Time-of-Day Pricing on Swiss Rail

From Departure-Time Choice Modelling to MATSim Simulation

MSc Thesis

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Time-of-Day Pricing on Swiss Rail

From Departure-Time Choice Modelling to MATSim Simulation

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Preface

Although it was difficult at times, I have really loved my Master's thesis project from start to finish. I want to thank my supervisors at SBB—Antonin Danalet and Joschka Bischoff—who were open to talking to a student they didn't know and finding a topic that was interesting for all of us, and for their support and the time they devoted to me, always being reachable and open to my questions, concerns and suggestions. Special thanks to Antonin for letting me know about the Swiss Transport Research Conference; presenting my thesis there was a great experience, and in general it was a really enjoyable time. I also want to thank my TU Delft supervisors, Maarten Kroesen and Oded Cats, for the guidance, support, and independence they gave me on this project. And to those behind the scenes: I want to thank Christian for the huge amount of support he has given me throughout the whole process, always being there to encourage me and take care of me. Thank you to my course mates, who made this degree fun and enjoyable, and were always there to rant about the thesis when it was needed. Lastly, thank you to my family and friends from home—you are the absolute best, and I wouldn't be here without you.

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Summary

Since most people work, study, and operate businesses according to a shared daily schedule, their travel coincides in the same time periods, typically around 7 am and 5 pm. This produces sharp demand peaks which heavily affect the transport network. For the rail network, heavy peak passenger concentration requires operators to expand infrastructure and rolling stock, as well as increase service frequency. Consequently, significant investments are made for extra capacity that is used for only a few hours a day. For passengers, this concentration brings crowding, delays, and safety risks.

One way to manage peak demand is time-of-day pricing, which involves adjusting travel fares based on the time of day. Usually, this is done through peak surcharges, off-peak discounts, or a combination of both. Without requiring large capacity expansion investments from the operator, time-of-day pricing aims to reduce peak demand by creating a financial incentive for travellers to shift their departure time. How travellers actually respond to such pricing is difficult to predict. Additionally, its wider effects on ridership, revenue, and fairness are seldom studied alongside the peak-spreading effects. This thesis examines to what extent time-of-day pricing for rail could spread passenger demand across the day, and how it would affect the modal split, ridership, revenue, and welfare. Swiss rail is used as a case study, fitting both thematically and methodologically.

The thesis addresses the research question through a full methodological pipeline that links a behavioural choice model to a large-scale agent-based simulation. Traveller sensitivities are first estimated from the departure-time stated-preference experiment (SP4) of the 2021 Swiss Mobility and Transport Microcensus, using the subsample of morning public transport users (180 respondents, 1,076 observations). A departure-time choice model is specified as a three-alternative time-shift model in which travellers trade off cost, travel time, transfers, crowding, schedule delay early and late, and a time-of-day arrival preference. Socio-demographic and trip covariates are interacted with the key sensitivities to capture heterogeneity across the population. The estimated parameters are then integrated into the scoring function of SIMBA MOBi—SBB's agent-based model of the entire Swiss transport system—and used to simulate the departure-time and mode responses of a synthetic population of Switzerland. Four pricing scenarios are designed and simulated: a peak surcharge, an off-peak discount, a combined surcharge-and-discount, and a joint rail-and-road peak surcharge, each tested across several value levels.

The choice model shows that morning rail travellers in Switzerland have relatively high valuations of travel time (19.9 CHF/h) and of schedule delay early (24.6 CHF/h) and schedule delay late (16.9 CHF/h). They also show a distinct preference to arrive between 7:00 and 7:40 in the morning, for which they are willing to pay about 5.5 CHF. Notably, earliness is penalised more heavily than lateness (an SDL/SDE ratio below one), which is contrary to the pattern most common in the literature but consistent with several other rail studies, including one estimated on the same dataset. To continue, these sensitivities are not uniform: household size and half-fare subscription influence cost sensitivity, and study-purpose trips and socio-professional category shift schedule-delay sensitivities. Thus, different population segments respond differently to the same alternatives.

The simulation results highlight the trade-offs between the four policies, which differ mainly according to whether the instrument charges or rewards travellers. A peak surcharge is effective at reducing peak trips (up to roughly -9.7% at the highest level tested) but does so by partly diverting demand away from rail. The surcharge lowers ridership, the public transport modal share, and mean agent welfare, and results in a negative financial balance. An off-peak discount has an opposite effect, where it improves revenue, ridership, modal share, and welfare but redistributes demand by attracting additional off-peak travel rather than removing peak trips. Thus, it fails to relieve the peak demand. Adding a parallel road surcharge to a rail surcharge protects ridership and the modal split, keeping them close to baseline if the road charge exceeds the rail charge. However, it weakens the peak reduction and produces a slight reduction in welfare for the agent population. When combining a peak surcharge with an off-peak

discount, the two instruments appear to complement each other, pairing the surcharge's peak-reducing effect with the discount's ridership-attracting effects. At a 50% surcharge and 50% discount, it reduces peak trips by roughly 9% while even slightly improving ridership, revenue, modal share, and mean agent welfare. Across all scenarios, the welfare and equity effects are moderate and show no evidence of the strongly negative or unfair outcomes sometimes assumed in public debate. Where differences between socio-demographic groups occur, they are largely explained by how frequently each group uses rail rather than by the policy itself.

Beyond the results of the analysis, there are three main contributions of this work:

1. Extending the evaluation of public transport time-of-day pricing beyond peak trip reduction.
2. Estimating a departure-time choice model that captures timing preference in terms of both a discrete off-peak aversion and a continuous schedule-delay penalty, with both price and scheduling sensitivities varying across traveller and trip segments.
3. Presenting a methodological example of combining a socio-demographically heterogeneous behavioural model estimation, which provides policy-specific sensitivities, with a network-wide simulation that translates them into system outcomes.

Taken together, the results suggest that time-of-day pricing could be a useful demand-management tool for Swiss rail, provided the instrument and its design are chosen carefully, with the combined surcharge-and-discount policy offering a reasonable balance between the competing objectives among the policies considered. These findings should nonetheless be read as an indication rather than a definitive prediction. They rest on a single, not perfectly population-representative stated-preference sample, and the policies are not fully comparable given the different time windows and price levels applied. Furthermore, the simulation does not account for responses such as activity reordering and trip suppression, although these generally could work in favour of reducing peak demand. These limitations lead to clear next steps: a larger, more representative, and policy-specific dataset, a choice model that accounts for random taste heterogeneity, and a simulation model extended to capture the additional response mechanisms. Together, these would improve the realism of the modelled effects, thus informing rail policy with greater confidence.

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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 23% of all daily rail travel at Zurich's main train station occurs within only two hours of the day: 7 to 8 am and 5 to 6 pm (Figure 1.1) [37].



Figure 1.1: Hourly distribution of train passengers at Zurich main train station (regional rail, workday, 2025) [37]

This concentration has negative impacts on both passengers and operators. For passengers, overcrowding reduces comfort and can raise safety concerns [18] or lead to longer travel times and reduced reliability of train travel [35]. The experience of a commuter on the Lausanne-Bern route showcases the extent of crowding: "I have to be out before six every morning to avoid overcrowding on the train, even in first class" [42]. For operators, meeting peak demand requires large investments in infrastructure, rolling stock, and high service frequencies. This is a heavy financial burden even though this additional capacity is mainly used for a limited number of hours each day [18]. Le News [26] states that the regional network profits of SBB, the Swiss rail operator, decreased from CHF 18.3 million to CHF -5.9 million in the first half of 2024, mainly due to rolling stock maintenance costs.

An alternative to capacity expansion is to redistribute demand away from the peak through time-of-day

pricing. Time-of-day pricing can take the form of a surcharge during peak hours, a discount during off-peak hours, or a combination of both. In this way, operators can create a financial incentive for travellers to shift their departure times and spread out demand more evenly throughout the day [18, 35, 43]. Empirical evidence confirms that such methods can be effective: free early-bird tickets in Melbourne shifted more than 2,000 rail passengers out of the peak per day [8], and a large-scale peak avoidance experiment in the Netherlands reduced peak trips by 22% among participants [35].

Currently, in Switzerland, time-of-day pricing is not applied, although discounts are offered on specific long-distance trains when occupancy is expected to be low. Furthermore, a large share of passengers hold subscription-based tickets, which provide either unlimited or discounted travel [22]. Within this context, this thesis explores the potential effects of introducing time-of-day pricing on Swiss rail, by estimating passenger preferences using choice modelling and integrating these into an agent-based simulation to assess network-wide effects.

1.1. Societal relevance

Managing peak demand more effectively is in the interest of both operators and users of the rail network. Rather than expanding the supply to accommodate a peak that lasts only a few hours, better utilisation of existing capacity through peak spreading could offer a more cost-efficient alternative alongside the benefits in passenger comfort [18]. As parts of SBB's operations and infrastructure are subsidised with public funds, such efficiency could reduce future public investments needed to sustain the network.

Additionally, transport pricing interventions can be a controversial topic. Both international and Swiss studies have found that respondents often do not support time-differentiated pricing in public transport [10, 29], with some perceiving it as unjust and not aligned with government policies aiming to reduce car usage [47]. Therefore, before such a policy can be brought to the public, there needs to be evidence not on a single outcome, but on the full set of effects that jointly determine whether such a policy is both feasible and beneficial. On the demand side, this means understanding how effectively the pricing spreads travel across the day, how it affects mode choice, and how the resulting gains and losses are distributed across the population, since acceptability depends not only on the aggregate effect but on who is affected. On the operator side, it means knowing the effect it may have on ridership and the financial balance, which are decisive for a policy's viability. Assessing these effects side by side is what allows the trade-offs between them to be observed and analysed, which is essential for determining whether the policy is worth pursuing.

1.2. Problem statement and contribution

Although time-of-day pricing is widely used to manage peak demand, its full effects across the network remain difficult to anticipate. The same aggregate effect, such as a reduced peak, can be a result of retiming, changing mode, or not travelling at all. Combining a behavioural model, which provides the policy-specific sensitivities, with a network-wide simulation that translates them into system outcomes helps to capture these effects. In the few studies that have applied this approach to public transport, the focus has been on off-peak discounts and demand redistribution, leaving the comparison of pricing instruments, the resulting modal shifts, and the distributional and welfare effects across population segments largely unexamined.

This is particularly relevant for Switzerland, where such pricing changes require broader institutional approval and thus also sufficient supporting evidence, which is difficult to produce. Transferring parameters from existing studies is not recommended, since behavioural responses to pricing are highly context-dependent and shaped by local fare structures [45]. At the same time, no robust departure-time choice model with time-of-day pricing exists yet for Swiss public transport – the closest attempt, in the report on the stated preference survey 2021 as part of the Swiss Mobility and Transport Microcensus [17], yielded inconclusive results for the peak charge coefficient. SBB's simulation model SIMBA MOBi [39] provides the infrastructure for scenario evaluation but lacks the behaviourally grounded parameters for time-of-day pricing analysis. Thus, Switzerland provides both a policy-relevant and methodologically fitting setting.

This thesis will therefore provide policy-specific sensitivities that are heterogeneous across traveller seg-

ments, a methodological example of integrating choice-model estimation into an agent-based model, and a comparison of four pricing policies across demand, financial, and welfare effects.

1.3. Research aim

The aim of this thesis is to answer the central research question:

> *To what extent could time-of-day pricing on Swiss rail spread passenger demand across time, and what would its impacts be on modal split, welfare, ridership and revenue?*

This involves answering the following sub-questions:

- *How sensitive are Swiss rail travellers to time-of-day pricing and to shifts in their departure time?*
- *To what extent do these sensitivities vary across population segments?*
- *How do different forms of time-of-day pricing differ in their effects?*
- *How does the level of time-of-day pricing affect the redistribution of passenger demand?*
- *What are the wider effects on modal split, ridership, revenue, and welfare?*

The research questions are answered using a step-wise approach outlined in Figure 1.2. To estimate price and schedule sensitivities, a stated preference experiment from the Swiss Mobility and Transport Microcensus is used. A departure-time choice model is formulated and estimated, with the inclusion of socio-demographic covariates. The behavioural parameters from the choice model results are integrated into an existing agent-based model, which has the capability to simulate the Swiss population and transport system. Four pricing policy scenarios are designed and simulated in the model, providing detailed outputs. The outputs are thoroughly evaluated in terms of departure-time distribution, modal split, ridership and revenue, as well as welfare.

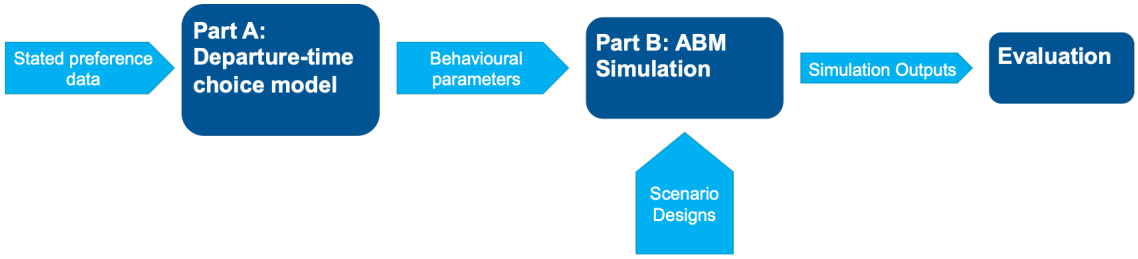


Figure 1.2: Overview of the thesis structure

1.4. Document structure

The remainder of this report is structured as follows: Chapter 2 presents the related literature, Chapter 3 describes the methodology, Chapter 4 presents the results of the choice model estimation, Chapter 5 presents the results of the simulation, and Chapter 6 provides the discussion and the conclusions.

2

Related Literature

Transport pricing interventions have been studied as a demand management instrument for both road and public transport with various applied methodologies. The following review of related literature (approach outlined in Section B.1) spans three main topics: response to time-of-day pricing, departure-time choice modelling and system-wide modelling. While each of these areas is well-developed on its own, the integration of estimated individual-level choice behaviour into network-level evaluation, especially for public transport, is limited. Finally, this chapter presents the scientific contribution of this thesis.

2.1. Response to tariff differentiation

2.1.1. Possible responses

A change in travel cost for specific times of the day can result in travellers responding in several different ways, from which changing departure time is only one. Commonly modelled short-term responses to pricing are departure-time, mode and route choice. The set can be extended further, however, both to other short-term adjustments such as trip chaining and activity scheduling, and to longer-term choices such as public transport subscription ownership, residential location and work location, which adjust over greater time horizons and affect the choices available in the short run. A review on traveller response to road pricing policies by Khademi and Timmermans [25] shows that most studies concentrate on departure-time and route choice, and, to a lesser extent, mode choice [25]. For public transport specifically, it is more common to model departure-time choice jointly with mode choice (Table B.3). Nevertheless, other dimensions exist and have also been studied, including trip frequency, destination choice, and the scheduling of activities across the day [25], however, these are distinguished and reported less frequently. For public transport pricing-response literature, the response to pricing is commonly captured through the fare elasticity of ridership, which is an aggregate demand measure [29]. It reflects the net change in demand but does not reveal which behavioural dimension produced it. Distinguishing between the responses requires disaggregate, multidimensional models, which are not always available. Even where such models are used, aggregate demand changes and modal split often remain the primary reported outcomes. While this broader selection of responses jointly determines the overall response to pricing, the redistribution of demand across the day depends most directly on the departure-time response, which is the main focus of the second part of this review.

2.1.2. Effects of pricing interventions

Research done on tariff differentiation provides several insights into the effects of pricing interventions. In general, studies show that pricing is an effective way to manage demand, whether done through peak surcharges or off-peak discounts. Beyond this, the following studies offer insights into how temporal demand shifts occur. Liu and Charles [29] provide a review of empirical evidence on spreading peak demand via differential fare policies. They find that passengers tend to shift to the nearest available cheaper time period rather than moving further away from their preferred departure time. As a

result, this can concentrate demand in shoulder periods rather than distributing it evenly throughout the day, an effect also noted by Thommen and Hintermann [43]. The reviewed studies also confirm that peak surcharges are more effective in reducing crowding than equivalent off-peak discounts, while a combination of both produces the strongest behavioural response [29]. To continue, Weesie et al. [47] find that the utility of a discount is non-linear, increasing steeply at low discount levels and flattening at higher ones, while Huber, Wallimann, and Meier [22] find that discounts of 30% or more raise the share of demand shift more than smaller discounts. Finally, Currie [8], who examines Melbourne's free pre-peak ticket policy (free train travel before 7 am), suggests that such interventions can even be revenue-neutral for operators, as reductions in necessary trains in peak hours can offset the cost of the train tickets lost. Overall, these studies indicate that pricing reliably shifts temporal demand but does so imperfectly: responses concentrate in shoulder periods rather than spreading evenly, vary non-linearly with the size of the incentive, and depend on the instrument chosen, with combined surcharge–discount schemes offering the strongest behavioural response.

2.1.3. Influencing factors

Price levels alone do not determine departure-time choice. Many travellers face constraints in their schedules due to fixed work and school timings, intra-household interactions, biological rhythms such as sleep patterns, and institutional factors such as business opening hours, all of which limit individual schedule flexibility [43, 18]. Traveller aversion to crowding can also play a role, as high passenger densities reduce comfort and perceived safety [18]. Crowding aversion has been modelled either as a stand-alone penalty or by interacting it with in-vehicle time, so that the disutility scales with exposure, for example, Whelan and Johnson [49], who express overcrowding penalties per minute of in-vehicle time. One variable shown to have significant influence in previous studies is trip purpose. For instance, business travellers are more likely to select unrestricted alternatives and show lower tolerance for schedule shifts, while leisure and shopping travellers have more flexibility [47, 5]. To continue, some studies estimate departure-time preferences separately for outbound and return trips or morning and evening trips, as behaviour is shown to be different between the two segments [50]. Peer, Knockaert, and Verhoef [35] specify schedule delay separately for the morning and evening commute and find that earliness is penalised more highly in the morning. Additionally, travellers to and from education are found to be more sensitive to late departure than early departure [9]. In addition to these, a range of socio-demographic and trip characteristics have been found to influence departure-time choice, including age [46, 23], weekday [35], employer travel cost compensation [5], education level [23], commute distance [8], income [45, 9] and ticket subscription type [47]. For example, season ticket holders show almost no significant shift towards off-peak travel [47] and employer travel cost compensation significantly reduces traveller price sensitivity [5]. In combination, these findings show that departure-time choice is not only influenced by price but also highly depends on the constraints and characteristics of a person, such as schedule rigidity, trip purpose, journey direction, and a large set of socio-demographic factors. This implies that any attempt to model pricing effects must account for this heterogeneity to capture behaviour realistically.

2.2. Modelling departure-time choice

2.2.1. Discrete choice models

Discrete choice models are commonly used in transport economics and travel behaviour research to model individual decision-making. They allow deriving behavioural parameters, such as sensitivity to cost, and valuations, such as the value of travel time, directly from both revealed and stated choice data [4]. Discrete choice models are based on Random Utility Maximisation (RUM) theory and represent travellers' trade-offs between alternatives by assuming that a decision-maker n chooses the alternative i that maximises utility U:

$$U_{in} = V_{in} + \epsilon_{in},$$

where V_{in} captures observable attributes such as travel time and cost, and ϵ_{in} represents unobserved factors [4].

2.2.2. Schedule delay

When preferred departure or arrival times are available, a key term to use in the choice model utility function is schedule delay. The concept means that travellers have disutility when departing earlier or later than their preferred time, captured by the schedule delay early (SDE) and schedule delay late (SDL) terms. By introducing these in the utility function, the schedule delay is traded off against other terms, such as crowding, cost, travel time, etc. This allows to gain insights into how flexible travellers are in their departure-time choice.

Drawing from results of reviewed studies, schedule delay penalties prove to be asymmetric. This means that earliness has a different magnitude of disutility than lateness, although their relative proportions vary greatly across studies. A common parameter value relationship is |SDL| > |SDE|, meaning lateness is penalised more than earliness, however, this is case-dependent. For example, Vrtic et al. [46] finds that the absolute parameter value for late departure is approximately twice that of the early departure, matching the conventional order. However, Peer, Knockaert, and Verhoef [35] find the opposite, with a stronger penalty for departing earlier than later. This asymmetry motivates estimating separate SDE and SDL parameters rather than a single combined penalty. Furthermore, since the magnitude and direction of the asymmetry are context-dependent, the parameters are best estimated for the specific population under study rather than transferred from other contexts.

2.2.3. Time-period model vs Time-shift model

A key modelling decision in departure-time choice is the choice between a time-period model, where alternatives represent fixed time slots (e.g. 8:00-8:30; 8:30-9:00 etc.), and a shift model, where alternatives are defined relative to a respondent's reference departure-time and the deviation from it (e.g. ref. time; +30min; -30min). The choice is mainly based on the type of data available. Hess et al. [20] suggest that time-shift models may have more behavioural grounding, but require individual preferred arrival or departure-time data, which is often unavailable in large-scale forecasting applications. They also state that moving from a shift model to a time-period model in such contexts almost inevitably means a loss in model performance and forecasting accuracy [20]. Similarly, Fox et al. [16] state that schedule delay is best used when there is data available on the preferred arrival or departure time. Thus, a shift model is fitting when preferred arrival or departure times are available both in the estimation data and in any further models the parameters feed into.

