay space. The remaining monetary parameters - PT peak surcharge, car fuel cost, and car toll - were not significantly different from each other (Table 6 in the Appendix), supporting consolidation into a single β_{cost}. Wald tests further confirmed no significant difference between PT and car parameters for SDE, SDL, and travel time, supporting their consolidation into generic parameters across all alternatives (Table 5 in the Appendix).

Second, alternative crowding formulations and time-of-day dummy specifications were compared using model performance criteria. Tables 1 and 2 summarise the model development steps. Based on this comparison, the two-level crowding formulation and an off-peak dummy based on arrival time (reference: arrival between 7:00 and 7:40) were selected for further use in testing interaction variables.

Table 1: Model development: Selection of crowding formulation

Specification	Final LL	AIC	BIC	# par.	ρ^2	$\bar{\rho}^2$
4-level crowding dummies	-948.82	1917.64	1949.57	10	0.136	0.127
No crowding	-952.67	1919.33	1941.68	7	0.133	0.126
Linear crowding	-950.47	1916.94	1942.48	8	0.135	0.128
2-level: high vs. low	**-948.92**	**1913.84**	**1939.38**	**8**	**0.136**	**0.129**

Table 2: Model development: Time period dummy selection

Specification	Final LL	AIC	BIC	# par.	ρ^2	$\bar{\rho}^2$
Departure-time: pre-peak/peak/post-peak	-941.75	1903.49	1935.42	10	0.143	0.134
Departure-time: off-peak/shoulder/peak	-944.12	1908.25	1940.18	10	0.141	0.132
Departure-time: off-peak/ peak	-944.33	1906.67	1935.41	9	0.140	0.132
Arrival-time: off-peak/ shoulder/ peak	-940.62	1901.25	1933.18	10	0.144	0.135
Arrival-time: off-peak/ peak	**-941.55**	**1901.09**	**1929.83**	**9**	**0.143**	**0.135**

The utility function of alternative i for individual n of this base model is as follows:

$$
\begin{aligned}
V_{in}^{\text{PT}} &= \text{ASC}_i + \beta_{\text{cost}} \cdot \text{Surcharge}_{in} + \beta_{\text{SDE}} \cdot \text{SDE}_{in} + \beta_{\text{SDL}} \cdot \text{SDL}_{in} \\
&\quad + \beta_{\text{tr}} \cdot \text{Transfers}_{in} + \beta_{\text{TT}} \cdot \text{TravelTime}_{in} + \beta_{\text{cr}} \cdot \text{Crowding\_High}_{in} + \beta_{\text{TOD}} \cdot \text{OffPeak}_i \\
V_{in}^{\text{Car}} &= \text{ASC}_3 + \beta_{\text{cost}} \cdot (\text{Fuel}_{in} + \text{Toll}_{in}) + \beta_{\text{SDE}} \cdot \text{SDE}_{in} + \beta_{\text{SDL}} \cdot \text{SDL}_{in} \\
&\quad + \beta_{\text{TT}} \cdot \text{TravelTime}_{in} + \beta_{\text{TOD}} \cdot \text{OffPeak}_i \qquad (1)
\end{aligned}
$$

Where $\text{ASC}_1 = 0$ (reference alternative), $\text{Crowding\_High}_{in}$ is a dummy for crowding levels 3 and 4 relative to levels 1 and 2, and OffPeak_i is a dummy equal to 1 when the arrival time falls outside the peak window (7:00 - 7:40).

Following this, the base model was used to test interactions with sociodemographic and trip variables. Overall, 220 models runs were executed, from which 13 had at least one significant meaningful interaction variable.

After incorporating all statistically significant interaction terms jointly and removing those that became insignificant, had negligible effect sizes, or could be combined due to no significant difference, the final model is presented in Table 3.