2.2.4. Model specification

The Multinomial Logit (MNL) is the simplest and most widely used choice model specification. However, the MNL has the Independence of Irrelevant Alternatives (IIA) property. The property can be problematic for departure-time choice modelling where adjacent time slots are behaviourally more similar than distant ones, which could lead to unrealistic substitution patterns [3]. More advanced specifications such as Nested Logit, Error Components Logit, and Cross-Nested Logit relax this constraint through using correlation structures across alternatives [3, 27]. Alternatively, Ordered Generalised Extreme Value (OGEV) specification allows for correlation between adjacent alternatives, fitting well if alternatives are in the form of sequential time periods [51]. Additionally, latent class extensions allow estimating separate parameter values for population subgroups, enabling the capture of preference heterogeneity [35]. Nevertheless, MNL remains a valid and common baseline, especially for studies where the choice set is small, or the size of the data limits the feasibility of more complex model specifications.

Across several reviewed studies (an overview can be found in Tables B.2 and B.3 in the Appendix), response to pricing policies has been modelled using the MNL specification as their baseline [47, 46, 45, 5, 23]. Some studies also extend the modelling to Nested Logit, Mixed Logit, or Error Components Logit [5, 23, 9] and Latent class MNL [35], with all advanced formulations reporting notably improved fit relative to MNL. This is consistent with the literature review of time period choice modelling performed by RAND Europe, where they find that the majority of departure-time studies use MNL, while studies modelling departure-time together with mode choice more commonly use Nested Logit formulations [16]. Both the report and the reviewed studies show that models are frequently segmented by trip purpose or work-time flexibility [23, 9], or include socio-demographic variables directly in the utility function [46, 45, 23, 9, 5] (overview in Table B.2). Additionally, for variable specification, non-linear

functional forms are found to improve model fit: Jong et al. [23] find that quadratic scheduling penalties outperform linear SDE and SDL terms, while Vrtic et al. [45] show that cost parameters react non-linearly to income and travel distance, and that travel time parameters react non-linearly to overall trip costs. Across the literature, the MNL specification, thus, serves as the standard baseline, with improvements in fit achieved through more advanced error structures, model segmentation or direct socio-demographic term inclusion, and non-linear functional forms.

2.2.5. Data sources: SP, RP and the combination

Departure-time choice models are estimated from either revealed preference (RP) data, stated preference (SP) data, or a combination of both. RP data, derived from observed travel behaviour, has the advantage of reflecting actual choices. However, it can often be limited in both attribute variation and available alternatives, since it cannot include hypothetical scenarios – such as peak pricing interventions that have not yet been implemented [48]. SP data addresses these limitations by presenting respondents with controlled hypothetical choice situations designed specifically for understanding specific trade-offs [48]. Nevertheless, the limitation for SP data is a potential hypothetical bias, which occurs because respondents may behave differently in real-life settings than what they state in a survey. Having a hybrid dataset, which is a combination of RP and SP data, can alleviate these problems – the RP reference trip anchors observations to realistic behaviour, while the SP survey allows to still explore hypothetical alternatives with experimentally controlled attribute variation [17, 48].

2.2.6. Conceptual model

Figure 2.1 presents a conceptualisation of the literature findings. Response to time-of-day pricing incentives is governed by random utility maximisation theory, where an individual evaluates the available alternatives and selects the one that provides the maximum utility. The alternatives available are on different choice dimensions, with departure-time choice being one among others such as mode choice or not travelling. Within departure-time choice, the alternatives are defined on a time-shift basis. Alternatives vary in many attributes, with the figure naming the ones relevant for departure-time choice, such as cost, travel time, and schedule delay. The choice is shaped by the characteristics specific to the traveller, which enter the model as covariates. Unlike trip attributes, these do not vary across alternatives but remain constant for a given respondent, differing only between respondents.

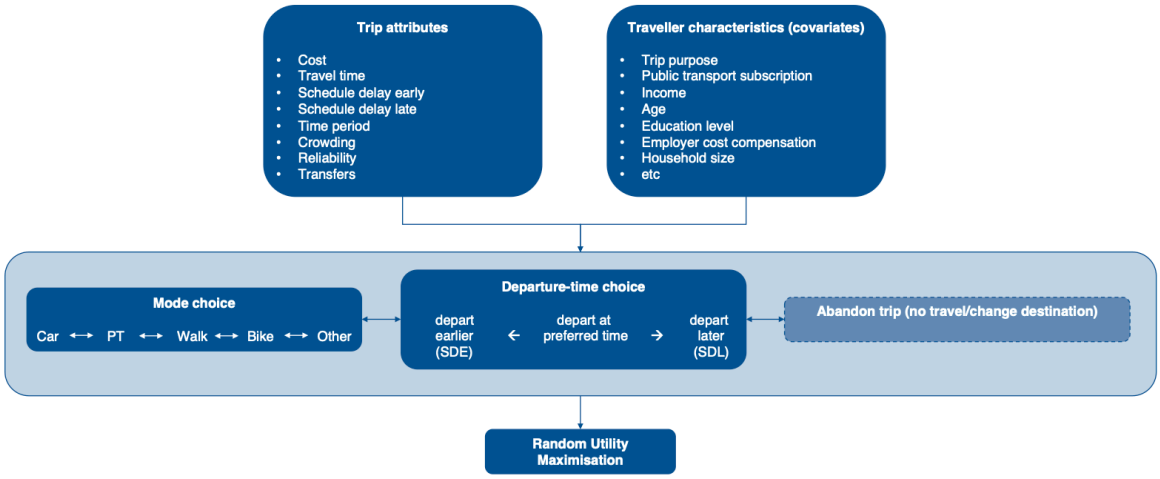


Figure 2.1: Conceptual model

2.3. System-wide modelling

A common limitation in peak pricing studies is that behavioural response is primarily analysed at the individual level without embedding in network assignment or simulation frameworks. Studies such as Berg, Kroes, and Verhoef [5], Daly et al. [9], Jong et al. [23], Vrtic et al. [45], Huber, Wallimann, and Meier

[22], and Thommen and Hintermann [43] estimate choice parameters, elasticities, and willingness-to-pay values. Although these do give insights into likely system-wide effects, these are extrapolated from individual-level responses and do not capture network dynamics such as crowding feedbacks or capacity constraints. To elaborate, demand elasticity may indicate that ridership will reduce, but it does not show where these travellers are going instead, what mode they are switching to, and if this then impacts another corridor, mode or the riders themselves. These effects are especially important for public transport policy assessment since a peak surcharge that causes a modal shift to car is a very different outcome than a departure-time shift within rail, even if the demand elasticity might be the same. Liu and Charles [29] support this, noting that elasticity estimates do not provide enough information on the demand structure and, thus, function more as preliminary estimates rather than precise predictions. Overall, while individual behavioural responses to pricing exist in the literature, system-wide effects are crucial for policy assessment and thus require integration into a network or simulation model.

2.3.1. Network-wide models

Several modelling approaches exist for evaluating system-wide impacts, the most common being aggregate four-step models as well as activity-based and agent-based simulations. Traditional four-step travel demand models treat the time-of-day distribution of trips as a fixed input determined outside the model, meaning that how individual travellers adjust their departure times in response to pricing cannot be represented within the model structure [36]. Furthermore, four-step models work with aggregate origin-destination flows rather than individual travellers, making it impossible to capture the heterogeneous responses across population groups that pricing policies are likely to produce [36].

2.3.2. Activity-based models

Activity-based models represent each individual's daily travel as a sequence of activities—such as work, shopping, and leisure—with departure times, modes, and routes determined jointly as part of a scheduling decision [6]. The idea behind this is that the demand for travel arises from the demand for activities [6]. In this context, travel gives disutility that people are only willing to accept if the net utility of the activity and travel is larger than performing an activity that requires no travel [6]. Agent-based models extend this further by simulating the interactions between individual agents and the transport network. In these models, each agent acts according to their own preferences and constraints, and the collective behaviour of all agents produces network-level outcomes such as congestion and crowding, which in turn again influence the agents and their choices.

Rather than solving for equilibrium analytically, agent-based models rely on iteration. Agents modify their plans across simulated days, evaluating and maximising daily scores. The simulation is complete once the total of all agent scores is no longer increasing. The evaluation of daily plans is done using the scoring function, which gives the net of the travel disutility and activity utility for each agent across the day. In the scoring function, parameters determine the different sensitivities agents have and, thus, how each agent's plans are scored. The parameters can have various sources, such as taken from generic parameter presets [31] or estimated from discrete choice models [21, 33]. A widely used open-source agent-based simulation platform is MATSim. It uses an iterative co-evolutionary framework in which agents adjust their activity plans - including departure times, routes, and modes - until a stable equilibrium is reached [2, 33, 38]. It provides a suitable framework for studying transport pricing, allowing to incorporate behavioural responses at the individual level as well as accounting for interactions within the network.

2.3.3. Policy evaluation using agent-based simulation

Several agent-based and activity-based models have been applied to simulate the effects of transport pricing policies, illustrating both the capabilities of the approach and the types of outcomes that can be obtained. Meyer de Freitas, Schuemperlin, and Balać [32] apply MATSim to a cordon pricing scheme for Zurich, varying toll levels to obtain a desired level of traffic reduction and analysing distributional outcomes. The study illustrates how the framework can effectively identify both traffic effects as well as support welfare analysis. Müller et al. [33] embed terms with behavioural sensitivity parameters in the MATSim utility function from a latent class mode choice model. This shows that class-specific parameters can be used to represent preference heterogeneity within the simulation.

In terms of public transport pricing policy simulations, Lovrić et al. [30] apply the SimMobility activity-based simulation platform with calibrated parameters from observed data to evaluate Singapore's free pre-peak travel policy and explore off-peak discount effects. They find that peak ridership was reduced while public transport trips overall increased, suggesting that an off-peak price reduction strategy can help manage demand without reducing public transport total ridership. Furthering their work, Adnan et al. [1] use the same model to demonstrate the capabilities of agent-based modelling by simulating multiple off-peak discount pricing scenarios and analysing them in terms of revenue, ridership and modal split. Their implementation involves reducing the price attribute value in the time-of-day choice model before the traffic simulation, which limits the response to departure-time shift. Mode change is then approximated by a calibration factor from observed data. Lastly, Kaddoura et al. [24] test public transport fares in a MATSim-based simulation on a synthetic corridor, optimising the general fare level.

A review of pricing simulation studies is shown in Table 2.1 (a larger overview including methodological papers can be found in Table B.5). The table highlights that the main aspects analysed in the studies are changes in demand, modal split and revenue, with some welfare and distributional equity analysis done in road cordon pricing but not for rail time-of-day pricing. Among the PT pricing studies, only Kaddoura et al. [24] consider welfare, however, they optimise a general fare level rather than simulating time-of-day pricing, and they treat aggregate welfare as an optimisation objective rather than a distributional outcome to be analysed.

Table 2.1: Overview of reviewed pricing policy simulation studies

Title	Model	Objective	Metrics	Welfare / equity
Public transport pricing				
Modelling the impact of alternative fare structures on train overcrowding [49]	Fare/demand model (not agent-based), rail	Effect of peak surcharges and off-peak discounts on train overcrowding	Peak load factor, ticket-type demand, operator revenue	No
Evaluating off-peak pricing strategies in public transportation with an activity-based approach [30]	SimMobility, all modes	Evaluate free pre-peak travel and off-peak discounts	Peak/off-peak ridership, PT mode share, PT trips, average fare, operator revenue	No
Agent-based microsimulation of a passenger rail system using customer survey data and an activity-based approach [31]	MATSim, rail operator	Predict impact of fare pricing strategies on peak rail demand	Peak arrival/departure volumes, correlation with passenger counts	No
Examining impacts of time-based pricing strategies in public transportation: a study of Singapore [1]	SimMobility, all modes (PT focus)	Evaluate nine time-based pricing strategies (free pre-peak MRT and off-peak discounts)	Peak/off-peak PT ridership, PT mode share, operator revenue, denied boardings, PT trips; by income, person type, gender	No
Agent-based optimisation of public transport supply and pricing [24]	MATSim, synthetic corridor (car, bus)	Joint optimisation of PT fare and headway; effect of departure-time adaptation	Operator profit, bus mode share, waiting time, optimal fare/headway	Social welfare (optim. objective)
Road / cordon pricing				
Road pricing: an analysis of equity effects with MATSim [32]	MATSim, Zurich (car, PT)	Equity effects of a cordon peak-hour toll	Cordon crossings, VKT, mode share, agent score change by income group	Yes
A validated multi-agent simulation test bed to evaluate congestion pricing policies by time-of-day in New York City [19]	MATSim-NYC (car, PT)	Evaluate cordon congestion pricing by population segment and time of day	Car trip reduction, consumer surplus by segment, share negatively affected, departure-time distribution, revenue	Yes

Together, these studies demonstrate the capabilities of agent-based models for transport policy analysis. However, the application of such models to public transport time-of-day pricing remains limited, particularly in terms of the pricing policies considered (predominantly off-peak discounts), the analysis of distributional equity, and the representation of socio-demographic heterogeneity in behavioural sensitivities. The most closely related work is that of Zhao et al. [52], published during the course of this research, which combines a stated-preference departure-time choice model with an agent-based simulation framework to evaluate public transport pricing. However, it focuses on variations in off-peak discount cut-off times for a single pricing instrument, rather than comparing alternative pricing strategies or examining their broader behavioural and welfare implications.

2.3.4. Conceptual model

The conceptualisation derived from the literature is depicted in Figure 2.2. The figure comprises two main steps: initialisation and network simulation. The initialisation step represents the information provided to the simulation, including both network and traveller inputs. The second step represents the simulation process, in which agents iteratively execute their daily plans until convergence is reached. Importantly, this iterative process accounts for both plan execution and plan scoring, thereby incorporating agents' preferences into their subsequent choices. Finally, the simulation produces a variety of network-level effects, providing information at both agent and system level.

The policy intervention directly affects the network inputs by defining the costs. However, the extent to which these costs affect individual agents and their trips depends on choices made within the simulation, such as departure time, mode, and route, which then contribute to the score achieved in the scoring function. Consequently, the effects of the intervention can vary across iterations as agents adapt their plans.

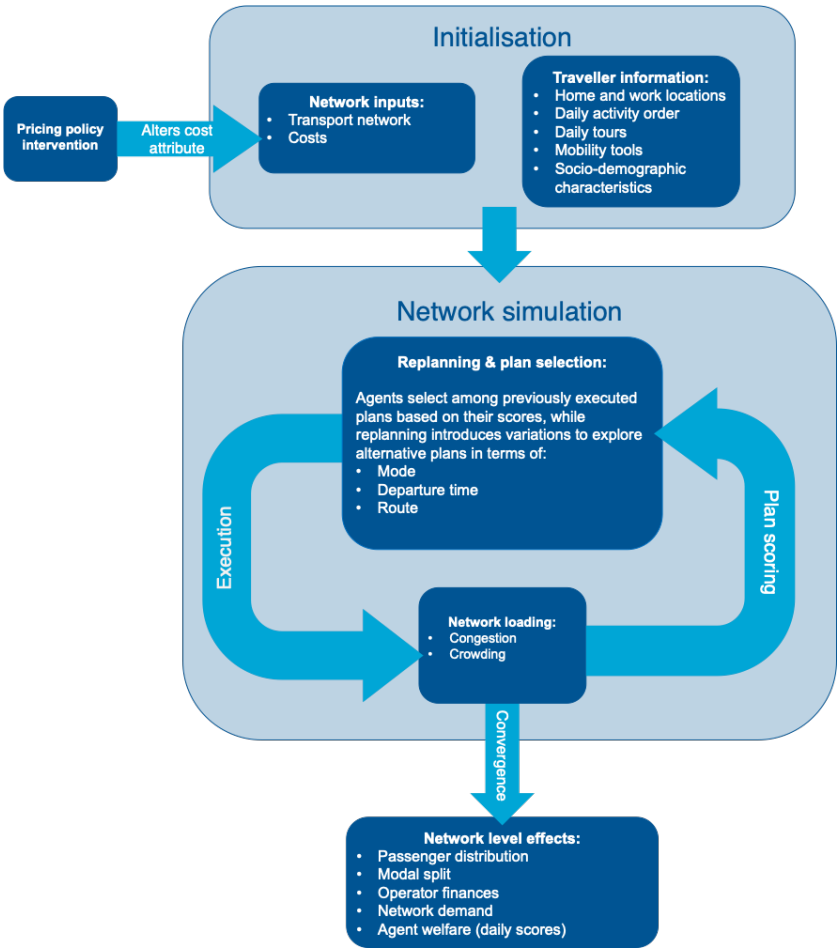


Figure 2.2: Simulation conceptual model

Across the literature, the implemented simulation models can differ in multiple ways, with the structure depicted in Figure 2.2 reflecting the approach used in MATSim. In this example, mode, departure time, and route are changed within an iterative simulation loop while other dimensions are held as fixed inputs. Simulation models, however, can differ in which choices are endogenous, with some also including trip generation, suppression, or activity sequencing in the simulation loop. Models may also differ otherwise, for example, in how plans are generated and evaluated and how network feedback is incorporated.

2.4. Contribution

Evaluating time-of-day pricing solely by its effect on peak demand is insufficient: an equal reduction in peak demand can arise from travellers retiming within public transport or from switching to the car. These are completely different outcomes for a policy intended to manage rather than drive away rail demand. Distinguishing between these responses, and assessing their welfare implications across population groups, requires a multimodal network simulation that represents departure-time, mode, and route choice while incorporating behavioural parameters specific to the policy under evaluation. As the preceding review shows, existing agent-based applications to public transport time-of-day pricing address these aspects only partially. Most focus on off-peak discount policies and analyse a relatively limited set of outcomes, with less attention given to distributional impacts and socio-demographic differences in behavioural response.

Building on this body of work, this thesis makes contributions at four levels. At the choice modelling level, previous estimations on the same SP4 data concluded that significant socio-demographic interaction coefficients were difficult, if not impossible, to obtain [17]. This thesis instead extends the departure-time choice model with segment-specific cost and scheduling interactions, capturing heterogeneity in behavioural response. At the methodological level, the thesis provides an example of integrating an estimated departure-time choice model, together with this heterogeneity, into an activity-based simulation, demonstrating the applicability of agent-based models to public transport policy analysis. At the evaluation level, the framework is used to compare alternative pricing strategies, including how the addition of a road charge alters the outcomes of rail-only pricing. The evaluation also extends beyond the departure-time shifts and peak reduction that prior studies focus on by also analysing operator revenue, the split of demand response between retiming within public transport and switching mode, as well as distributional equity across socio-demographic groups. Finally, the thesis contributes to literature in terms of the effects and trade-offs identified in this thesis for time-of-day public transport pricing policies.

3

Methodology

3.1. Dataset

The Mobility and Transport Microcensus (MTMC) is Switzerland's national travel survey, conducted every five years by the Federal Statistical Office (FSO) and the Federal Office for Spatial Development (ARE). It is a survey in which respondents report all trips and activities performed on a reference day. As part of the Microcensus, a linked stated preference (SP) survey is conducted, given to a subsample of respondents who agree to participate. For each respondent, a personalised questionnaire was generated based on one of their own trips reported in the MTMC, in order to increase the realism of the hypothetical choice situations [48]. Along with trip data, the survey records a set of individual and household attributes such as age, employment status, education level, household size, income, mobility tool availability (vehicle ownership, season ticket type) and more.

The most recent available survey (2021) was carried out between April and December 2021 and is the first time a departure-time choice experiment was conducted [17]. The 2021 SP survey contains four choice experiments in total: SP1 (mode choice), SP2 (car route choice), SP3 (PT route choice), and SP4 (departure-time choice), with SP4 being the one used in this thesis. The report provided by the Federal Office for Spatial Development [17] also included choice model estimation on the SP4 data. In that estimation, however, different variable definitions were used, socio-demographic covariates and a separate time-of-day period term were not included, and morning and evening travellers were combined. Additionally, most models were also estimated jointly across car and public-transport users and specified as combined time-and-mode choice models. This study includes the same shift-based structure for departure-time choice, including schedule delay variables, but applies it to a narrower, policy-relevant sample with a more in-depth specification. The data is filtered to morning travellers. This is done in order to prevent the return leg trips, which may have different sensitivities, indicated by studies such as the one by Peer, Knockaert, and Verhoef [35], from impacting the estimates. Furthermore, the data is also filtered for public-transport travellers, since they are the target group of the policy. Lastly, the socio-demographic covariates explore the sensitivities for various population segments, which was not carried out in the official report. In short, this study builds on the earlier SP4 analysis by retaining its shift-based structure and dataset, while re-estimating the model on morning public-transport travellers, and including a time-of-day period variable and a set of socio-demographic covariates.

The dataset is well suited for the research objective, as it provides departure-time choice data under peak pricing for a sample of Swiss travellers. Because Switzerland does not currently apply peak/off-peak timing-based pricing, a stated preference experiment is one of the few available means of gaining insight into the behavioural response to such a policy. The dataset also contains extensive socio-demographic information on each respondent, allowing the role of socio-demographics in choice behaviour to be tested. Therefore, by using this data, the first two research sub-questions can be addressed directly. In addition, the experiment is pivoted around each respondent's own reference situation, which increases the realism and credibility of the choice tasks presented to them. Finally, the data were collected at a national level, which supports the representativeness of the results. The following

section outlines the design of the dataset, after which the specific sample used in this study is analysed.

3.1.1. The SP4 departure-time experiment

The Departure-Time Stated Preference Survey was presented to respondents who had travelled during the weekday around the morning or evening peak, whose reference trip mode was car or public transport with an urban origin and/or destination. Each respondent completed six choice tasks constructed based on their reference trip, which means that the data has a panel structure. After data quality exclusions, the full SP4 sample contains 860 respondents and 5,160 observations; the PT subsample of morning travellers used in this thesis contains 180 respondents and 1,076 observations. Each respondent was given three alternatives - their current mode at approximately their reference departure time, their current mode at an earlier or later departure time, and an alternative mode at the reference departure time. An example of a choice situation is given in (Table 3.1).

Table 3.1: Example stated preference choice task

Attribute	**Alt 1 – PT (reference time)**	**Alt 2 – PT (time shift, same mode)**	**Alt 3 – Car (reference time, mode switch)**
Departure	08:15	07:30	08:15
Base ticket/fuel cost	CHF 12.40	CHF 12.40	CHF 6.80
Peak surcharge/toll	CHF 5.00	CHF 0.00	CHF 3.50
Travel time	42 min	42 min	28 min
Crowding	High	Low	–
Transfers	1	1	–

The attributes presented to public transport (PT) respondents are: departure time, base ticket cost, surcharge, travel time, crowding level (four ordinal categories: low, medium, high, overcrowded), and number of transfers. In the survey, base ticket cost does not vary between the two PT alternatives, since ticket prices are not changed - only a surcharge is applied. The attributes presented for the car alternative are departure time, travel time, fuel cost and surcharge.

The attribute value range and generation are presented in Table 3.2. Note that the departure time of Alternative 1 is slightly varied by $\pm$ 5 minutes to avoid learning bias, and Alternative 2 is pivoted around Alternative 1 using one of two randomly assigned shift sets (-60/-30/+30/+60 min or -45/-15/+15/+45 min). Car travel times in option C are set asymmetrically to make PT relatively more attractive, given road's larger market share [34]. Furthermore, the PT base price depends on the respondent's subscription and the route type, as well as trip distance, as it's calculated on per-km rates [34]. Similarly, the car costs are also based on a per-km rate with toll defined as a percentage of 0.128 CHF/km, which is an inflation-updated fuel cost for driving. The toll is set to be a maximum of 200% to match the road-pricing levels tested in the Zug and Geneva Swiss mobility-pricing studies [34]. Lastly, attribute levels are combined using Bayesian D-efficient factorial designs, with priors drawn from the 2015 Microcensus SP study.

Table 3.2: Attribute values used in the stated preference experiment

Attribute	**Alt 1 – PT (reference time)**	**Alt 2 – PT (larger time shift)**	**Alt 3 – Car (mode switch)**
Departure time	-5 to +5 min from reference (-5 / 0 / +5 min)	-60 to +60 min from Alt 1 (-60/-30/+30/+60 or -45/-15/+15/+45 min)	Same as Alt 1 –
Base ticket / fuel cost	CHF 0.2–64.3 (-30 / -15 / +25 / +50% of ref trip level)	Same as Alt 1 –	CHF 0.1–39.5 (-25 / +25 / +50 / +100% of ref trip level)
Additional charge	CHF 0.1–59.8 (50 / 100 / 150 / 200% of 0.20 CHF/km)	CHF 0.00 –	CHF 0.0–39.5 (50 / 100 / 150 / 200% of 0.12 CHF/km)
Travel time	7–204 min (-25 / 0 / +15 / +25% of ref trip level)	Same as Alt 1 –	5–172 min (-40 / -25 / +25 / +40% of ref trip level)
Crowding	Levels 2–4 (reference trip level)	Levels 1–3 (-2 / -1 from ref trip level)	– –
Transfers	0–5 (-1 / 0 / +1 from ref trip level)	0–5 (-1 / 0 / +1 from ref trip level)	– –

Limitations of the experiment

Although the dataset is well suited for the research objective, it has four limitations that prevent the conceptual model from being fully operationalised.

First, the choice experiment does not include a *no travel* alternative. While this is common in comparable studies, it means the model cannot capture trip suppression, that is, the possibility that a change in price or service level leads to travellers abandoning the trip altogether, which is a plausible response to peak pricing. The estimated choice probabilities are therefore conditional on travelling, and the shares of departure-time shifting and mode switching may be overstated relative to a specification in which suppression is possible.

Second, of the attributes commonly used in the literature, all are available with the exception of reliability. Reliability may vary across the day, thus any effect it has on departure-time choice is absorbed into the schedule-delay and time-of-day parameters rather than identified separately. Given the relatively uniform service reliability of the Swiss rail network, this effect is expected to be limited, which is also a likely reason for its exclusion from the experimental design.

Third, the set of available covariates is broad and exceeds most comparable studies. Nevertheless, it does not contain employer cost compensation. This variable was found to be highly significant in the study done by Berg, Kroes, and Verhoef [5], with travellers whose costs are reimbursed being substantially less price sensitive than those paying their own fare. Since both compensated and non-compensated travellers are considered together in this dataset, it is likely that the estimated price sensitivity is lower in comparison to only self-paying travellers.

Finally, the dataset contains no measure of how travellers perceive time-of-day pricing. A subjective rating, for example, could have helped to control for a potential bias where respondents may have expressed stronger resistance to pricing out of opposition to its implementation rather than to its effect on their travel behaviour. This may have resulted in responses that show more rigid behaviour (stronger schedule delay sensitivities) or lower cost sensitivity.

The exact resulting effects of these data limitations are not fully known. However, the omission of an employer cost compensation and pricing opinion covariate could both result in more rigid and less price-sensitive behaviour, which needs to be acknowledged upon the interpretation of the results.

Covid-19 pandemic effects

In addition to experimental design limitations, since the data was collected in 2021, effects of the Covid-19 pandemic are also possible. For the mode and route choice experiments (SP1–SP3) in the SP report, direct effects were assessed using an indicator of pandemic intensity, incorporated as an interaction variable within the joint SP–RP models [17]. The most significant indicator was the number of weekly hospitalisations in the respondent's canton of residence, which was interacted with the public transport value of travel time, the crowding and transfer coefficients, and the mode-specific constants for public transport and cycling. The estimated effects were weak and significant only for specific trip purposes. The analysis concluded that attribute perceptions were not strongly affected in 2021, however, since there was no Covid-free reference week in 2021, there may have been a masked effect [17]. For the departure-time experiment (SP4), no similar analysis was performed, likely because departure-time choice is expected to be less sensitive to pandemic conditions than mode choice, and because no SP–RP model was estimated. Additionally, since the experiment is based on hypothetical choice rather than observed choices under existing conditions, the direct effect on the estimated parameters is expected to be limited. Nevertheless, the experiment is rooted in performed trips, and the unknown effects of the pandemic should be acknowledged as a limitation of the data used in this thesis.

3.1.2. Descriptive statistics of the subsample

After quality exclusions, there are 860 respondents in the SP4 (departure-time experiment) dataset and 5160 observations. In the public transport morning travel subset - respondents whose reference trip was done by public transport and the choice task is between 5:00 and 12:00 - there are 180 respondents and 1076 observations. Each respondent has exactly 6 choice tasks except one who has 2 (due to timing exclusions).

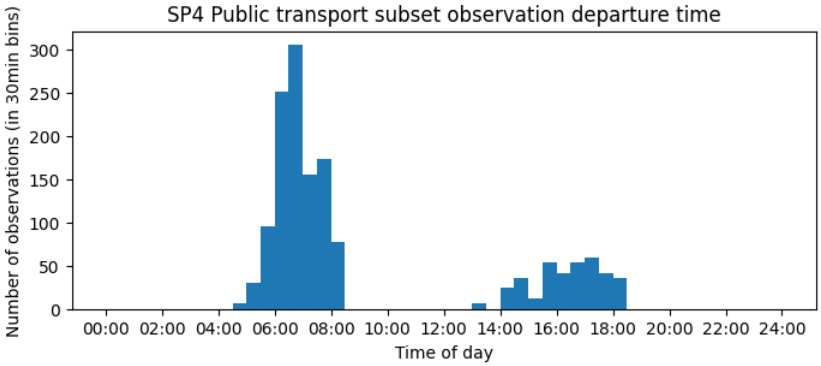


Figure 3.1: Departure times of the SP4 PT subset observations

Choice task attribute statistics

Table 3.3 summarises the statistics for the choice task attributes at the observation level. The car alternative was presented only to respondents who had access to a car. The share of respondents who had this alternative is shown in the table as well.

Table 3.3: Choice task attribute statistics (observation level, $n = 1{,}076$)

Variable	Description	Mean	Std	Min	Median	Max
PT Alternative A (apprx. ref. time)						
Departure time (min)		433.92	44.65	304.80	430.20	535.20
Ticket Cost (CHF)		7.63	8.15	0.20	4.95	64.30
Peak surcharge (CHF)		7.94	9.58	0.10	4.30	59.80
Transfers		1.12	1.06	0.00	1.00	5.00
Crowding level	1–4 ordinal	2.97	0.93	2.00	3.00	4.00
Travel time (min)		47.64	33.81	7.00	37.00	204.00
PT Alternative B (time shift)						
Departure time (min)		434.02	59.54	270.00	435.00	589.80
Ticket Cost (CHF)		7.63	8.15	0.20	4.95	64.30
Peak surcharge (CHF)	Always 0			0.000		
Transfers		1.14	1.06	0.00	1.00	5.00
Crowding level	1–4 ordinal	1.69	0.80	1.00	1.00	3.00
Travel time (min)		47.64	33.81	7.00	37.00	204.00
Car Alternative C (apprx. ref. time - mode switch)						
Departure time (min)		349.46	174.74	0.00	415.20	529.80
Fuel cost (CHF)		4.53	6.16	0.00	2.10	39.50
Toll/surcharge (CHF)		4.17	6.08	0.00	1.80	39.50
Travel time (min)		29.64	30.03	0.00	21.00	172.00
Available	Share			80.9%		

Figure 3.2 shows how often each alternative was chosen. The choices made by SP4 subset participants reflect a willingness to shift departure time. In the subset, in 44.1% of choice tasks the respondent chose the time-shifting alternative, with only 19.9% of choices being made for the alternative mode option.

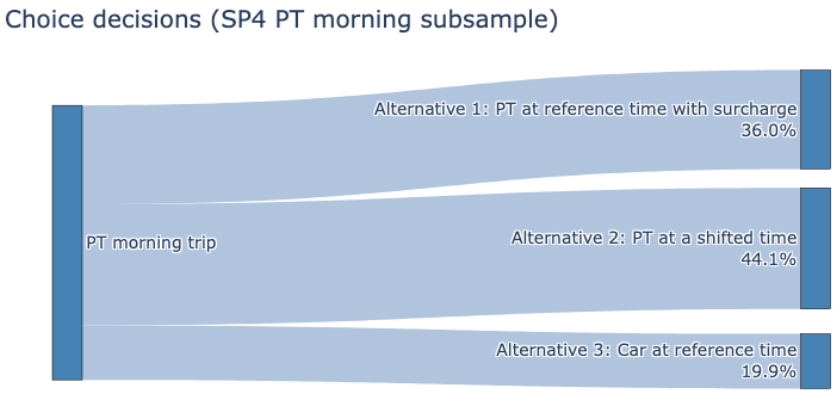


Figure 3.2: Choice decisions

Socio-demographic characteristics

Tables 3.4 to 3.7 present the socio-demographic characteristics of the sample at the respondent level ($n = 180$), alongside the corresponding statistics for the Swiss permanent resident population in 2021. Since there is no available benchmark for morning PT traveller socio-demographics, a direct comparison with this population segment is not possible.

The sample is used for the choice model estimation, and some of the resulting parameters are subsequently applied to a synthetic population representing all Swiss travellers. The comparison therefore serves two purposes: to break down the composition of the sample, thus providing insights into how the sample composition may affect the estimated sensitivities; and to assess how well these sensitivities can be transferred to the simulation.

Since the sample consists of morning public transport travellers, a close correspondence with the general population is not expected, with some deviations being likely, such as in PT subscription ownership, due to the recruitment of the experiment. What matters is that each characteristic is sufficiently represented for its effect to be estimated and accounted for, and that deviations can have a plausible explanation. As the policies explored in this thesis target rail morning peak travellers, adequate representation of this group is the most important requirement.

Table 3.4: Personal characteristics

Variable	**Unit**	**Mean**	**Std**	**CH 2021 mean**
Age	Years (Continuous)	40.5	14.5	42.2
Variable	**Category**	**Count**	**Share**	**CH 2021 share**
Gender	Female	97	53.9%	50.4%
Education level	No answer	1	0.6%	–
	Primary (1)	13	7.2%	17.9%
	Secondary (2)	53	29.4%	41.9%
	Post-secondary (3)	24	13.3%	17.5%
	Tertiary (4)	89	49.4%	22.7%
Language region	German	132	73.3%	70.8%
	French	44	24.4%	24.8%
	Italian	4	2.2%	4.2%
CSP category	Employee (3)	115	63.9%	–
	Management/Director (4)	41	22.8%	–
	Other (0,1,2)	24	13.3%	–

Note: CH 2021 values are for the permanent resident population of 2021 [14]. Education is the 15+ completed-education distribution, excluding those still in education; Language shares are of the total population; Romansh (0.2%) has no sample category. CSP categories: 0 - not active; 1 - independent; 2 - apprentice/training.

In terms of personal characteristics, the sample mean age is almost two years younger than that of the Swiss population and females are over-represented by 3.5%. The sample is also in general more highly educated since it has more than double the share of tertiary degree holders. In regard to language regions, the proportions are relatively similar, with a slight oversampling of German and undersampling of Italian. For the career role category, an equivalent population statistic was not found. The shares of the sample indicate a relatively high share of higher-level-positioned respondents, as most of the sample (86.7%) fall in the employee or management categories.

Table 3.5 shows that the average household size is comparable to the population mean, while the household monthly income is more than 2000 CHF per month higher, indicating a much wealthier sample in comparison to the population. This aligns with the shares found for the career role categories.

Table 3.5: Household characteristics

Variable	**Unit**	**Mean**	**Std**	**CH 2021**
Household size	Nr of people (Continuous)	2.82	1.25	2.90
Monthly income	Ordinal (1–9)	5.39 (apprx CHF 9800)	2.81	CHF 7052
Variable	**Category**	**Count**	**Share**	**CH 2021**
Urban level	Urban	142	78.9%	65.0%
	Suburban	24	13.3%	21.3%
	Rural	14	7.8%	13.8%
Region	Région lémanique	37	20.6%	–
	Espace Mittelland	37	20.6%	–
	Nordwestschweiz	28	15.6%	–
	Zürich	37	20.6%	–
	Ostschweiz	25	13.9%	–
	Zentralschweiz	15	8.3%	–
	Ticino	1	0.6%	–

Note: CH 2021 values are for the permanent resident population of 2021 [14].

The sample generally aligns with the urban typology, having a much larger share of urban persons versus suburban or rural. Nevertheless, the urban sample is slightly oversampled and intermediate and rural undersampled, yet this is likely a result of the recruitment since for SP4 the trip required to have either an urban origin or destination.

Table 3.6 shows the mobility tools and subscriptions for the sample as well as the Swiss population. In general, a large share of the sample possesses a driving license and owns a car, with shares matching the population values well. However, the sample contains surprisingly few bicycle owners - approximately 30% of the sample - while the population shares are around double that, at the same time oversampling e-bike owners.

Table 3.6: Mobility tools and subscriptions

Variable	**Count**	**Share**	**CH 2021**
Driving licence	151	83.9%	83%
Car ownership	145	80.6%	78%
E-bike	49	27.2%	20%
Bicycle	59	32.8%	61%
Any PT subscription	166	92.2%	53%
GA subscription	64	35.6%	9%
Half-fare subscription	64	35.6%	35%
Regional travelcard	50	27.8%	11%
Modular travelcard	12	6.7%	–
Seven25 travelcard	0	0.0%	–

Note: CH 2021 from the Mikrozensus Mobilität und Verkehr 2021 [15]. Driving licence and PT subscriptions refer to persons aged 16+/18+; car, bicycle and e-bike are household ownership.

The travel subscription ownership is high in the sample, with approximately 92% of respondents having some kind of subscription. The most popular subscriptions are the Half-fare travel card (“Demi-tarif”)

which provides a 50% discount on most tickets and the Unlimited travel card (“General Abonnement”) which allows travel without extra cost on all public transport. About 28% of the sample hold a regional travel card (“Communautaire”) for unlimited travel within a region. Meanwhile, the set route travel card (“Parcours”) and Seven25 (free travel at night) travel card are significantly less prevalent in this dataset.

Compared to the population shares, the any PT subscription ownership greatly exceeds the 53% of the population. While the Half-fare subscription is accurately represented, the sample highly oversamples the GA subscription and undersamples the Regional travel card. One reason could be due to the higher income of the sample. The GA is the most extensive of the available subscriptions, but also the most expensive, and could be more prevalent in the higher income households. Additionally, since the subsample is of people who have done a trip by rail, it has a bias towards rail users, where the presence of the highest coverage subscription might be higher.

Table 3.7: Trip characteristics

Variable	**Unit**	**Mean**	**Std**
PT distance	km	32.22	33.08
Car distance	km	30.78	32.90
Total PT time	min	55.01	32.49
In-vehicle PT time	min	40.61	31.09
PT headway	min	20.73	19.46
Variable	**Category**	**Count**	**Share**
Trip could be done by walking	Yes	28	15.6%
Trip purpose	Work	138	76.7%
	Study	22	12.2%
	Leisure	10	5.6%
	Other	10	5.6%
Distance class	$<$10 km	59	32.8%
	10–30 km	50	27.8%
	$>$30 km	71	39.4%
Main PT mode	Bus	48	26.7%
	Tram	9	5.0%
	Local train	78	43.3%
	Intercity train	43	23.9%
	Regional express	2	1.1%
Destination type	Urban	170	94.4%
	Suburban	6	3.3%
	Rural	4	2.2%
Origin type	Urban	140	77.8%
	Suburban	24	13.3%
	Rural	16	8.9%

Lastly, in Table 3.7 it can be seen that the trips of the sample are on average quite long in terms of time, with the mean total PT time being 55 minutes. However, the standard deviations for all of the distance and time variables are notable, implying that the spread is large, spanning both very short and very long trips.

It is also important to note that the sample is mainly composed of work-purpose trips. This is likely due to the experiment filtering respondents for peak time trips with destination or origin urban. The sample also has a large share of train use, and the trips mainly have the destination urban.

Overall, the sample deviates from the Swiss population most notably in having higher income, higher education level, greater public transport subscription ownership, a larger share of urban and suburban residents, and lower bicycle ownership, while corresponding relatively closely on the remaining characteristics. To continue, the reference trips are predominantly for work purposes, relatively long, with a high share of rail use and urban origin and/or destination. The trip characteristics can largely be attributed to the recruitment of the experiment, and are a good fit for the target group of the policies. This is similar for the personal characteristics, with the exception of high income and education level, which may be somewhat attributed to the selected sample, but the extent is unknown and might indicate a bias.

Most characteristics show sufficient coverage and variation for their effects to be estimated. The exceptions, such as Seven25 travelcard ownership and residence in the Italian language region, are not expected to matter substantially, as they represent small shares of the population in any case.

With respect to the two purposes of this comparison stated at the beginning of this section, the choice model sensitivities may be influenced by the high income and education level. These are expected to affect the estimated sensitivities since higher available means suggest lower price sensitivity. In terms of the transfer of sensitivities to the synthetic population, the sample is sufficient although not perfectly representative, matching the population on many characteristics. Its bias towards peak public transport users is largely aligned with the intended application, since the simulation is mainly used to assess this same group.

3.2. Choice model estimation

Following the reviewed literature, the model is formulated as a shift-based departure-time choice model, also with an option to switch mode to car. In each choice task, respondents choose between three alternatives pivoted around their actual reference departure time - their current mode (PT) at approximately their reference departure time, their current mode (PT) at an earlier or later departure time, and an alternative mode (Car) at approximately their reference departure time. Since the option to *not travel* was not part of the experiment, the model also does not contain it. The attributes mentioned in the literature mainly overlap with the ones available in the dataset, except for reliability, and are, thus, included in the formulation. Overall, the choice model formulation followed a stepwise procedure outlined in the following section, with selection at each stage based on final log-likelihood, ρ^2, $\bar{\rho}^2$, AIC, and BIC.

A Multinomial Logit (MNL) specification is used. More flexible structures were considered, including a Mixed Logit to account for the panel structure of the data and a latent class model to capture distinct traveller segments. Two nested structures are also possible: one grouping the two public transport alternatives (correlation by mode), and one grouping the public transport reference alternative with the car alternative (correlation by departure time). The MNL is retained for two reasons. First, the estimated parameters are subsequently transferred to the SIMBA MOBi scoring function, which is additive in its utility components and provides no counterpart for the scale parameters of a nested specification. Retaining a structure whose parameters map directly onto the simulation therefore avoids complications in the transfer. Second, with 180 respondents and 1,076 observations, there is a limited number of parameters the sample can estimate reliably. Furthermore, observations are grouped by the respondent identifier and robust standard errors are reported. This does not capture taste heterogeneity across respondents in the way a Mixed Logit would, but it accounts for the correlation between the repeated choices of the same individual when assessing the significance of the estimates.

3.2.1. Schedule delay calculation

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.

Schedule delay is calculated relative to each respondent's preferred departure time (PDT). To obtain the PDT of respondent n, the preferred arrival time (PAT) which is reported in the SP4 introductory questionnaire, as well as the reference trip travel time, are used:

$$\mathsf{PDT}_n = \mathsf{PAT}_n - \mathsf{TravelTime}_n^{\mathsf{ref}} \tag{3.1}$$

Schedule delay early and late are then defined for each alternative i and respondent n as:

$$\mathsf{SDE}_{in} = \max\left(\mathsf{PDT}_n - \mathsf{DepTime}_{in},\ 0\right) \tag{3.2}$$

$$\mathsf{SDL}_{in} = \max\left(\mathsf{DepTime}_{in} - \mathsf{PDT}_n,\ 0\right) \tag{3.3}$$

where $\mathsf{DepTime}_{in}$ is the departure time of alternative i for respondent n. This formulation is applied for all three alternatives, including the car alternative.

3.2.2. Base model formulation

The estimation begins with the attributes provided in the choice experiment with the addition of the derived SDE and SDL. Thus, for the two PT alternatives, the explanatory variables are: base ticket cost, peak surcharge, number of transfers, four crowding levels, travel time and schedule delay early (SDE), schedule delay late (SDL). For the car alternative, the variables are: fuel cost, toll, travel time, SDE, and SDL.