Table 3: Final departure-time choice model with sociodemographic interactions

Parameter	**Interpretation**	**Estimate**
B_{TR}	Nr of transfers	-0.2142***
B_{COST}	Monetary cost sensitivity [chf]	-0.1216***
B_{SDE}	Schedule delay early [h]	-1.6377***
B_{SDL}	Schedule delay late [h]	-2.7698***
B_{TT}	Travel time [min]	-0.0259***
$B_{\mathrm{CRWD,HIGH}}$	High crowding (ref. low)	-0.2921
B_{OFFPEAK}	Off-peak arrival (ref. peak)	-1.2045***
Interactions		
$B_{\mathrm{COST}\times\mathrm{NbHH}}$	Monetary cost × Household size	0.0234***
$B_{\mathrm{COST}\times\mathrm{AboDT}}$	Monetary cost × Half-fare subscription	-0.0438***
$B_{\mathrm{SDL}\times\mathrm{MotifWork}}$	Late delay × Work trip purpose	1.4099**
$B_{\mathrm{SDL}\times\mathrm{Dist3}}$	Late delay × Trip distance >30km	0.8319**
$B_{\mathrm{SDE}\times\mathrm{CSP4}}$	Early delay × CSP category 4	-1.1125**
$B_{\mathrm{OFFPEAK}\times\mathrm{MotifOther}}$	Off-peak × Non-work/study trip	3.1732**
$B_{\mathrm{OFFPEAK}\times\mathrm{PossVP\_EB}}$	Off-peak × Car or e-bike available	0.6487***
ASC_2	Alternative-specific constant (time-shift)	0.3704**
ASC_3	Alternative-specific constant (car)	-0.9593***
Model fit		
Final log-likelihood		-897.40
AIC		1826.80
BIC		1877.88
ρ^2		0.183
$\bar{\rho}^2$		0.169

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5 Discussion and Conclusions

Overall, the choice modelling results form a behaviourally grounded base for the ABM implementation. Although more advanced model structures could improve how correlation and heterogeneity are captured, the MNL serves as a reliable foundation for the analysis and ensures straightforward integration into the simulation framework. All base parameters carry expected signs and are highly significant, except for the crowding parameter. This may be due to limited variation in crowding levels within the morning PT subsample, but should be explored further. The strong negative ASC for the car alternative (-0.96)

is possibly due to the PT-oriented sample, while the positive ASC for the time-shifting alternative (0.37) implies a general willingness to shift departure time when incentivised.

The schedule delay asymmetry - with early delay ($B_{SDE} = -1.77$) penalized more than late delay ($B_{SDL} = -1.24$) (values from the final base model without interactions Table 7 in the Appendix) aligns with the values in the ARE Report, where SDE is also viewed as less preferable than SDL (Gayda *et al.*, 2024).

The inclusion of sociodemographic interaction terms notably improves model fit compared to the base specification, with the final log-likelihood improving from -941.55 to -897.40, a reduction in AIC from 1901.09 to 1826.80, in BIC from 1929.83 to 1877.88, and an increase in ρ^2 and $\bar{\rho}^2$, despite the addition of 7 parameters. All interaction parameter signs are as expected except for the positive late delay and work trip interaction, which implies that work travellers have a weaker aversion to late arrival than education or leisure travellers. While the overall SDL disutility remains negative for work trips, the reduced penalty relative to other purposes may reflect greater schedule flexibility at the workplace compared to the strict activity start times of education trips, although further investigation is needed.

Nevertheless, several limitations should be acknowledged. The PT morning subsample of 180 respondents is relatively small, which possibly impacts the reliability of interaction terms. Base ticket cost showed an insignificant impact and was, thus, excluded. Finally, no Covid correction was applied to the dataset, meaning pandemic-related effects may be present in the data. To address the reliability of the interaction terms given the sample size, additional validation methods will be considered before finalising the model specification.

The next stage integrates the estimated parameters into SIMBA MOBi by introducing schedule delay disutility terms and peak preference into the replanning step, with parameters differentiated across subpopulations. Pricing scenarios with varying surcharge levels will then be evaluated in terms of departure-time redistribution, modal split, and passenger kilometres travelled at the national network level. Overall, the authors aim to provide both a methodological example of a full choice modelling to network simulation study and produce meaningful results on peak pricing policy effects on Swiss rail.