Parameter consolidation

Initially, parameters are differentiated between PT and car alternatives for the attributes that are shared across all alternatives. This includes TT, SDE, and SDL. Similarly, all four monetary parameters ($\beta_{\text{cost ticket}}$, $\beta_{\text{cost surcharge}}$, $\beta_{\text{cost fuel}}$, $\beta_{\text{cost toll}}$) are estimated separately as well. A Wald test is then performed to test if parameters can be combined. A Wald test is a statistical test that assesses whether one or more estimated parameters differ significantly from each other by comparing the difference to the standard error. Parameters are then combined, where Wald tests indicate that they are not significantly different.

Crowding formulation

The base model is then refined in two additional steps. The first step is testing alternative crowding formulations for the PT alternatives. The formulations are dummy coding for each level of crowding in the data, linear, two-level (high vs. low), and without crowding. The former means that for a crowding variable with four levels, three dummy variables are created, each taking value one when the trip is at that crowding level and zero otherwise. One level is left out as the reference category, and the estimated coefficient of each dummy then measures the disutility of that crowding level relative to the reference level. The linear formulation uses a single coefficient applied to crowding treated as an ordered numerical variable. It assumes that each step up in crowding adds a constant amount of disutility, requiring fewer parameters to be estimated, but imposing equal spacing between levels. The two-level formulation collapses crowding into a single dummy distinguishing the higher levels from the lower crowding levels (several thresholds are tested). This focuses the estimation only on whether the trip is highly crowded or not rather than the specific level. The final formulation excludes the crowding entirely, testing if the variable is adding to the model fit and serving as a baseline.

An additional specification is also tested where crowding is specified multiplicatively instead of additively. The high-crowding dummy is interacted with travel time so that crowding scales the disutility of time spent travelling rather than imposing a fixed penalty per trip. This is a formulation commonly used in the rail crowding literature and also applied by Gayda et al. [17].

Time period variable addition

The second step compares alternative time-of-day representations. Schedule delay captures the disutility of deviating from the preferred schedule, however, travellers also might have a preference to depart or arrive at specific times of the day. Since the model is formulated as a time-shift model rather than a time-period model due to the structure of the dataset and the general benefits of this formulation, there is no association with the time of day. Thus, a time-specific term is tested to observe whether there are significant preferences in departure or arrival time. To do this, dummy-coding is applied to each alternative. The variable takes the value one if the alternative falls in a certain time period in a day and zero otherwise. Furthermore, both departure and arrival time are tested as the reference as well as different separations of time periods: pre-peak/peak/post-peak; off-peak/shoulder/peak; and off-peak/peak. The cut-off times of the time periods are chosen based on model fit.

3.2.3. The final base model

The best-performing formulations for both crowding and time-of-day are then used for the final base model. The corresponding utility functions are given in Equations 3.4 and 3.5:

Alternative 1 and 2 (PT):

$$\begin{aligned} V_{in}^{\text{PT}} = {} & \text{ASC}_i + \beta_{\text{cost ticket}} \cdot \text{BaseTicketCost}_{in} + \beta_{\text{cost surcharge}} \cdot \text{Surcharge}_{in} \\ & + \beta_{\text{TR}} \cdot \text{Transfers}_{in} + \beta_{\text{TT,PT}} \cdot \text{TravelTime}_{in} + \beta_{\text{CR}} \cdot \text{Crowding}_{in} \\ & + \beta_{\text{SDE,PT}} \cdot \text{SDE}_{in} + \beta_{\text{SDL,PT}} \cdot \text{SDL}_{in} + \beta_{\text{TOD}} \cdot \text{TOD}_{in} \end{aligned} \tag{3.4}$$

Alternative 3 (Car):

$$V_{in}^{\text{Car}} = \text{ASC}_3 + \beta_{\text{cost fuel}} \cdot \text{Fuel}_{in} + \beta_{\text{cost toll}} \cdot \text{Toll}_{in} + \beta_{\text{TT,Car}} \cdot \text{TravelTime}_{in} + \beta_{\text{SDE,Car}} \cdot \text{SDE}_{in} + \beta_{\text{SDL,Car}} \cdot \text{SDL}_{in} + \beta_{\text{TOD}} \cdot \text{TOD}_{in} \tag{3.5}$$

where parameters shared across alternatives are combined where supported by Wald tests; the monetary parameters $\beta_{\text{cost ticket}}$, $\beta_{\text{cost surcharge}}$, $\beta_{\text{cost fuel}}$, and $\beta_{\text{cost toll}}$ are assessed for potential consolidation into a single generic cost parameter; TOD_i is a time period dummy applied across all alternatives.

3.2.4. Model with interaction terms

Beyond the attributes of the alternatives, systematic utility can be specified in a way that captures the influences of characteristics of the decision-maker and their trip. These characteristics are added in the form of covariates rather than attributes, because they do not vary across the alternatives within a choice situation, but only between respondents. Covariates are not implemented in the utility function directly, but instead they can be implemented as interaction terms. This means a covariate is combined with an attribute so that the sensitivity of that attribute is allowed to vary across respondents according to their characteristics.

To illustrate, without covariate interaction terms, the contribution of an attribute k to the utility of alternative i is expressed as follows:

$$\beta_k \, x_{kin}, \tag{3.6}$$

where x_{kin} is the value of attribute k for alternative i and respondent n, while β_k is the taste parameter of that attribute and is the same for all respondents.

By introducing an interaction with a covariate, the contribution becomes:

$$(\beta_k + \gamma_k \, z_n) \, x_{kin}, \tag{3.7}$$

where z_n is the covariate value of respondent n, β_k is the base sensitivity to the attribute, and γ_k is the interaction parameter capturing how that sensitivity shifts with the covariate. γ_k therefore indicates whether z_n has a significant influence on the sensitivity to attribute k and also the direction and magnitude of the effects.

The best-performing base model is thus used to test personal and trip variable interactions. All relevant variables available in the dataset are tested (see Table C.3). This systematic approach is adopted because, while the literature consistently finds heterogeneity in departure-time preferences, which traveller characteristics significantly interact varies considerably across studies and datasets [9]. Therefore, there is no established set of interactions to test, and restricting the search to expected effects would risk omitting relevant heterogeneity. A similar strategy is applied by Bwambale, Choudhury, and Hess [7], who test a range of interactions between socio-demographic characteristics and the schedule delay and travel time parameters, retaining only those that are behaviourally intuitive. Gayda et al. [17] likewise carry out a broad search over candidate interactions for the SP1–SP3 models, though with a focus on the value of travel time and cost coefficients. For SP4, no interactions are estimated, as the main parameters are estimated with limited precision; heterogeneity is instead addressed through separate models by trip purpose.

Each personal and trip variable is then interacted individually with each of the parameters relevant for this thesis:

- cost sensitivity (β_{cost}),
- schedule delay early (β_{SDE}),
- schedule delay late (β_{SDL}),
- time-period dummy (β_{TOD})

The four parameters are selected because they are central to the peak pricing response by capturing the effect of the cost changes and the rescheduling behaviour for departure time. Additionally, these parameters are shown in literature to vary across population groups and trip variables, such as trip purpose, subscription type, and income (Section 2.1).

Interactions with transfers and travel time are not tested since they do not strongly contribute to the public transport time-of-day pricing mechanism. Additionally, in the case of travel time, the value is held equal for both PT alternatives in a choice situation in this dataset. Thus, it both theoretically does not impact departure-time choice within PT and practically is limited in its estimation power. Although crowding can influence departure-time choice, this interaction analysis is scoped to the parameters directly related to cost and rescheduling response, and the reviewed literature does not imply that heterogeneity based on personal and trip characteristics is expected (Section 2.1).

Once tested, the interaction variables that are individually significant ($p < 0.05$) are then combined into a single model formulation and refined in several respects. First, they are assessed for behavioural realism: interactions whose effect is against expectation or lacks a behavioural grounding are removed. The functional form of the interactions is also re-evaluated. For instance, where a linear interaction implies a behaviourally implausible effect, such as a sensitivity that grows without bound or changes sign, a piecewise-linear form is tested instead, allowing the interaction to vary over part of the covariate's range and to be held constant beyond it. Finally, because combining the interactions can cause some parameters to become insignificant or negligible, these are removed to reach the final specification.

3.3. Simulation

To assess system-wide impacts, the estimated behavioural parameters are integrated into SIMBA MOBi, the national activity-based transport model developed by SBB [39]. Following this, the model is used to simulate time-of-day pricing scenarios and evaluate their effects on departure-time distribution, modal split and other relevant metrics at the national level. The simulation set-up follows the conceptual model presented in Section 2 Figure 2.2. The cost attribute is specified before the simulation loop, which then, based on trip characteristics, is or isn't applied to agents. The plan scores reflect differences between plans that have peak or non-peak trips, as increased costs or schedule delay can reduce the scores agents obtain for their plans. Once the simulation converges, the resulting effects are read from the simulation outputs.

The simulation methodology employs some elements from the studies reviewed in Section 2.3.3. While there are several approaches to integrate the choice model results into the agent-based model, this thesis adds the behavioural parameters in the MATSim scoring function, a method used by Müller et al. [33] as well as He, Chow, and Zhang [19]. Additionally, the welfare analysis is inspired by Meyer de Freitas, Schuemperlin, and Balać [32], who evaluate the percent change in mean agent score change across population segments for a road cordon charge.

3.3.1. SIMBA MOBi model context:

SIMBA MOBi is built on the MATSim framework and simulates transport demand for the whole of Switzerland. This is achieved through creating a synthetic population of Switzerland, where each agent performs their daily activity schedule by interacting with the road and public transport network. It is a multi-modal model, has person-level precision, and simulates a weekday (average demand for Monday to Friday).

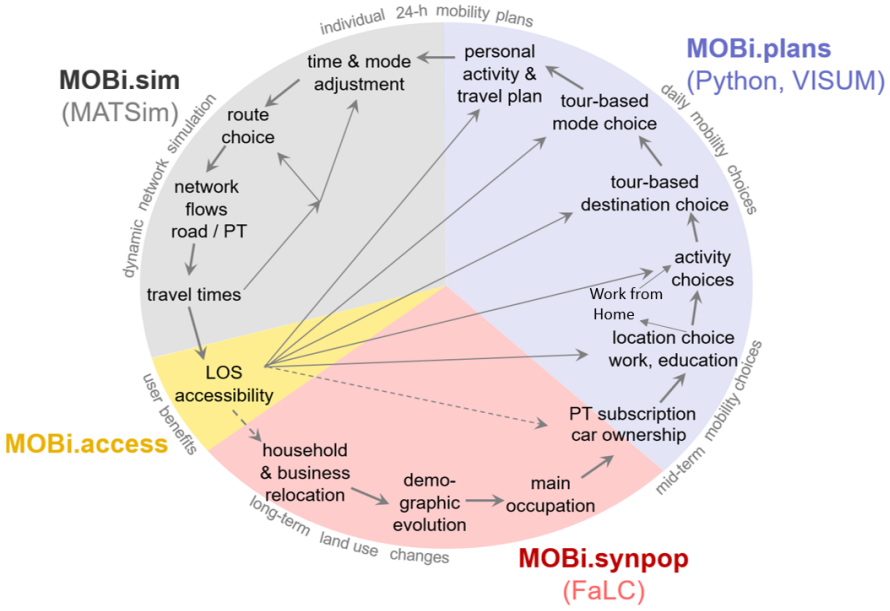


Figure 3.3: SIMBA MOBi Model Structure (Source: SBB) (All solid arrows represent automated dependencies)

SIMBA MOBi is generally structured in three parts: MOBi.synpop (and access), MOBi.plans, and MOBi.sim (Figure 3.3). MOBi.synpop and MOBi.plans can be considered as a preprocessing step for the simulation. The former focuses on generating attractions, such as business locations, as well as a synthetic population with person-specific characteristics such as vehicle ownership and travel

subscriptions. The latter focuses on generating activity information. This involves activity chains, durations, destinations and more for each agent. Finally, MOBi.sim is the MATSim simulation, where the generated agents execute their activities and, thus, traffic demand is simulated over a full workday. In this thesis, the preprocessing steps - MOBi.synpop and MOBi.plans - remain unchanged, and only the simulation step (MOBi.sim) is modified and executed.

It is important to note that departure time and mode of tours is already generated in the MOBi.plans stage. The mode is based on a mode-choice model, while departure time is based on empirical probabilities of activity start times that determine activity timing and order and, consequently, provide the departure time. However, in the simulation, agents iteratively adjust their activity plans, including departure time and mode (Figure 3.4). An iteration involves the execution of agents' plans across the simulated day, scoring the day based on a scoring function and modifying some agents' plans, after which the cycle is performed again. The plans with a higher score from the scoring calculation are more likely to be selected. The iterations are repeated until the total score of all agents stabilises across iterations, after which the simulation is concluded.

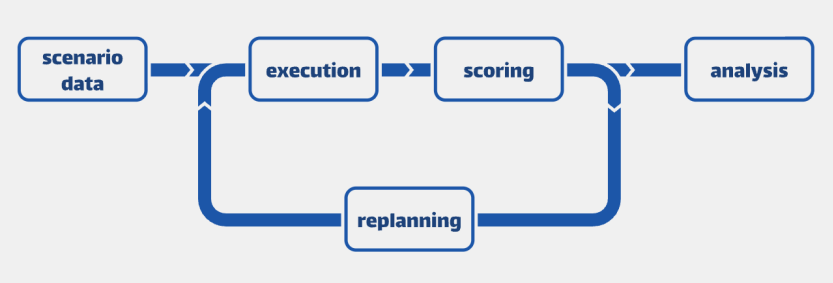


Figure 3.4: Matsim Process (Source: matsim.org)

This procedure allows the simulation to capture interactions between individual behaviour and network conditions, such as congestion and crowding.

3.3.2. Behavioural parameter integration:

The next stage of the methodology consists of integrating the estimated behavioural parameters into SIMBA MOBi. This is achieved by introducing peak-preference and schedule delay early and late parameters into the model's scoring function. To reflect heterogeneity, parameters are differentiated based on person or trip characteristics.

To be integrated, they must first be scaled to be consistent with the existing parameters of the scoring function. Thus, the estimated parameters are converted to willingness-to-pay space by dividing with the estimated cost sensitivity parameter. Then, they are again converted to the utility space by multiplying with the cost parameter of MOBi.sim.

3.3.3. Model set-up:

The model settings are adjusted for the specific model use case. The model is set to allow agents temporal replanning of maximum $\pm$ 1 hour (instead of the current $\pm$ 30 minute limit). This allows a meaningful shift in the daily schedule and matches the time variation of 60 min used in the SP4 experiment. Furthermore, due to the extensive time and computational requirements of the simulation, it is run on 10% of the Swiss population and then extrapolated.

3.4. Experimental design

3.4.1. Pricing scenarios

The simulation scenarios are designed to isolate how different time-of-day pricing policies affect three outcomes central for assessing such policies' feasibility: the redistribution of peak rail demand across the day, the modal split, and the welfare and equity of the resulting changes. The combination of these effects shows the trade-off faced by operators where a balance is needed between flattening the demand peak while maintaining ridership, revenue, and fairness.

To examine this trade-off, four pricing scenarios are defined (Figure 3.5). The first three correspond to the time-differentiated pricing instruments identified in literature - increasing the peak fare, decreasing the off-peak fare, and combining the two [29]. The fourth scenario extends beyond the rail system to also price the competing mode. Each scenario thus contributes to the overall analysis by addressing a distinct objective:

- **S1 – Peak surcharge:** isolates the effect of a pure deterrent on the morning peak and quantifies its consequences for ridership, welfare and equity.
- **S2 – Off-peak discount:** tests whether a pure positive incentive achieves a comparable demand redistribution.
- **S3 – Combined surcharge and discount:** evaluates whether combining the two instruments yields a stronger peak reduction, and whether the discount's gains can offset the surcharge's adverse effects on ridership and welfare.
- **S4 – Rail and road peak surcharge:** determines whether also pricing the competing mode limits the shift to car, and thus protects the modal split.

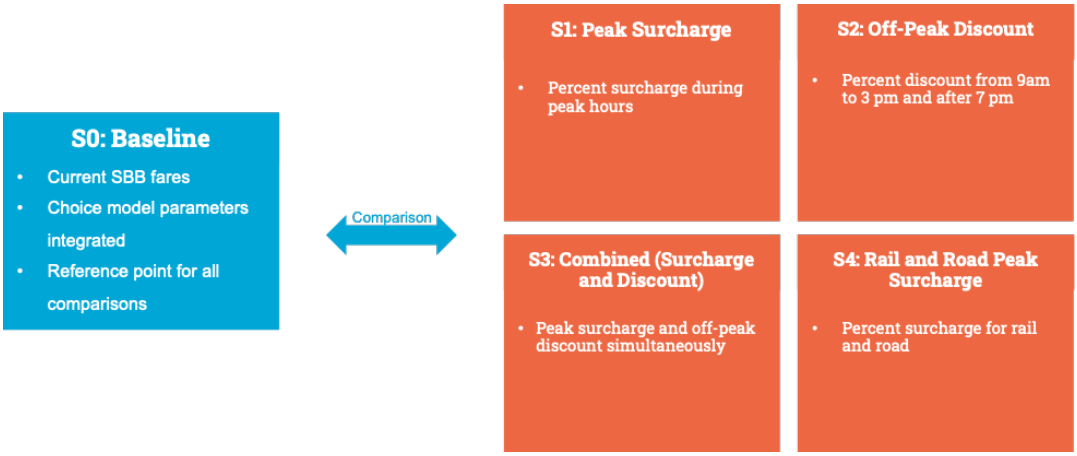


Figure 3.5: Simulation scenarios

Within each scenario, several pricing levels are simulated rather than a single value, in order to observe the trade-off relationship and to detect any threshold effects in the response. It is important to note that each simulation run requires considerable time and processing resources, thus, only a limited number of values can be tested.

All scenarios follow the outlined specification:

- **Percent-based surcharge/discount (instead of per km or flat fare):** Percent-based fares are commonly used in practice, for example, in the Netherlands, UK and Belgium. By using a percent-adjusted cost instead of a flat fare, the policy does not penalise short trips in comparison to longer trips. Percent-based costs are also easier to apply and calculate for the operator, because current (or future) ticket prices can be used, as they are easy to understand for the consumer.
- **Rail only (no buses or trams):** This is in the scope of the SBB case study as it is a rail operator.

- **Country-wide implementation (all passenger trains):** Sufficient for the scope of the analysis.
- **Peak window: 07:00–09:00:** Based on SBB convention and observed travel patterns.

S1: Peak surcharge. The surcharge is applied to the morning peak window (07:00–09:00) and acts as a deterrent from travelling during this time. Surcharge levels from 10% to 50% are tested. These are chosen to cover a range that is reasonable for an operator to implement while being wide enough to reveal how the response develops as the surcharge grows. The lower end is comparable to the levels examined in earlier studies, where Douglas, Henn, and Sloan [12] and Whelan and Johnson [49] test surcharges of 10% and 30%. The range is deliberately extended to 50% to allow for the possibility that a stronger price signal might be needed to produce a noticeable behavioural response. The main drawback of a peak surcharge is mainly loss of ridership to competing modes and public acceptance, since it may be perceived as unfair. For this reason, a thorough evaluation is performed alongside the demand effects.

S2: Off-peak discount. This scenario rewards off-peak travel rather than penalising peak travel, and is generally the more publicly preferred instrument. The literature finds the off-peak discount less effective at reducing peak demand than an equivalent surcharge, because travellers must be offered a sufficiently large saving before they reschedule [29]. Thus, due to the assumption that discounts generally need to be larger to have a demand redistribution effect as well as due to limited simulation run budget, the smaller discount levels of 10% and 20% are omitted, and discounts of 30% to 50% are tested. The discount is applied to the off-peak periods following the morning peak (09:00-15:00 and after 19:00). This is designed to imitate existing policies, for example, in the Netherlands where any time outside of the peak is considered off-peak. The reason the pre-peak period is not discounted is because of the specific practical context of Swiss railways. Since there is already a significant amount of rail travel occurring before 7 am, it would be undesirable to move the high demand towards the earlier morning.

S3: Combined surcharge and discount. The combined policy aims to leverage both the peak-deterrent effect of the surcharge and the off-peak attracting effect of the discount to achieve demand redistribution while balancing any unwanted effects in revenue, modal split and welfare. The test combinations pair surcharge and discount levels of 10 & 50, 20 & 30, 20 & 40 and 50 & 50 %. These are chosen to test the asymmetry of the ratios, ranging from discount-heavy to equal in order to observe how the effects balance. The final value combination of 50 & 50% is also the strongest policy tested and is thus used to observe the extent of redistribution possible with this range of values.

S4: Rail and road peak surcharge. A risk for a single mode peak surcharge is that demand may shift to another mode instead of shifting in time. While for road transport this is acceptable and even preferable, for public transport pushing ridership away from public transport and towards car use is an undesirable outcome. This scenario therefore adds a parallel peak surcharge for car use, to test whether pricing the competing mode contains this leakage and preserves the modal split. The rail surcharge is held fixed at 30% while the road surcharge is varied (10%, 30%, 50%), so that the marginal effect of the road charge relative to the equivalent rail-only surcharge can be isolated as well as to inform the ratio that is required for rail vs road surcharge in order to maintain the modal split. The road surcharge is applied to the fuel and direct operating cost of the car (0.24 CHF/km in the SIMBA MOBi model) and excludes depreciation.

3.4.2. Evaluation metrics

Each simulation run is evaluated in terms of the policy dimensions of interest, which are demand redistribution, modal split, and welfare and equity, together with the ridership and financial balance, which determine the viability of the policy. Thus, each dimension is evaluated across several selected metrics, which are outlined in this subsection.

Demand redistribution:
These metrics quantify whether, and by how much, the policy flattens the morning peak, and trace how the original peak trips are redistributed.

- **Rail use time distribution:** The morning (05:00-12:00) rail use distribution is compared to the baseline, and the changes are analysed. It is obtained from plotting the middle time distribution output from SIMBA MOBi for the rail submode.
- **Rail use spatial distribution:** Since peak demand does not occur evenly across the network, a map of the rail network is examined. It shows passenger demand during the peak time (07:00-09:00) and absolute change in passenger numbers for the scenario relative to baseline. With this depiction, it is possible to observe where most demand is reduced during the peak time and whether these rail links are busy corridors or minor lines.
- **Transition diagram for baseline peak trips:** Since the main aim of the policies is to reduce peak time rail demand, the rail trips occurring at peak time for the baseline are tracked to observe how they change in the time-of-day pricing scenarios. They are then categorised into three groups: remain the same, shift time, change mode. This allows insight into how the pricing policy is affecting the peak trips specifically. The classification procedure is detailed in Section D.1.3. While the tracking and comparison show clear trip behaviour switch, it is important to note that the MATSim equilibrium is reached through iteration and random replanning. Thus, although a proportion of agents may shift their departure time, this is not necessarily due to the policy. Therefore, the main purpose of this analysis is to be simply insightful and support cross-policy evaluation instead of being taken as absolute.
- **Peak share of the day:** the share of daily rail trips that occur during the peak period:

$$\text{Peak share} = \frac{N_{\text{peak}}}{N_{\text{day}}}, \tag{3.8}$$

  where N_{peak} is the number of rail trips in the peak period and N_{day} is the number of rail trips over the whole day.
- **Percent change in peak rail trips:** the change in the number of peak rail trips relative to baseline expressed as a percentage:

$$\Delta N_{\text{peak}} = \frac{N_{\text{peak}}^{\text{scenario}} - N_{\text{peak}}^{\text{baseline}}}{N_{\text{peak}}^{\text{baseline}}} \times 100, \tag{3.9}$$

Modal split:
These metrics are used to observe the overall change in mode choice as well as specifically within the peak trips.

- **Mode share:** Obtained directly from the model outputs, it provides the modal share for each of the main modes classified in the model: car, public transport, walk, bike. The modal split is reported at the level of public transport as a whole, because a rail-specific mode share was not available in the simulation outputs used. Changes in the public-transport share are therefore assumed to be mainly caused by rail due to the fact that the pricing applies only to rail, however, this cannot be taken as certain.
- **Transition diagram for baseline peak trips:** The diagram tracking how the baseline peak trips change across the scenario runs shows the peak trips that switch mode as well as to which mode they have switched. This is done at the submode level - car, walk, bike, rail, bus, tram, bus and tram, other - for which the derivation is shown in the Appendix (Section D.1.1) of the report.

Revenue:
These metrics quantify the revenue consequences for the operator.

- **Surcharge income:** The total income from the surcharges paid across the day is obtained directly from the model outputs.
- **Discount revenue loss:** The total loss in profit from the discounts applied across the day is obtained directly from the model outputs.
- **Change in ticket revenue**: This is the change in revenue due to decreased or increased ridership. The value is based on the total passenger kilometres using an approximate SBB valuation:

$$\Delta TicketRevenue = \Delta PassengerKMs \cdot 0.2CHF/km \tag{3.10}$$

where the change in passenger kilometres compared to baseline is multiplied by the generalised value for SBB for each passenger kilometre.

- **Net balance:** The values are added to achieve the total financial effect.

Welfare and equity:
These metrics capture the welfare effects of the policy and how they are distributed across the population.

- **Change in agent score:** the agent score is the total score of an agent's daily plan, rewarding completed activities and penalising factors such as cost, travel time and plan alterations. Therefore, the score indicates how "successful" the agent's day is, and its change relative to the baseline shows whether the policy leaves agents better or worse off. For each agent, the percentage change in executed score is:

$$\Delta S_i = \frac{S_i^{\text{scenario}} - S_i^{\text{baseline}}}{S_i^{\text{baseline}}} \times 100, \tag{3.11}$$

  where S_i is the executed score of agent i.The mean score change is calculated both at the population level as well as examined across socio-demographic variables to analyse distributional effects. The computation and subgroup segmentation are described in detail in the Appendix (Section D.1.4).

- **Schedule delay (SDE, SDL):** Policy's effects are not only in terms of costs, but can also affect people's preferred scheduling. To capture this, the mean change in an agent's departure time relative to baseline is calculated and categorised into schedule delay early (SDE) and late (SDL) to reveal any asymmetry:

$$\Delta t_j = t_j^{\text{scenario}} - t_j^{\text{baseline}}, \qquad \text{SDL} = \Delta t_j \text{ if } \Delta t_j > 0, \quad \text{SDE} = \Delta t_j \text{ if } \Delta t_j < 0. \tag{3.12}$$

  It indicates the extent to which agents re-time their trips under the policy, although there is no indication whether this is forced or voluntary. Similar to the agent score, the values are examined across socio-demographic variables and the computation and subgroup segmentation are detailed later in the Appendix (Section D.1.4).

4

Choice Model Estimation

The model is specified as a three-alternative MNL, with alternatives based on the respondent's reference trip: an alternative with an added surcharge (Alternative 1), an alternative that is shifted in departure time without a surcharge (Alternative 2) and an alternative that is switched in mode (Alternative 3). The model also includes covariate interactions. Due to the MNL specification, the panel effects are addressed only by grouping a respondent's answers, which corrects the standard errors and, thus, the parameter significance. The following section outlines the results of each step of choice modelling that led to the final model.

4.1. Base model

4.1.1. Initial model estimation and parameter consolidation

The results of the initial base model estimation are presented in Table 4.1. The results show that all parameters are significant except the sensitivity of the base ticket cost, schedule delay late car and crowding levels.

Table 4.1: Initial estimation results for the base model

Parameter	Interpretation	Estimate	Rob. t-stat.	Rob. p-value
PT alternatives				
β_{TR}	Nr of transfers	-0.2187	-3.36	0.0008
$\beta_{\text{cost surcharge}}$	Peak surcharge	-0.0475	-3.76	0.0002
$\beta_{\text{cost ticket}}$	Base ticket cost	-0.0454	-1.16	0.2476
$\beta_{\text{SDE,PT}}$	Schedule delay early	-1.7053	-7.42	<0.0001
$\beta_{\text{SDL,PT}}$	Schedule delay late	-1.3942	-5.36	<0.0001
β_{CRWD2}	Crowding level 2 (ref. 1)	0.0461	0.16	0.8697
β_{CRWD3}	Crowding level 3 (ref. 1)	-0.3135	-0.91	0.3655
β_{CRWD4}	Crowding level 4 (ref. 1)	-0.1264	-0.23	0.8220
$\beta_{\text{TT,PT}}$	Travel time	-0.0264	-2.59	0.0095
Car alternative				
$\beta_{\text{cost fuel}}$	Fuel cost	-0.1279	-3.10	0.0020
$\beta_{\text{cost toll}}$	Toll/surcharge	-0.0746	-2.41	0.0160
$\beta_{\text{SDE,Car}}$	Schedule delay early	-1.8335	-2.40	0.0164
$\beta_{\text{SDL,Car}}$	Schedule delay late	-1.2805	-1.94	0.0520
$\beta_{\text{TT,Car}}$	Travel time	-0.0287	-3.52	0.0004
Alternative-specific constants				
ASC_2	Alt 2 (PT larger shift)	0.4805	1.51	0.1322
ASC_3	Alt 3 (Car)	-0.6977	-1.16	0.2451
Model fit				
Final log-likelihood	-943.463			
AIC	1918.926			
BIC	1970.013			
ρ^2	0.141			
$\bar{\rho}^2$	0.127			

Based on the estimation and Wald test results, the base ticket cost attribute is excluded, as its parameter is insignificant and the Wald tests show it cannot be combined with the other monetary parameters (Table C.2). For the remaining monetary attributes — the PT peak surcharge, car fuel cost, and car toll — the Wald tests confirm no significant difference between them, allowing them to be combined into a single generic cost parameter. This is theoretically preferable and also simplifies the transfer of the parameters to the simulation, since a single cost coefficient can be used to scale the values for the MATSim scoring function. Finally, the Wald tests show no significant difference between the PT and car parameters for schedule delay early (β_{SDE}), schedule delay late (β_{SDL}), and travel time (β_{TT}), so each pair is combined into a generic parameter across alternatives (Table C.1).

4.1.2. Crowding formulation

Table 4.2 summarises the estimation results of models with various crowding formulations. The formulations that are tested include four-level dummies, linear, two-level (high vs. low, multiple thresholds tested with the best fitting reported), and crowding excluded.

Table 4.2: Model development: Selection of crowding formulation

Specification	Final LL	AIC	BIC	# par.	ρ^2	$\bar{\rho}^2$
No crowding	-952.67	1919.33	1941.68	7	0.133	0.126
4-level crowding	-948.82	1917.64	1949.57	10	0.136	0.127
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**

Based on this comparison (Table 4.2), the two-level crowding formulation, where Crowding_High$_{in}$ is a dummy for crowding levels 3 and 4 relative to levels 1 and 2, is selected. This formulation allows to reduce the number of parameters used for crowding from three parameters – for each level above the reference – to a single parameter contrasting high crowding in reference to low. The better fit of this specification implies a threshold effect rather than a linear or gradual increase in crowding sensitivity, however, the difference in the fit between these formulations is limited.

4.1.3. Time period variable addition

Table 4.3 outlines the main results of adding a time-period parameter. Several formulations were tested with varying time windows, of which 7:00–7:40 provided the best fit and parameter significance. Thus, based on the model-fit results, an off-peak dummy OffPeak$_i$ that is equal to 1 when the arrival time falls outside the preferred time window (7:00 - 7:40) is selected. This points to a relatively early arrival-time preference, which may be attributed to the high proportion of rail trips in the sample. Rail trips often can be followed by another trip leg to reach the final destination and therefore imply an earlier arrival at the station. The results also show that a formulation based on arrival time outperforms departure-time based ones, although the differences in fit are small. This could indicate that the respondents hold a general preference both for a departure time and an arrival time.

Table 4.3: Model development: Time period dummy selection

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

4.1.4. The final base model

After integrating model refinements, the final base model utility specification is as follows:

$$V_{in}^{\text{PT}} = \text{ASC}_i + \beta_{\text{cost}} \cdot \text{Surcharge}_{in} + \beta_{\text{SDE}} \cdot \text{SDE}_{in} + \beta_{\text{SDL}} \cdot \text{SDL}_{in} + \beta_{\text{tr}} \cdot \text{Transfers}_{in} + \beta_{\text{TT}} \cdot \text{TravelTime}_{in} + \beta_{\text{CR HIGH}} \cdot \text{Crowding_High}_{in} + \beta_{\text{OFFPEAK}} \cdot \text{OffPeak}_i$$

$$V_{in}^{\text{Car}} = \text{ASC}_3 + \beta_{\text{cost}} \cdot (\text{Fuel}_{in} + \text{Toll}_{in}) + \beta_{\text{SDE}} \cdot \text{SDE}_{in} + \beta_{\text{SDL}} \cdot \text{SDL}_{in} + \beta_{\text{TT}} \cdot \text{TravelTime}_{in} + \beta_{\text{OFFPEAK}} \cdot \text{OffPeak}_i \quad (4.1)$$

Where $\text{ASC}_1 = 0$ since it's the reference alternative.

The estimation results are presented in Table 4.4 and show the sensitivity parameters for the base variables, the alternative-specific constants and the model fit. Overall, all parameters carry the expected sign and are significant at the 1% level, with the exception of the marginally insignificant crowding term ($\beta_{\text{CR_HIGH}}$, $p = 0.06$).

Table 4.4: Final base model

Parameter	Interpretation	Estimate	Rob. t-stat.	Rob. p-value
PT alternatives				
β_{TR}	Nr of transfers	-0.2044	-3.26	0.0011
β_{COST}	Cost sensitivity	-0.0602	-4.77	<0.0001
β_{SDE}	Schedule delay early (hr)	-1.7658	-7.47	<0.0001
β_{SDL}	Schedule delay late (hr)	-1.2355	-4.57	<0.0001
β_{TT}	Travel time (min)	-0.0264	-3.30	0.0010
$\beta_{\text{CR HIGH}}$	High crowding (ref. low)	-0.3326	-1.85	0.0648
β_{OFFPEAK}	Off-peak arrival (ref. peak)	-0.3946	-2.86	0.0043
Alternative-specific constants				
ASC_2	Alt 2 (PT larger shift)	0.3309	1.96	0.0499
ASC_3	Alt 3 (Car)	-0.9841	-4.12	<0.0001
Model fit				
Final log-likelihood	-941.546			
AIC	1901.091			
BIC	1929.828			
ρ^2	0.143			
$\bar{\rho}^2$	0.135			

The schedule-delay parameters, β_{SDE} and β_{SDL}, are both negative and significant, confirming that travellers experience disutility from earliness and lateness. The two are estimated separately, and the early penalty is larger than the late one. This asymmetry indicates that travellers are more reluctant to bring their departure forward than to push it back, which is relevant for peak-spreading, since encouraging earlier travel might be more difficult or require stronger pricing incentives. The parameter values and direction of the asymmetry (SDE $>$ SDL) are compared with literature in Section 4.4.

The crowding parameter insignificance is a counter-intuitive outcome, since crowding is an important motivation for peak management and would be expected to deter peak travel. A likely reason for the insignificance is collinearity between crowding and the peak surcharge and departure-time attributes. Alternative 1 is based on the reference trip, which is a peak-time trip and therefore tends to have higher crowding, while Alternative 2 is designed with a crowding level which is one or two levels below Alternative 1's. As a result, the high crowding, peak surcharge and peak departure time of Alternative 1 consistently coincide, as do the lower crowding, absence of surcharge and shifted departure time of Alternative 2. Because these attributes move together across the alternatives, the model struggles to separate the effect of crowding from that of the surcharge and timing attributes. This is supported by the fact that the crowding coefficient remains sizeable ($B_{CRHIGH} = -0.33$) and has the expected sign despite being insignificant, indicating an effect that is present yet poorly identified. Additionally,

B_{CRHIGH} was significant in the step before the off-peak dummy was introduced. Although it may suggest the two are capturing overlapping variation, the correlation matrix (see Figure C.2) shows a low correlation. Therefore, it is plausible that simply the addition of more parameters reduced the estimation power and turned a barely significant parameter into an insignificant one. An interaction between crowding and travel time was also tested, on the basis that crowding discomfort may increase with the duration of exposure, however, the crowding term remained insignificant.

To continue, the off-peak arrival parameter ($B_{OFFPEAK}$) shows the dis-preference to arriving off-peak compared to during the peak. The peak here is taken from what provided the best model-fit for this data as outlined in Section 4.1.3, which is the period between 7:00 and 7:40 in the morning. While 7:00 to 7:40 is a very early arrival time, there are two observations that could explain this result. First, the sample has a high proportion of rail trips. Rail trips are often only a part of the full journey having another trip leg following afterwards, such as a walk or bus ride. For this reason, arrival at the station might be preferred to be between 7:00 and 7:40, however, arrival at the destination might be later. Second, the verification microcensus counts displayed in the Appendix Figure C.1 show that the peak of rail travel is right after 7 am, aligning well with this finding of early rail travel.

In terms of alternative-specific constants, the car alternative constant (ASC_3) is negative and significant (-0.98), which likely reflects the PT-oriented sample, which is less inclined to use or switch to the private vehicle. From the description of the design of the experiment, it is also known that the attribute levels were specifically selected to pose Alternative 3 as the less advantageous compared to the PT alternatives. The alternative-specific constant for the time-shifting alternative is positive (0.37) but only borderline significant ($p = 0.0499$). This suggests that there might be a general willingness to shift departure time when incentivised, though the weak significance means this can only be interpreted cautiously.

Overall, the consistency of the signs with behavioural expectations, along with the high significance of the cost and scheduling parameters which are central to the pricing response, indicate that this model serves as a solid base for the following analysis.

4.2. Model with interaction terms

The base model is used to test interactions with socio-demographic and trip variables. Overall, 220 model runs are executed across the four model parameters (cost, schedule delay early, schedule delay late, and off-peak), from which 13 had a significant interaction term (see Table C.3). All statistically significant interaction terms are incorporated in a single model. After an iterative process of removing interaction terms that become insignificant or have negligible magnitude or lack a behavioural explanation, the final model is obtained, presented in Table 4.5.

The estimation results show that all parameters carry the expected sign and are significant at the 0.01 level, with the exception of crowding, which closely misses the 0.05 level (B_{CRHIGH} p = 0.08). This is the same outcome as for the final base model.

For the base variables, while the interactions changed the absolute parameter values (mainly due to the covariate interactions), observations from the final base model continue to be relevant. The base parameters remain highly significant and correctly signed. Furthermore, the values of the alternative-specific constant are similar across the models, with ASC_3 remaining highly significant while ASC_2 becomes insignificant. Since ASC_2's p-value in the base model results was marginally significant (0.0499), it's likely that the added parameters decreased the estimation power for the constant and, thus, tipped it over the threshold.

In terms of interaction effects, all added variables have significant parameters and expected signs.

Cost with Household size: The first, $\gamma_{\text{COST}\times\text{NbHH}}$, is an interaction between the cost sensitivity and household size and is negative and significant. This indicates that cost sensitivity decreases with household size. It is specified as piecewise-linear rather than linear: a linear form would imply that cost sensitivity keeps decreasing and eventually changes sign, which would suggest that larger households prefer more expensive travel. The interaction is therefore estimated as linear up to a household size of four (based on model fit) and constant beyond it. This cap is supported by the data, as the linear term

Table 4.5: Final departure-time choice model with socio-demographic and trip variable interactions

Parameter	Interpretation	Estimate	Rob. t-stat.	Rob. p-value
β_{TR}	Nr of transfers	-0.2227	-3.45	0.0006
β_{COST}	Cost sensitivity	-0.1505	-4.90	< 0.0001
β_{SDE}	Schedule delay early (hr)	-1.6297	-6.68	< 0.0001
β_{SDL}	Schedule delay late (hr)	-1.1236	-4.15	< 0.0001
β_{TT}	Travel time (min)	-0.0254	-3.36	0.0008
$\beta_{\text{CR HIGH}}$	High crowding (ref. low)	-0.3136	-1.75	0.0800
β_{OFFPEAK}	Off-peak arrival (ref. peak)	-0.4251	-2.94	0.0033
Interactions				
$\gamma_{\text{COST}\times\text{NbHH}}$	Cost $\times$ Household size	0.0309	3.92	0.0001
$\gamma_{\text{COST}\times\text{AboDT}}$	Cost $\times$ Half-fare subscription	-0.0385	-2.23	0.0256
$\gamma_{\text{SDL}\times\text{MotifStudy}}$	Late delay $\times$ Study trip purpose	-1.4453	-2.40	0.0166
$\gamma_{\text{SDE}\times\text{CSP4}}$	Early delay $\times$ CSP category 4	-1.1495	-2.20	0.0275
ASC_2	Alternative-specific constant (time-shift)	0.2744	1.65	0.0992
ASC_3	Alternative-specific constant (car)	-0.9658	-4.08	< 0.0001
Model fit				
Sample size	180			
Observations	1076			
Final log-likelihood	-913.272			
AIC	1852.543			
BIC	1894.052			
ρ^2	0.169			
$\bar{\rho}^2$	0.157			

is no longer significant past a household size of four, indicating no further change in cost sensitivity for larger households. This interaction may be explained by larger households having more contributors to household income, resulting in greater financial capacity and thus lower cost sensitivity. It is important to note that household income was also tested as an interaction but, counter to expectations, was not significant. However, this does not rule out that income has an influence. The insignificance could be because income was recorded in nine bands rather than as an exact amount, which, combined with the small sample, may not have provided enough variation and estimation power to detect an effect. Additionally, income was tested in both linear and piecewise-linear forms, but other formulations might have provided a better fit. It is also likely that household size captures effects beyond income alone. For instance, it may correlate with the presence of children, which could motivate households to keep their schedule more fixed, thus responding less to pricing and lowering cost sensitivity.

Cost with Half-fare subscription: The second interaction, $\gamma_{\text{COST}\times\text{AboDT}}$, is between cost sensitivity and possession of a half-fare subscription, formulated as a dummy variable equal to one for holders and zero otherwise. The half-fare subscription provides a 50% discount on most public transport tickets. The interaction term is negative and significant, suggesting that half-fare holders are more sensitive to cost. This follows expectations best explained by comparing to GA holders or people with no subscription. GA holders have most of their travel costs covered by their subscription and therefore pay little attention to individual ticket prices, while those without a subscription tend to travel by rail rarely, if at all. Half-fare holders, by contrast, are more likely to be occasional rail users who still pay a fare on each trip and are accustomed to checking prices, which could explain their higher cost sensitivity.

SDL with Study trip purpose: The third interaction, $\gamma_{\text{SDL}\times\text{MotifStudy}}$, combines schedule delay late and study trip purpose. The high negative and significant coefficient indicates that study purpose trips are more sensitive to schedule delay late. This means that these respondents have a strong dispreference for late arrival. Again, this is a reasonable effect since generally educational institutions have strict program start times such as classes and lectures, where even a small delay can be perceived very negatively.

SDE with Socio-professional category: The fourth interaction is $\gamma_{\text{SDE}\times\text{CSP4}}$, which suggests that people whose job position falls into the management category are more sensitive to schedule delay

early. This is plausible, since management roles are relatively senior and those holding them are likely to have the autonomy and resources to keep their preferred schedule rather than shift earlier. For morning travellers, a shift earlier also means leaving home sooner, reducing time at home and sleep, which such travellers may be particularly reluctant to give up.