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A Initial base model with separate parameters

Table 4: Initial three-alternative base model

Parameter	Interpretation	Estimate
PT alternatives		
B_{TR}	Nr of transfers	-0.2187***
B_{sur}	Peak surcharge [chf]	-0.0475***
B_{ticket}	Base ticket cost [chf]	-0.0454
$B_{\text{SDE,PT}}$	Schedule delay early [h]	-1.7053***
$B_{\text{SDL,PT}}$	Schedule delay late [h]	-1.3942***
B_{CRWD2}	Crowding level 2 (ref. 1)	0.0461
B_{CRWD3}	Crowding level 3 (ref. 1)	-0.3135
B_{CRWD4}	Crowding level 4 (ref. 1)	-0.1264
$B_{\text{TT,PT}}$	Travel time [min]	-0.0264***
Car alternative		
B_{fuel}	Fuel cost [chf]	-0.1279***
B_{toll}	Toll/surcharge [chf]	-0.0746**
$B_{\text{SDE,Car}}$	Schedule delay early [h]	-1.8335**
$B_{\text{SDL,Car}}$	Schedule delay late [h]	-1.2805*
$B_{\text{TT,Car}}$	Travel time [min]	-0.0287***
Alternative-specific constants		
ASC_2	Alt 2 (PT larger shift)	0.4805
ASC_3	Alt 3 (Car)	-0.6977
Model fit		
Final log-likelihood		-943.463
AIC		1918.926
BIC		1970.013
ρ^2		0.141
$\bar{\rho}^2$		0.127

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

B Wald test results

Table 5: Wald tests for parameter consolidation in the initial base model

Test	Parameter 1	Parameter 2	Difference	t-stat	p-value
Travel time PT vs Car	−0.0264	−0.0287	0.0023	0.275	0.783
SDE PT vs Car	−1.7053	−1.8335	−0.1282	−0.174	0.862
SDL PT vs Car	−1.3942	−1.2805	0.1137	0.191	0.849

Table 6: Wald tests for monetary parameter consolidation in the initial base model

Test 1 — all monetary parameters (H_0: $B_{sur} = B_{toll} = B_{fuel} = B_{ticket}$)

Parameter	B_{sur}	B_{toll}	B_{fuel}	B_{ticket}
Estimate	−0.0475	−0.0746	−0.1279	−0.0454

Wald statistic = 10.912, degrees of freedom = 3, p-value = 0.012

Conclusion: rejected at 5% — single cost parameter not supported

Test 2 — excluding base ticket cost (H_0: $B_{sur} = B_{toll} = B_{fuel}$)

Parameter	B_{sur}	B_{toll}	B_{fuel}
Estimate	−0.0475	−0.0746	−0.1279

Wald statistic = 4.486, degrees of freedom = 2, p-value = 0.106

Conclusion: not rejected at 5% — single cost parameter supported after excluding base ticket cost

C Final base model results

Table 7: Final base model prior to interaction testing

Parameter	**Interpretation**	**Estimate**
PT alternatives		
B_{TR}	Nr of transfers	-0.2044***
B_{cost}	Monetary cost sensitivity [chf]	-0.0602***
B_{SDE}	Schedule delay early [h]	-1.7658***
B_{SDL}	Schedule delay late [h]	-1.2355***
B_{TT}	Travel time [min]	-0.0264***
$B_{\text{CRWD,HIGH}}$	High crowding (ref. low)	-0.3326*
B_{OFFPEAK}	Off-peak arrival (ref. peak)	-0.3946***
Alternative-specific constants		
ASC_2	Alt 2 (PT larger shift)	0.3309**
ASC_3	Alt 3 (Car)	-0.9841***
Model fit		
Final log-likelihood		-941.546
AIC		1901.091
BIC		1929.828
ρ^2		0.143
$\bar{\rho}^2$		0.135

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$