Hypothetical bias towards peak pricing: Finally, one could argue that emotional resistance to peak pricing, combined with the hypothetical choice situations in the survey, may have led to biased survey data. Although this is a possibility, the results suggest that it has not occurred at a significant level. Firstly, if respondents who do not wish peak pricing to be implemented answered tactically, they would either pick alternative one, showing that they are rigid in behaviour and the peak charge cannot make them shift, or alternative three, abandoning rail once the charge is present. The results, however, show a positive constant for alternative two and a negative constant for alternative three — the opposite of what such behaviour would produce. Secondly, in the choice model estimation, the peak surcharge and ticket cost sensitivities proved not to be significantly different; had tactical responses inflated resistance to the surcharge specifically, one would expect these to diverge. Thus, while it cannot be concluded definitively, there is little evidence of such a hypothetical bias.

Overall, the inclusion of socio-demographic and trip interaction variables notably improves model fit compared to the base specification and adds valuable insights into how sensitivities vary for different population segments. The final log-likelihood improves from -941.55 to -913.27, there is a reduction in AIC from 1901.09 to 1852.54, in BIC from 1929.83 to 1894.05, and an increase in ρ^2 and $\bar{\rho}^2$, despite the addition of four parameters.

4.3. Interpretation and implications

4.3.1. Willingness-to-pay valuation

In Table 4.6, the final parameter values in willingness-to-pay space are presented for the sample mean in order to provide a comparable result. The valuations are used to inform what trade-offs occur as well as to inform the scenario design and expectations of the outcomes of the simulation analysis. Values for schedule delay and travel time are validated in the following section with literature, since they are a key outcome for the policy analysis.

Table 4.6: Parameter valuations at the sample mean

Parameter	Description	Valuation
Rates (CHF/h)		
V_{SDE}	Value of schedule delay early	24.6
V_{SDL}	Value of schedule delay late	16.9
V_{TT}	Value of travel time	19.9
Per-unit penalties (CHF)		
V_{TR}	Value of a transfer (per transfer)	2.89
V_{OFFPEAK}	Off-peak arrival penalty	5.52
$V_{\text{CR_HIGH}}$	High crowding penalty	4.07

Note: Obtained by dividing the parameter by β_{COST} at sample mean equal to -0.0771.
The high crowding penalty is derived from an insignificant coefficient.

4.3.2. Behavioural trade-offs

The valuations in Table 4.6 express, in monetary terms and evaluated at the sample mean, how travellers value the timing and comfort of a trip. The results show that a traveller experiences departing one hour earlier than preferred as equivalent to a cost of 24.6 CHF, and departing one hour later as 16.9 CHF, compared with a value of travel time of 19.9 CHF/h. The order $V_{SDL} < V_{TT} < V_{SDE}$ is itself informative. Schedule delay late being valued less negatively than travel time implies that, for the same amount of time, a traveller would sooner accept lateness than additional time in the vehicle. This is contrary to the common assumption that the late-arrival penalty exceeds the early-arrival

penalty, reflecting the cost of arriving late under a fixed arrival constraint, as conventionally assumed in scheduling theory [11]. The switched order here suggests that, for this morning sample, late arrival is not as strongly constrained, whether because start times are flexible or because travellers have an arrival buffer. Additionally, the high V_{SDE} indicates a strong reluctance to depart earlier, and the positive value placed on arriving within the 7:00–7:40 window shows a tendency to travel very early in the morning. One possible interpretation is that travellers are already near the earliest departure they are willing to make, thus leaving little room to move earlier, but some being able to move later, thus explaining the variable order and the early preference window.

This order of scheduling valuations, however, is not uniform across the sample. The interaction terms show that sensitivity to lateness is concentrated in particular groups: study-purpose trips are significantly more averse to lateness, consistent with the fixed start times of classes and lectures. Thus, the average V_{SDL} reflects a majority which has more flexibility in arrival rather than a uniform tolerance of lateness. Sensitivity to earliness, however, is stronger for travellers in managerial positions, likely because their seniority provides the ability to keep a preferred schedule rather than shift earlier and lose valuable morning at-home time. The aversion to displacement in either direction is therefore specific to the population segment, showing distinct constraints acting on different traveller groups. Consequently, the direction in which a traveller can most easily be shifted is segment-dependent, since the groups least able to arrive later are not those least able to depart earlier.

Regarding the other attributes, the high-crowding penalty (4.07 CHF) is smaller than the off-peak penalty, indicating that the preference to arrive within the peak outweighs the disutility of the crowding encountered during travel. This is consistent with practice, where high crowding persists and is not in itself a large enough motivator for significant rescheduling. A transfer is valued at 2.89 CHF, which is about half of the off-peak penalty, meaning a traveller would trade approximately two additional transfers for a peak arrival. This, along with the relatively high schedule delay valuations, indicates that Swiss morning public transport travellers are relatively rigid in their scheduling.

4.3.3. Implications for the simulation

In combination, the values in Table 4.6 indicate the scale a pricing intervention must reach to change the average traveller's behaviour. Because a traveller must overcome both the schedule-delay cost of moving away from their preferred time and the positive value they place on a peak arrival, an incentive below the off-peak penalty (5.52 CHF) is unlikely to produce meaningful redistribution, and an incentive below the schedule-delay valuations will mainly move travellers already close to the peak boundary.

This informs the range of surcharge and discount levels tested in the simulation. Because the charges are proportional to the ticket price (a percentage of it), their size relative to the valuations depends on the trip. To illustrate the scale, the mean fare effectively paid in this sample (7.6 CHF) can be used as an example. It should be noted that the sample has many respondents who hold a full- or half-fare subscription that lowers what they effectively pay, thus, this mean functions more as a low reference rather than the population average. For the travel cost of 7.6 CHF, the levels of 10-50% correspond to only about 0.8–3.8 CHF. At this fare, the charge is below the value placed on a peak arrival (5.52 CHF) and well under the schedule-delay costs, motivating higher pricing levels to obtain a meaningful response, especially where the trip is also short and has subscription benefits. A meaningful response, thus, likely occurs towards the higher pricing levels, and first for longer, more expensive trips, where the same percentage translates into a higher absolute cost or discount. This is a reason why the value range tested is extended to 50%, beyond the 10-30% examined in comparable studies [12, 49].

Beyond the overall scale, the valuations also indicate how the simulation results are likely to be distributed. The asymmetry between earliness and lateness influences the direction a traveller can be shifted, although this also depends on their position within the peak window, meaning the distance to the nearest off-peak period. To continue, these valuations describe an average traveller, whereas the model's interaction terms imply that the underlying sensitivities differ across segments. Cost sensitivity varies with household size and half-fare subscription: it falls as household size rises (up to four), thus travellers in larger households face a higher effective threshold before the policy can alter their behaviour. At the same time, half-fare holders are more cost-sensitive and therefore respond at lower

charges. As described previously, there are also differences in scheduling sensitivities. Consequently, the valuations in Table 4.6 are not single population-wide thresholds but differ for each segment. A sharp threshold effect in the simulation results is therefore unlikely. Redistribution is expected to build gradually as rising price levels bring different segments past their respective thresholds, also depending on trip length, subscription and departure time relative to the peak window.

Overall, the valuations set two expectations for the simulation. First, that a substantial price signal is required to shift behaviour. Second, that the resulting redistribution will be gradual and uneven across segments rather than a uniform response at a single threshold.

4.4. Comparison with literature

The choice modelling results are presented and compared with values from reviewed studies in Table 4.7. The comparison first checks whether the overall level of the estimated valuations is consistent with established Swiss values, and then assesses whether the unusual ordering of the schedule-delay valuations is credible.

In terms of willingness to pay, the estimated VTT of the final model (19.9 CHF/h at the sample mean) is comparable to the value (21 CHF/h) reported in the Swiss microcensus of the same year for public transport in the 10-50 km distance band (the sample's mean trip length is 32 km) [17]. The microcensus result is revealed preference, and this thesis' estimate is stated preference. The alignment suggests the estimate is consistent with observed behaviour and shows no sign of strong upward hypothetical bias, which would otherwise inflate the stated-preference value above the revealed-preference one.

Compared to the SP4-specific model for the PT subsample (14.78 CHF/h) in the same report [17], this study's VTT is higher. While both generally use the same stated-preference data, the difference could be attributed to specification and data filtering. The official model estimates on both morning and evening travellers, differs in variable specification, and does not use socio-demographic covariates in the estimation. In contrast, this thesis only estimates the model for morning travellers, also including socio-demographic covariates. The difference might be an indication that morning travel has a higher value of time than evening travel. This aligns with a study performed by Tseng and Verhoef [44], where they find that value of travel time varies with the time of day. Nevertheless, this is not conclusive. Beyond the microcensus references, the estimate also aligns with the other studies apart from some specific segment-based outliers.

In regard to schedule delay, for most studies the SDL/SDE ratio is larger than one, implying that lateness is valued more negatively than earliness, aligning with the conventional assumption in scheduling theory that the early-arrival penalty is lower than the late-arrival penalty [11]. However, the results of the final model (at sample mean) show the opposite, with an SDL/SDE ratio below one (0.69), indicating that earliness is penalised more heavily than lateness. This finding is shared with some other rail and public transport studies reviewed:

- Gayda et al. [17]: estimated on the same dataset;
- Peer, Knockaert, and Verhoef [35]: a commute-based experiment in the Netherlands (separating schedule delay values for morning and evening commute);
- The business and education segments in Jong et al. [23];
- The flexible-PT and business commuters in Daly et al. [9].

Table 4.7: Comparison of estimated schedule delay and travel time valuations with the literature.

Study	Context	Detail	VSDE (CHF/h)	VSDL (CHF/h)	VTT (CHF/h)	SDL/SDE	SDE/TT	SDL/TT
This thesis	Swiss rail, SP	Base model	29.33	20.52	26.31	0.70	1.11	0.78
	2021 (MTMC SP4)	Final model (Sample mean)	24.55	16.94	19.85	0.69	1.24	0.85
Gayda et al. (2024)	Swiss PT, SP	SP4 PT-MNL	13.85	7.58	14.78	0.55	0.94	0.51
	2021	Microcensus 2021, PT (10-50km)	—	—	21	—	—	—
Peer et al. (2016)	Dutch rail, RP	Commute, morning	8.31	6.98	19.45	0.84	0.43	0.36
De Jong et al. (2003)	Dutch train, SP	Commute, flexible hrs	12.41	15.49	13.34	1.25	0.94	1.17
	2003	Commute, fixed hrs	13.47	23.52	13.34	1.75	1.02	1.79
		Business	30.48	24.13	42.34	0.79	0.72	0.57
		Education	8.44	6.90	30.16	0.82	0.28	0.23
		Other purpose	45.71	65.67	64.38	1.44	0.71	1.02
Daly et al. (2005)	London (1992), Car/PT, SP	Commute, flexible	20.03	35.40	18.25	1.76	1.10	1.94
		Commute, fixed hrs	20.03	68.61	18.25	3.43	1.10	3.76
	Netherlands (2000), rail, SP	Commute flexible, PT	15.16	10.95	28.07	0.72	0.54	0.39
		Commute fixed, PT	16.85	27.48	18.32	1.63	0.92	1.50
	UK W. Midlands (2003), PT, SP	Commute flexible	4.90	5.00	10.20	1.03	0.48	0.49
		Commute fixed	6.06	25.54	4.97	4.22	1.22	5.14
		Business	9.70	7.60	41.10	0.78	0.24	0.19
		Other	4.24	5.43	8.41	1.28	0.50	0.65
Vrtic et al. (2011)	Swiss PT, SP	Relative to current dep.	3.50	7.80	19.50	2.23	0.18	0.41
Wardman et al. (2016)	European PT review, meta model	Urban	—	—	—	2.14	0.92	1.97
	2010	Inter-urban	—	—	—	2.15	0.80	1.72

For VSDE and VSDL, the absolute valuations span a wide range across studies, with differences in country, year, and trip segment. The estimates of this thesis (VSDE 24.55, VSDL 16.94 CHF/h at the sample mean) are at the upper end of the range. This could be influenced by the composition of the sample, which has, on average, higher household income respondents than the population mean. The SDE/TT and SDL/TT ratios also vary considerably across studies and are thus hard to compare directly. In general, it seems that the SDL/TT ratio is most often above one, especially for commuters, meaning there is a high penalty for late departure relative to travel time. Flexible commuter segments have more variable and generally lower ratios. The results of the final model are at the higher end for SDE/TT (1.24) and around the middle of the range for SDL/TT (0.85), most closely aligning with the values reported by Gayda et al. [17] on the same dataset.

Overall, the literature presents a broad range of values for both schedule delay valuations and parameter ratios. While the results of this thesis match several existing studies, they oppose the conventional ordering of $|SDL| > |SDE|$. Because the estimates are large, stable and significant, and because the microcensus's own analysis found the same ordering, this appears to reflect the data itself rather than the model formulation. The reason for this result is not entirely clear. One possibility is that, for morning travel specifically, there is considerable motivation to stay home longer compared to day or evening travellers, allowing more sleep or time to prepare for the day, which raises the penalty on early departure. Another reason might be that the sample's higher average household income implies a higher opportunity cost of time. It could also imply better job positions offering more flexibility over arrival, so that late departure is penalised less heavily. A further possibility is an effect of the COVID pandemic: with more hybrid working, fixed work start times may have been less binding. Nevertheless, the estimates are robust and significant, and while the reversed ordering is unexpected, it appears to be a feature of morning travel in this context.

5

Simulation Results

5.1. Parameter scaling

Equations 5.1 to 5.3 contain the scaled parameters for integration in the simulation model. Since they are dependent on person-level or trip-level parameters, they are kept in equation form for the code integration:

$$V_{\text{SDE}} = \frac{-1.6297 - 1.1495 \cdot \mathbb{1}[\text{CSP4} = 1]}{-0.1505 + 0.0309 \min(\text{NbHH}, 4) - 0.0385 \cdot \mathbb{1}[\text{AboDT} = 1]} \tag{5.1}$$

$$V_{\text{SDL}} = \frac{-1.1236 - 1.4453 \cdot \mathbb{1}[\text{purpose} = \text{study}]}{-0.1505 + 0.0309 \min(\text{NbHH}, 4) - 0.0385 \cdot \mathbb{1}[\text{AboDT} = 1]} \tag{5.2}$$

$$V_{\text{offpeak}} = \frac{-0.4251}{-0.1505 + 0.0309 \min(\text{NbHH}, 4) - 0.0385 \cdot \mathbb{1}[\text{AboDT} = 1]} \tag{5.3}$$

where CSP4 = 1 means that the career role is either management or director; NbHH is the number of people in the household and is capped at 4; purpose = study means trip purpose is study related; AboDT = 1 means that the agent possesses a half-fare subscription.

5.2. Scenario results

5.2.1. S0: Base case

Scenario zero, or the base case, is the simulation run with the integrated behavioural parameters from the choice model estimation, but without any pricing policies applied. These results are used as the reference for the scenario evaluation and are presented below, along with a comparison with the count values from the Swiss 2015 Mobility and Transport Microcensus (MTMC) to analyse the realism of the outputs. While the Swiss 2021 MTMC counts are also available, the 2015 ones are more commonly used at SBB due to the influence of Covid-19 on the travel patterns in 2021.

Daily distribution of travel

The distribution across the day of passengers travelling via rail is shown in Figure 5.1. The distribution shows that for the base case the morning peak for rail travel happens right after 7.00, with increased travel starting already at approximately 6.00 and lasting until approximately 9.30 in the morning. The figure also shows a validation line, which is taken from the MTMC 2015 count data. Compared to the simulation outcome, the Microcenus distribution is showing higher peaks and lower ridership in between the peak times, meaning that in reality the peak concentration is higher than in simulation. Apart from that, the peaks are generally well aligned, with the morning peak occurring slightly earlier in the day for the simulation.

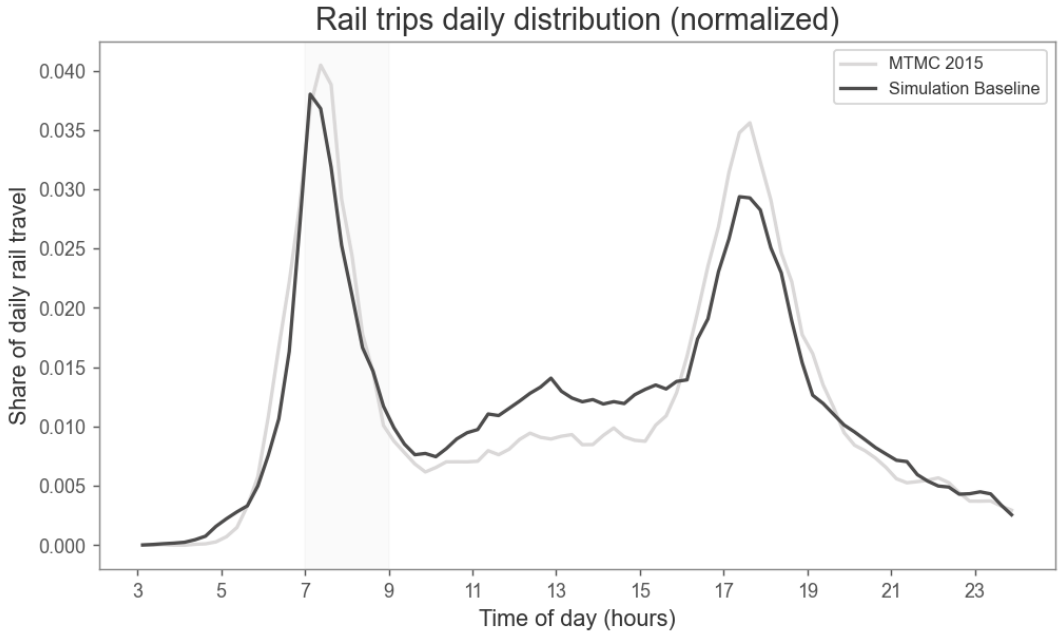


Figure 5.1: Base case: People travelling by rail daily distribution

Comparing the simulation baseline with Microcensus counts for other modes in Figure 5.2, it can be seen that overall the patterns match, with morning and evening peaks aligning for all modes. For car and bike modes, the travel in the simulation is occurring slightly later than in the Microcensus counts. Additionally, the simulation is not fully capturing the behaviour for the increased travel right before and after noon for walking, biking and driving. Lastly, public transport use is slightly overestimated, with a notable difference at noon.

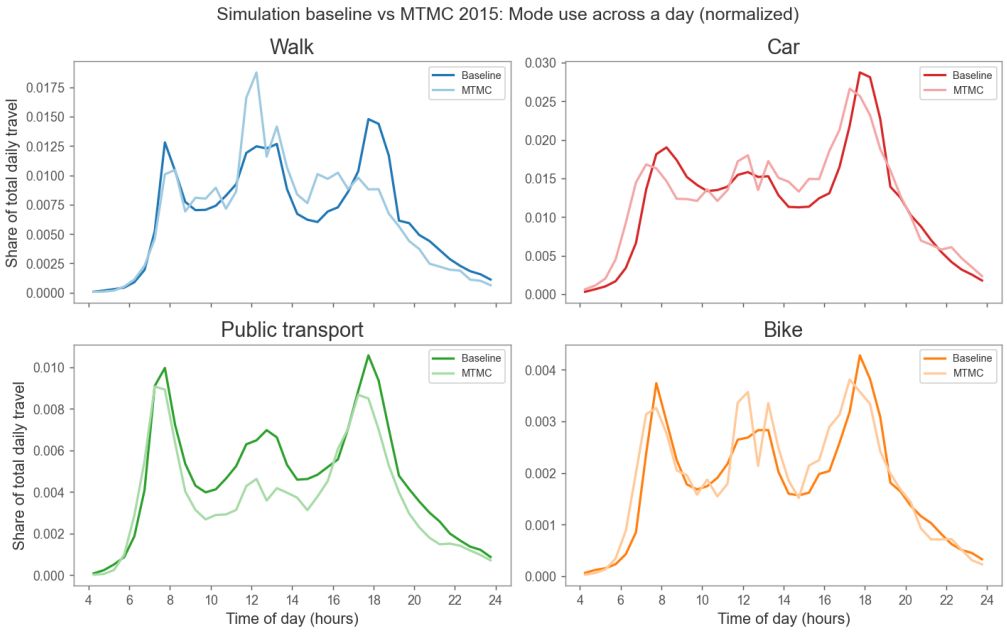


Figure 5.2: Simulation baseline with MTMC 2015 mode middle time distributions

Key metrics

The table below shows key metrics for scenario evaluation. It can be seen that for the simulation baseline, the peak share of daily travel for rail is approximately 19.60% while in the Microcensus it's 21.22%. This confirms the observation made from Figure 5.1 that the counts show a higher peak concentration. The modal shares are similar, with the exception of the car modal share being underestimated and the public transport share being overestimated compared to the Microcensus. The public transport share is presented for all its submodes (rail, bus and tram) together due to data availability.

Table 5.1: Baseline scenario results compared with the MTMC 2015 reference

Metric	Baseline	MTMC 2015
Total rail passenger trips [M]	2.03	–
Total rail passenger-km [M]	76.70	–
Peak share of day (rail) [%]	19.60	21.22
Mean agent score	50.03	–
Car [%]	48.1	51.0
PT [%]	18.5	15.1
Walk [%]	26.2	26.5
Bike [%]	7.2	7.5

5.2.2. S1: Peak surcharge

The first scenario explores the rail peak time surcharge applied for the morning peak (7.00-9.00). Surcharge amounts from 10 to 50% are tested to see the impact of different amounts and if there are any threshold effects.

Table 5.2 shows the key metrics across the simulation runs, giving an overall impression before the individual effects are examined in more detail in the following subsections. The policy causes a loss in ridership both in the number of trips and passenger kilometres, with a stronger decrease as the surcharge increases in level. The earnings from the surcharge do not compensate for this reduction in passenger-kms and, thus, all priced scenarios show a loss in total revenue.

Table 5.2: Simulation results under different peak surcharge scenarios

		Peak surcharge				
	Baseline	**10%**	**20%**	**30%**	**40%**	**50%**
Total rail passenger trips [M]	2.03	2.02 (-0.5%)	2.01 (-1.0%)	2.00 (-1.5%)	2.00 (-1.5%)	1.99 (-2.0%)
Total rail passenger-km [M]	76.70	76.44 (-0.3%)	76.14 (-0.7%)	75.80 (-1.2%)	75.55 (-1.5%)	75.22 (-1.9%)
Long-distance rail passenger-km (FV) [M]	41.94	41.83 (-0.3%)	41.70 (-0.6%)	41.48 (-1.1%)	41.35 (-1.4%)	41.24 (-1.7%)
Regional rail passenger-km (RV) [M]	27.11	26.95 (-0.6%)	26.80 (-1.1%)	26.73 (-1.4%)	26.56 (-2.0%)	26.41 (-2.6%)
Profit from surcharge [K]	0.00	22.62	44.12	64.46	84.11	102.51
Revenue change for tickets [K]	0.00	-52.31	-112.04	-179.23	-228.65	-295.42
Discount loss [K]	0.00	0.00	0.00	0.00	0.00	0.00
Balance [K]	0.00	-29.68	-67.92	-114.77	-144.53	-192.91
Peak share of day (rail) [%]	19.60	19.19	18.82	18.61	18.28	18.04
Change in peak rail trips [%]	0.00	-2.40	-4.70	-6.13	-8.15	-9.73
Mean agent score	50.03	50.02	50.02	50.01	50.01	50.00
Car [%]	48.1	48.1	48.1	48.1	48.1	48.2
PT [%]	18.5	18.5	18.5	18.4	18.4	18.4
Walk [%]	26.2	26.3	26.3	26.2	26.3	26.2
Bike [%]	7.2	7.2	7.2	7.3	7.3	7.2

The reduction in peak rail trips increases from -2.40% to -9.73% with increasing surcharge amount. The mean of agent scores is not greatly affected, but indicates a small decline. The PT modal split experiences a very small decrease while the car share has a slight increase at the highest surcharge level. It should be noted that the modal split reports the PT modal split, not the rail alone, and thus, the switching away from rail to bus or tram is not visible in these results. The changes in modal split, however, are relatively small. Nevertheless, the decrease in PT modal share implies that a part of the peak trips are reduced via mode switch, not only retiming.

Time distribution of travel

Figure 5.3 shows the rail use distribution for the morning hours for all tested surcharge amounts.

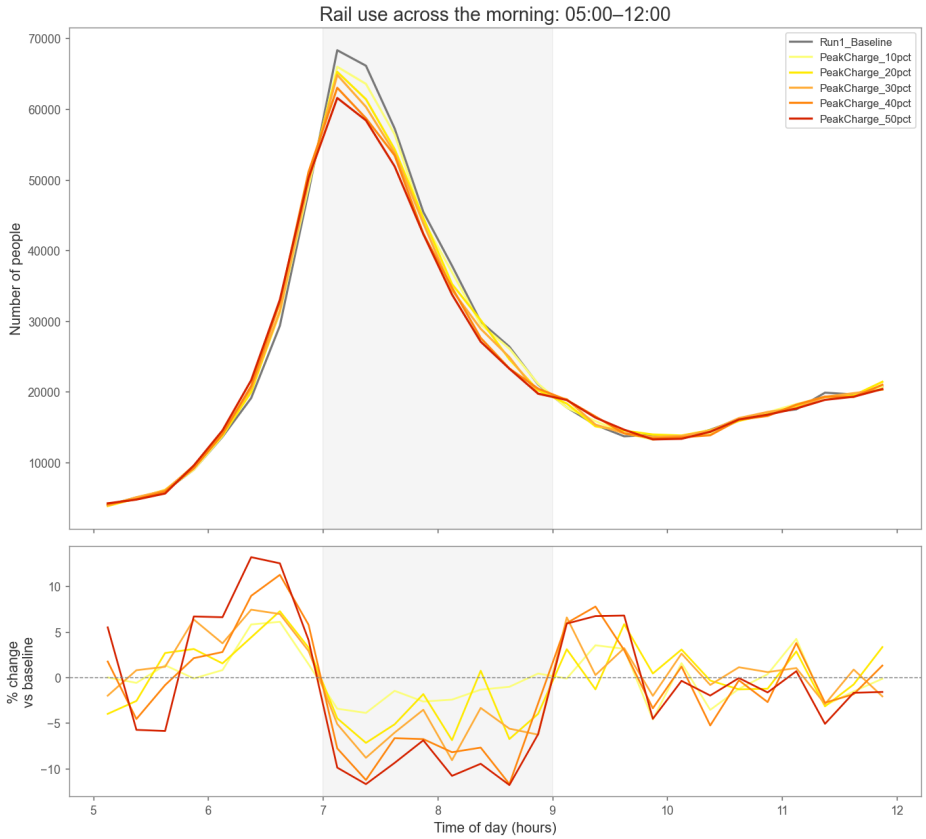


Figure 5.3: S1: Morning distribution of rail travel for various levels of peak surcharge

It can be seen that the highest peak occurs in the baseline scenario and decreases with increasing surcharge amount. Thus, the largest reduction in the morning peak is achieved with the 50% surcharge as expected. In general, there is a change in traveller numbers between approximately -12% and +14% compared to baseline, with reductions occurring in the peak period and the highest demand increase occurring at the shoulder periods (between 6:00-7:00 and 9:00-10:00). It can also be noted that a slightly larger increase in travel happens before the peak compared to after. This goes against expectations from the choice modelling results where the obtained earliness and lateness valuations indicated that people are more willing to be late than early. However, this could be explained by the fact that the highest demand peak is much closer to the beginning of the priced period, thus, requiring a smaller time shift and, thus, a smaller financial incentive.

Network demand

Since peak demand is both a temporal and spatial phenomenon, the change in network demand compared to baseline is shown in the map depicted in Figure 5.4. The corresponding maps for the two-hour periods pre- and post-peak can be found in the Appendix Section D.3, along with the maps depicting the whole country (Section D.4). The colour of the line indicates the number of passengers that differ from baseline, while the thickness of the line shows how many people travel on this line at baseline, allowing high-ridership corridors to be distinguished from minor ones.

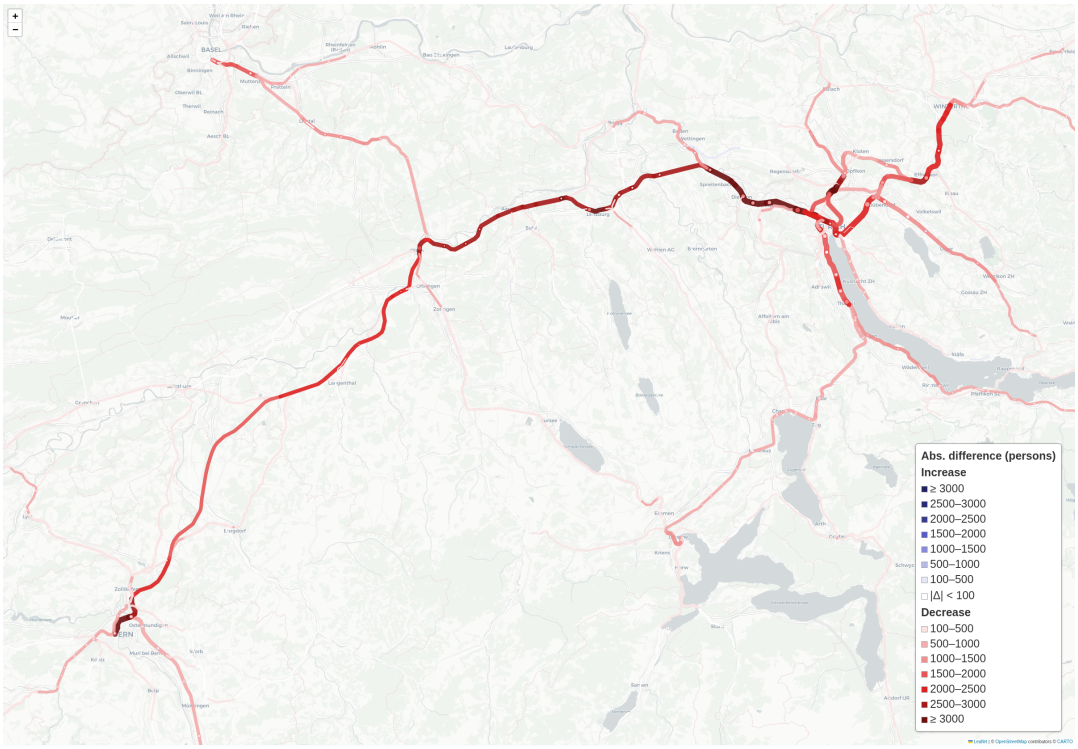


Figure 5.4: S1 (50% surcharge): Change in network demand during the peak (07:00-09:00) period compared to baseline

Although the surcharge is applied uniformly across the network, the resulting reductions in demand are not spatially uniform in terms of absolute numbers. Demand is reduced at a much larger scale on the busiest corridors and on the approaches to Zurich and Bern. The results indicate that the response scales with baseline ridership, providing the strongest relief on the corridors carrying the most passengers. This could be explained by the fact that the busiest corridors also contain the most travellers with the flexibility to shift, and thus absorb the largest reductions. There are no lines that gain passengers in this time window, which follows expectations. This also suggests that travellers are not switching to parallel cheaper lines in order to decrease the absolute surcharge amount while still travelling in peak. Thus, the displaced demand is partly redistributed into the adjacent time periods and partly shifted to other modes (no other alternatives are possible within the simulation framework).

Furthermore, the largest reductions occur on the approaches around Zurich and immediately east of Bern, exceeding 3000 passengers over the two-hour window. A reduction of this magnitude is operationally relevant: a modernised IC2000's (operated by SBB between Zurich and Bern) second-class coach can sit approximately 125 passengers, and a full train set close to 1000 [40]. This means a shift of this size is at least of the order of a coach's worth of load or more. Whether it means shortening a train set or simply relieving crowding depends on factors such as the train's running frequency, its seating and standing capacity, and the baseline occupancy, and cannot be concluded with full certainty. Nevertheless, the effects are not negligible. By contrast, the smaller regional lines either are unaffected or show reductions of roughly 100–500 passengers over the same window, which is likely too small to motivate any operational change. This is not a concern, however, since these lines are generally not expected to face capacity problems in the first place.

Rail peak trips

Figure 5.5 visualises the rail peak trips that occurred in the baseline scenario and what happened to them once the highest peak surcharge is applied.

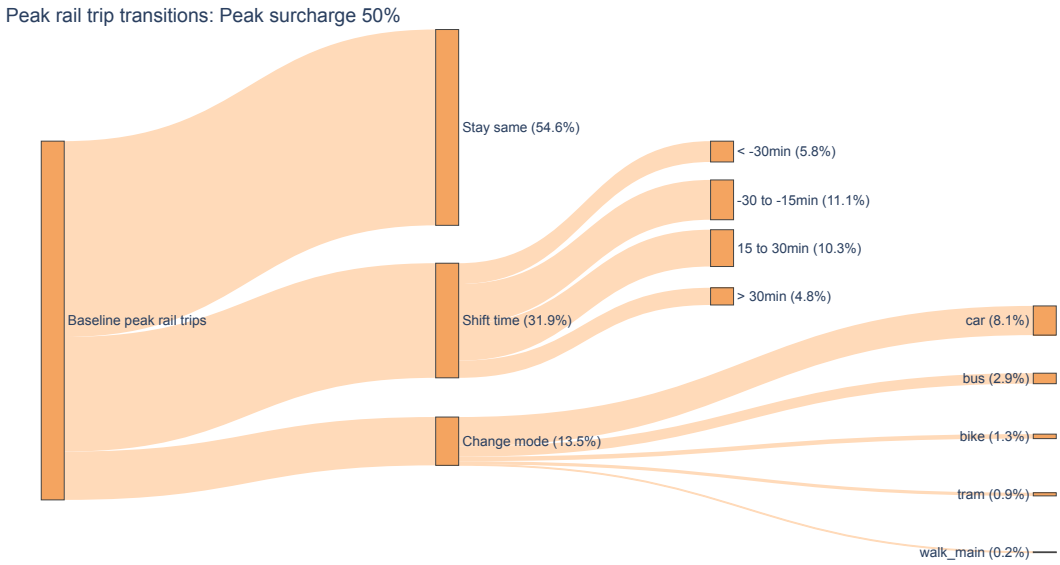


Figure 5.5: S1: Peak rail trips

The figure shows that 54.6% of trips remain largely unchanged (departure time change up to 15 minutes), while approximately a third of the trips change in departure time and about 14% change mode. The submode information shows that most of the switch occurs towards the car, although a notable share of the switchers - approximately 30% - change to other public transport modes.

It should be noted that even though the data shows that 31.9% of trips are shifted in time, this does not state that all of these shifts occur because of the pricing policy. Some might replan within the peak, some might replan independently to leave the peak, as the simulation involves stochastic processes. To infer a causal relationship, more detailed outputs are required, thus, the figure should be read as more of an indication that provides a comparison between the scenarios.

Distributional equity

Figure 5.6 below shows both the schedule delay and agent-executed score changes compared to baseline according to an increasing peak surcharge. Across all socio-demographic variables, the differences in SDE and SDL between the segments are minimal. SDE and SDL also seem to be symmetric. There is no increasing effect with increasing surcharge amount, so either the surcharge does not significantly affect the schedule delay, or there is a threshold effect between no surcharge and surcharge.

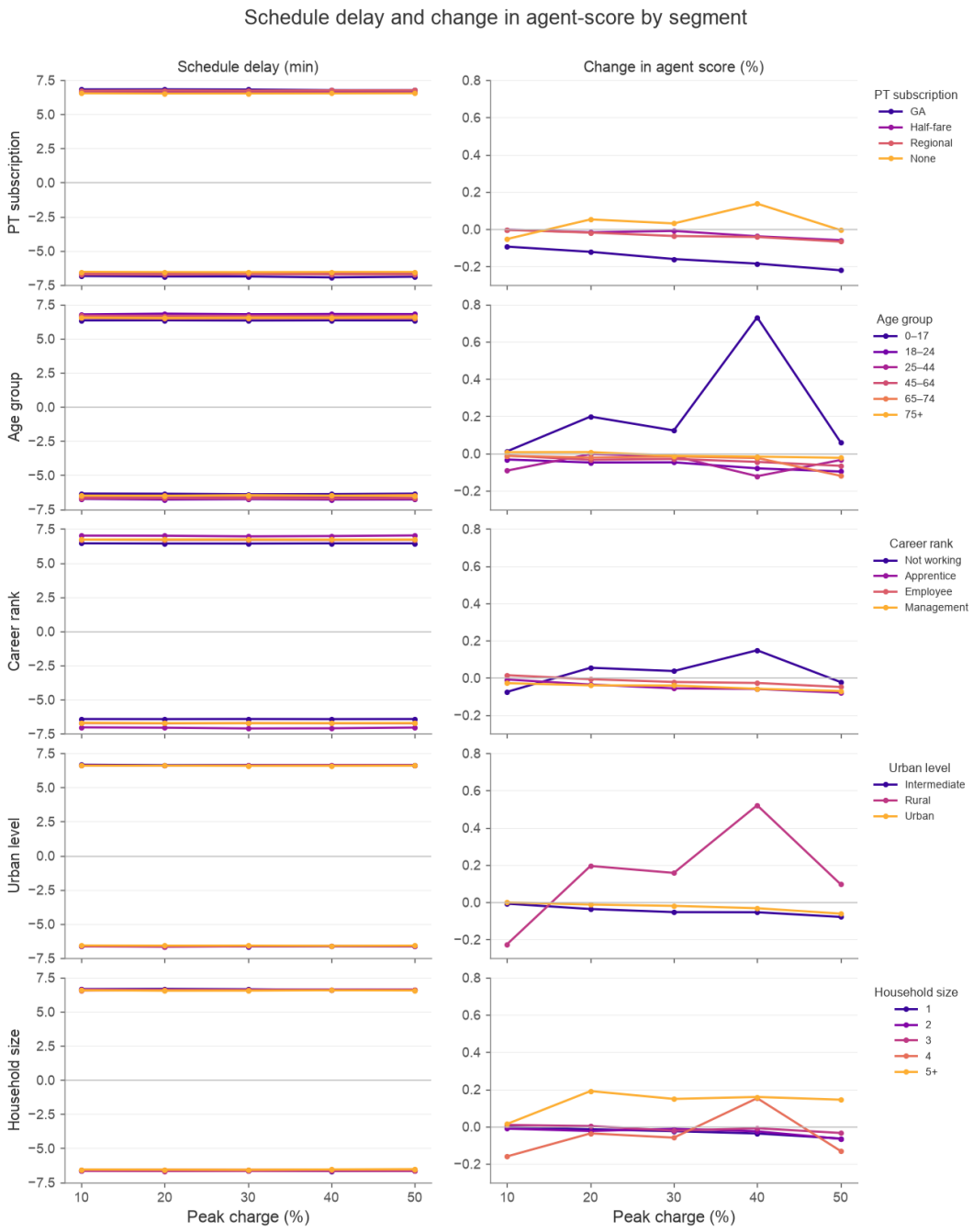


Figure 5.6: Schedule delay and agent score change compared to baseline for population segments based on the peak charge

In terms of agent score, the score is largely similar to baseline with a slight decline as the surcharge increases, which is expected due to increased costs. For this scenario specifically, it is illogical to have an increase in the agent score that is caused by anything other than stochasticity, since crowding is not part of the utility function so no gains could be achieved there, and otherwise the cost of travel is either increased or stays the same. Thus, although for each of the socio-demographic subgroups there are one or two levels that reach into the positive score change, this must be due to randomness. A commonality between these population segments is that they are generally less likely to use rail, for example, people with no subscription or rurally living persons, which could explain why the scores are showing random behaviour in terms of the surcharge applied for rail.

For the lines that fit the expected behaviour of decreasing in score with increased surcharge, the GA

subscription holders have a generally bigger score decrease than agents with the half-fare and regional subscriptions. Since GA is the highest-coverage subscription, it is often owned by frequent rail users. This implies that these agents are more likely to use rail and, therefore, are more exposed to the surcharge, which could explain the larger decrease in their score.

It is important to note that, in general, the changes in the agent score are limited. Combined with the fact that some levels show counter-intuitive behaviour, the welfare effects do not show a strong or confident change in agent scores. This implies that the peak surcharge policy - no matter which of the tested levels is applied - does not cause a strong effect on agent welfare and is distributed relatively equally across the population.

Summary of effects

In terms of **demand redistribution**, the surcharge does flatten the morning peak, with the effect growing as the surcharge increases and reaching a -9.73% reduction in peak rail trips at the 50% level. This is likely from both re-timing into the shoulder periods and partly from trips leaving rail, since the peak reduction is accompanied by a loss in ridership and modal share.

For the **modal split**, the PT share decreases, with a slight increase in car share. While the effect is relatively small in the context of the whole day (decrease in PT modal share is 0.1%), it is caused by pricing applied over a two-hour period, only on rail out of the PT submodes and calculated across the whole country, thus, it is still a noticeable change.

In terms of **revenue**, all tested levels result in a net loss, as the surcharge income does not offset the reduction in ticket revenue from lower passenger-kilometres. This suggests that, at least in this set-up, the surcharge is not self-financing and would need to be justified on demand-management rather than revenue grounds.

For **welfare and equity**, the changes in agent score are limited and show no strong or systematic pattern across socio-demographic groups. The GA subscription holders are a partial exception, since they see a slightly larger decline than other segments, but this could be explained by their higher likelihood to be exposed to the policy. Schedule delay is similarly small (approximately 7 minutes) and symmetric. These results should be read with some caution, as several subgroups show counter-intuitive trends that are most likely stochastic. Nevertheless, based on the available evidence, the policy does not appear to place a strongly uneven burden on any particular segment.

5.2.3. S2: Off-peak discount

The second scenario explores the off-peak discount, applied 9:00-15:00 and 19:00 onwards. Discount amounts from 30 to 50% are tested to see the impact of different amounts.

Table 5.3: Simulation results under different off-peak discount scenarios

		Off-peak discount		
	Baseline	**30%**	**40%**	**50%**
Total rail passenger trips [M]	2.03	2.09 (+3.0%)	2.11 (+3.9%)	2.13 (+4.9%)
Total rail passenger-km [M]	76.70	79.30 (+3.4%)	80.19 (+4.6%)	81.16 (+5.8%)
Long-distance rail passenger-km (FV) [M]	41.94	43.67 (+4.1%)	44.21 (+5.4%)	44.86 (+7.0%)
Regional rail passenger-km (RV) [M]	27.11	27.96 (+3.1%)	28.28 (+4.3%)	28.63 (+5.6%)
Profit from surcharge [K]	0.00	0.00	0.00	0.00
Revenue change for tickets [K]	0.00	520.54	698.09	893.18
Discount loss [K]	0.00	225.50	306.66	391.89
Balance [K]	0.00	295.04	391.44	501.29
Peak share of day (rail) [%]	19.60	19.11	18.87	18.68
Change in peak rail trips [%]	0.00	0.61	0.52	0.57
Mean agent score	50.03	50.06	50.07	50.08
Car [%]	48.1	47.8	47.8	47.7
PT [%]	18.5	18.7	18.8	18.9
Walk [%]	26.2	26.3	26.3	26.2
Bike [%]	7.2	7.2	7.2	7.2

Table 5.3 shows the key metrics across the simulation runs. Overall, there is an increase in rail passenger trips and passenger-kilometres, with a stronger percentage increase for long-distance rail compared to regional. This is opposite of the peak surcharge scenario, where the biggest effect (reduction) was on regional trains instead of long-distance. In terms of revenue, there are increased earnings from added passenger-kms alongside a loss from the discount on off-peak travel. The overall balance is positive, meaning the policy creates a profit for the operator. This, however, does not include any added costs if added train capacity is needed in the off-peak due to attracted demand.

Interestingly, in terms of reduction in peak rail trips, the off-peak discount actually resulted in an increase of peak demand of 0.52% - 0.61%, while the peak share of daily rail travel reduced from 19.60% in the baseline to 18.68% for the highest discount. This means that while the spread of rail demand across the day became more even due to added demand in the off-peak, the number of trips in the peak did not fall. This suggests that the off-peak discount is not significantly affecting trips occurring in the peak, but rather acting upon a different set of trips, most likely already happening in the off-peak and attracting them to use rail.

The mean of agent scores is slightly increased with increasing discount amount, indicating that on average there is a population benefit. The discount also provides up to a 0.4% decrease in car modal share and up to a 0.4% increase in PT modal share, with the effect dependent on discount size. The fact that the decrease in car share closely matches the increase in PT share suggests that the main effect of the off-peak discount is motivating a change from car trips to rail. In comparison to S1, the effect on modal share is larger for the off-peak discount than the peak surcharge. However, this might be due to the fact that the discount is applied across a longer time window than the surcharge.

In general, the severity of the effects increases with the discount, which follows expectations and indicates that at least in the tested range there are no clear threshold effects. These patterns are looked at individually in the following subsections.

Time distribution of travel

Figure 5.7 shows the rail use distribution for the morning hours for all tested discount amounts. It should be noted that the discount is applied after 9:00 and not before the peak hours. In general, there is a change in traveller numbers between approximately -4% and +27% compared to baseline. Rail demand remains roughly the same until approximately 8:30, where it has a slight drop followed by a significant increase that gradually diminishes towards the afternoon.

It can be seen that during the peak time there is practically no reduction of trips, except for a small reduction of approximately 4% compared to the baseline right before the peak period ends. This is likely due to people who were travelling right before 9:00 now being incentivised to make a small shift in time to travel after 9:00 and receive the discount. At some points, the discounted scenarios are even increasing the demand, which counters expectations. A plausible explanation might be that the added ridership also includes travellers on longer journeys that might utilise the off-peak discount, but a part of their trip is within the peak period, thus increasing the demand.

The result indicates that the discount is not successful in reducing rail peak trips, however, it is attracting a notable amount of new trips to rail.

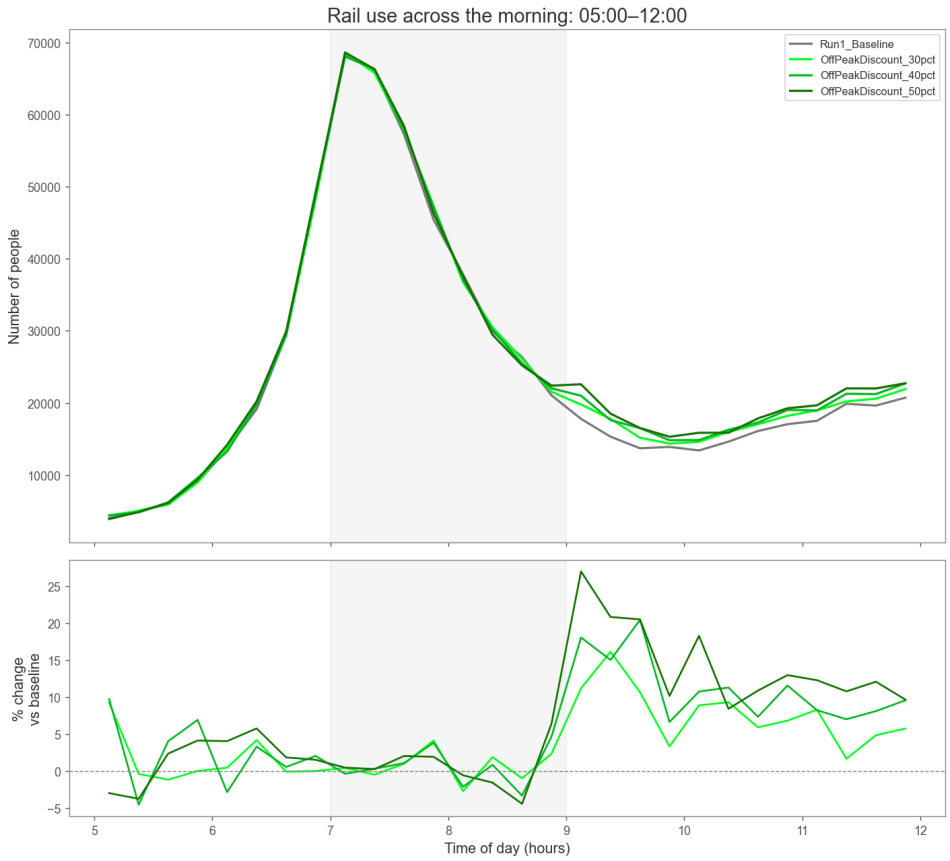


Figure 5.7: S2: Morning distribution of rail travel for various levels of off-peak discount

Network demand

The change in network demand under the off-peak discount is shown in Figure 5.8, with the pre- and post-peak maps and the national view in Appendix Sections D.3 and D.4. In contrast to the surcharge scenario, the discount produces a weak reduction of peak period demand. The reductions on the main corridors and around Zurich and Bern are present but considerably smaller, and some links even show a slight increase in peak demand rather than a decrease. As explained also for the time distribution graph, this might be due to attracted new trips that are partly within the discounted period and partly in the peak. The most notable increase is between Muttenz and Liestal (near Basel). However, here an alternative route shows an decrease, suggesting that the cause is travellers changing from one route to another.

The smaller effect is likely because a discount applied to off-peak travel lowers the relative attractiveness of the peak without imposing any direct penalty on peak travel itself, thus, the incentive to leave the peak window is weaker than with a surcharge. What is interesting to acknowledge is that under a discounted scenario, since there is no deterrent from the peak, the reduction in demand is caused

purely by attracting travellers to the off-peak, not by mode switch to car or other modes. Nevertheless, the net effect is only a modest flattening of the peak concentrated again on the busiest corridors.

Operationally, the reductions on even the busiest corridors remain mainly below 500, which is likely not sufficient even for removing a single coach since the reduction is summed over a two-hour period. As a stand-alone instrument, therefore, the off-peak discount is a weaker policy for peak spreading than the surcharge.

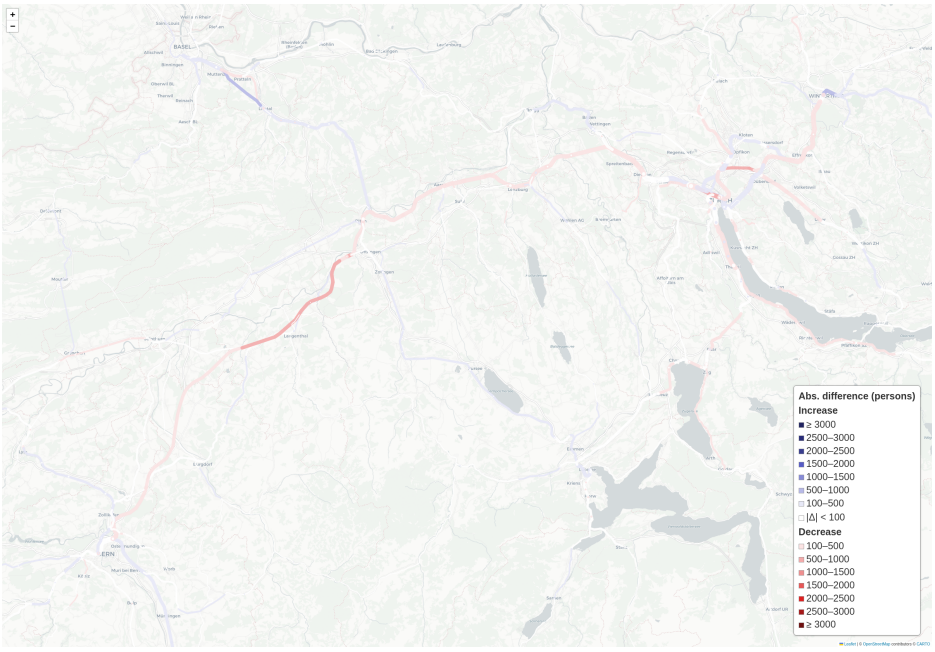


Figure 5.8: S2 (50% discount): Change in network demand during the peak (07:00-09:00) period compared to baseline

Rail peak trips

Looking at the rail peak trips in the baseline scenario and what happens to them once the highest off-peak discount is applied (Figure 5.9) shows that 56.5% of trips remain largely unchanged (this includes departure time change up to 15 minutes). Approximately a third of the trips change in departure time and about 10% change mode.

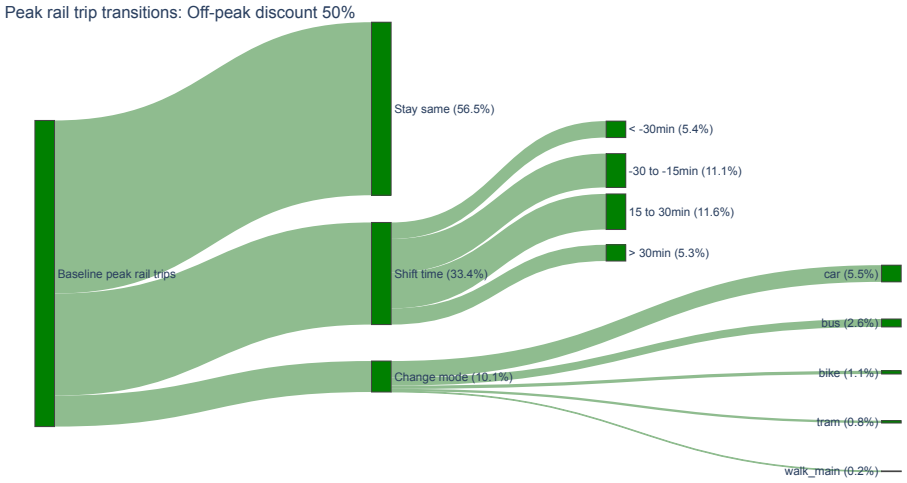


Figure 5.9: S2: Peak rail trips

Compared to the peak surcharge outcomes: the percent of trips staying the same is about 2% higher; the percent of trips shifted in time is 1.5% higher; and the percent of trips changing mode is 3.4% lower. The higher proportion of trips remaining unchanged and the decrease in mode switching are as expected for an off-peak discount policy. This is because literature indicates that discounts have a weaker effect in shifting people's behaviour, and a discount makes rail more, not less, attractive regarding the mode choice [29]. However, the small increase in time-shifted trips is counter-intuitive given the overall results table, which indicated only a small reduction in peak trips. It is possible that some longer trips switched within the peak in order to receive the discount on the end portion of their trip, thus not reducing the number of peak trips, but still counting as a shifted trip. Moreover, it could also be due to the stochastic nature of MATSim. Finally, the submode information shows that most of the switches occur towards the car, although by 2.6% less than under S1, while a third of the switchers change to other public transport modes.

Distributional equity

Figure 5.10 below shows both the schedule delay and agent-executed score changes compared to baseline according to an increasing off-peak discount.

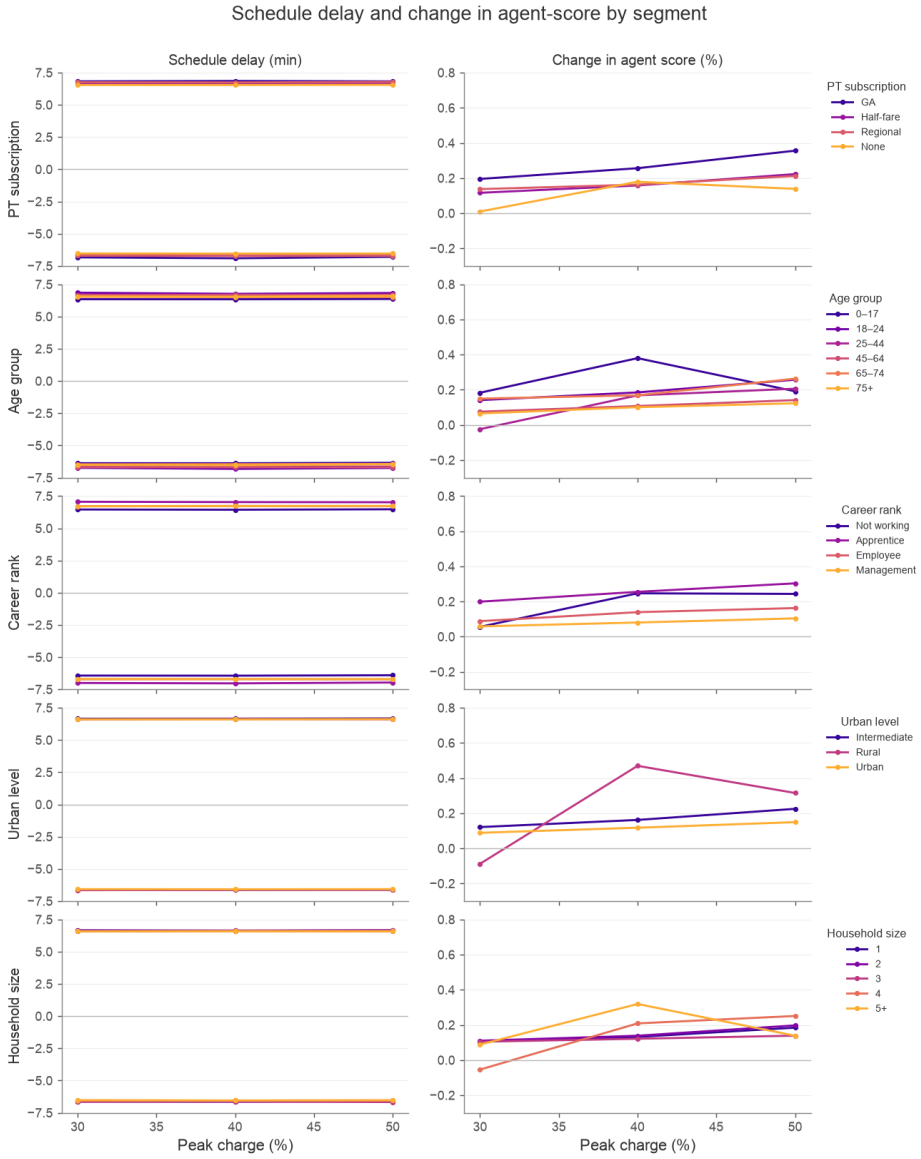


Figure 5.10: Schedule delay and agent score change for the off-peak discount compared to baseline for population segments

Similar to the peak surcharge scenarios, across all socio-demographic variables, the differences in SDE and SDL between the segments are minimal, with SDE and SDL also showing symmetry. There isn't an increasing effect with increasing discount amount, so either the discount does not significantly affect the schedule delay, or there is a step increase between discount and no discount. The average schedule delay is approximately 7 minutes, matching that of the peak surcharge.

For the agent utility, the score is largely similar to baseline with a slight positive offset and an increasing trend with increasing discount, which is expected due to decreased costs.

Similarly to S1, the levels that are typically expected to have a higher likelihood of rail use are the ones that follow an expected pattern - gradually increasing the mean score with increased discount. The levels that don't follow this pattern are PT subscription equals none, age category 0-17, career rank 0 meaning currently inactive, rural residents, and household size four and above. Thus, the less expected trends with increasing discount levels could be attributed to stochasticity rather than the pricing policy.

Furthermore, and in contrast to S1, there are clearer distinctions in the positive offset of each line, showing some difference across groups. The main benefits are gained by: GA subscribers, which are expected to use rail more frequently; age groups 18-44 and 65-74 compared to 45-64 and 75+, which are possibly the less car-reliant groups; apprentices, then employees, then management, which is plausible if considering who is more likely to use rail. To continue, urban and intermediate residents have similar scores, with intermediate benefiting slightly more, while household sizes below 4 show generally no distinction in benefit.

Nevertheless, the changes in the agent score are limited and might have some stochastic effects. That said, the expected behaviour and the upward-sloping trend indicate that the off-peak discount is having a small positive impact on the population. The lower score change can also be partly attributed to the fact that the changes are averaged over the whole population and so are likely to be drawn towards zero. Thus, based on the available evidence, the overall impact of the policy is small but positive and seems to benefit the groups expected to use rail the most.

Summary of effects

In terms of **demand redistribution**, the discount evens out the daily demand, with the peak share of rail travel falling from 19.60% to 18.68% at the highest discount. However, it does not reduce peak trips, which even increase slightly (0.52% - 0.61%). This is an important distinction: a more even distribution is achieved by adding off-peak trips rather than by removing peak ones, so the policy reduces the *share* without relieving the peak demand. This suggests that in this context the policy is not effectively working on peak trips, but rather the off-peak trips from other modes. This is also supported by the results for the **modal split**, giving up to a 0.4% increase in PT share and a corresponding decrease in car share, with walking and biking largely unaffected.

In terms of **revenue**, the balance is positive across all tested levels, as the additional passenger-kilometres outweigh the revenue lost to the discount. This is a more favourable outcome than the surcharge scenario. It should be noted that this does not account for any additional operating costs that might come if more train capacity needs to be added in the off-peak.

For **welfare and equity**, agent scores increase slightly with the discount, and the effect is more clearly differentiated across groups than in S1, with frequent rail users such as GA holders benefiting most. The changes remain limited in magnitude, and some groups that are less inclined to use rail show inconsistent effects. Thus, while the direction of the effect is plausible and positive, there seems to be a mix between stochastic and policy effects, both similar in size. For schedule delay, the change is again small and symmetric, with no strong distributional pattern.

Overall, the results suggest that the discount is not large enough to incentivise peak travellers to switch out of the peak. This could be related to the fact that many travel early in the peak windows, as shown in the daily distribution. A switch to post-9:00 is a significant time difference, which in terms of schedule delay valuations might require a larger sum of money to motivate the change. If perhaps the discount would be available before the peak, the effect might be larger. Another reason for the lack of peak trip reduction could be that there are cut-off times for some agent activity start times and that such a switch

is simply not possible. Either way, the off-peak discount is not sufficient as a single instrument for peak demand management, at least in its current set-up.

5.2.4. S3: Peak surcharge & Off-peak discount

The third scenario combines a peak surcharge with an off-peak discount, pairing surcharge and discount levels of 10 & 50, 20 & 30, 20 & 40 and 50 & 50 % to observe how the two instruments interact.

Table 5.4: Simulation results under combined peak surcharge and off-peak discount scenarios

		Peak surcharge & Off-peak discount			
	Baseline	**10% & 50%**	**20% & 30%**	**20% & 40%**	**50% & 50%**
Total rail passenger trips [M]	2.03	2.12 (+4.4%)	2.07 (+2.0%)	2.10 (+3.4%)	2.09 (+3.0%)
Total rail passenger-km [M]	76.70	80.90 (+5.5%)	78.82 (+2.8%)	79.59 (+3.8%)	79.71 (+3.9%)
Long-distance rail passenger-km (FV) [M]	41.94	44.64 (+6.4%)	43.40 (+3.5%)	43.81 (+4.5%)	44.06 (+5.1%)
Regional rail passenger-km (RV) [M]	27.11	28.61 (+5.5%)	27.71 (+2.2%)	28.07 (+3.5%)	28.03 (+3.4%)
Profit from surcharge [K]	0.00	22.86	44.44	44.44	103.14
Revenue change for tickets [K]	0.00	840.32	425.00	578.01	603.39
Discount loss [K]	0.00	392.24	225.79	306.56	390.84
Balance [K]	0.00	470.94	243.65	315.89	315.69
Peak share of day (rail) [%]	19.60	18.40	18.42	18.22	17.19
Change in peak rail trips [%]	0.00	-1.21	-3.74	-3.62	-9.21
Mean agent score	50.03	50.08	50.05	50.06	50.06
Car [%]	48.1	47.7	47.9	47.8	47.8
PT [%]	18.5	18.9	18.7	18.8	18.7
Walk [%]	26.2	26.2	26.2	26.2	26.2
Bike [%]	7.2	7.2	7.2	7.2	7.2

Table 5.4 shows the metrics for the combined scenarios. Broadly, this policy raises rail demand while also reducing the peak demand: passenger trips and kilometres increase, with long-distance rail gaining comparatively more ridership, while peak trips fall by between 1.21% and 9.21% depending on the level pairing. The financial balance is positive across all combinations, driven mainly by the change in ticket revenue rather than the surcharge income or discount loss on their own. Agent scores are slightly above baseline for all levels, and the modal split moves towards PT and away from car in every combination.

Time distribution of travel

Figure 5.11 shows the rail use distribution for the morning hours for the tested combined surcharge and discount amounts.

Overall, there is a change in traveller numbers between approximately -14% and +30% compared to baseline, which exceeds both the surcharge-only and discount-only scenarios. It can be seen that the rail demand is reduced during the peak time while increased in both of the shoulder periods (6-7 am and 9-10 am) as well as slightly higher continuing further in the noon time.

The combined effect draws the demand curve down in the peak and up on either side of it, so the two instruments appear to act together, the surcharge suppressing peak travel while the discount pulls trips into the neighbouring periods. This result aligns with literature, where studies found that most of the retiming occurs to the nearest shoulder periods rather than evenly throughout the day.

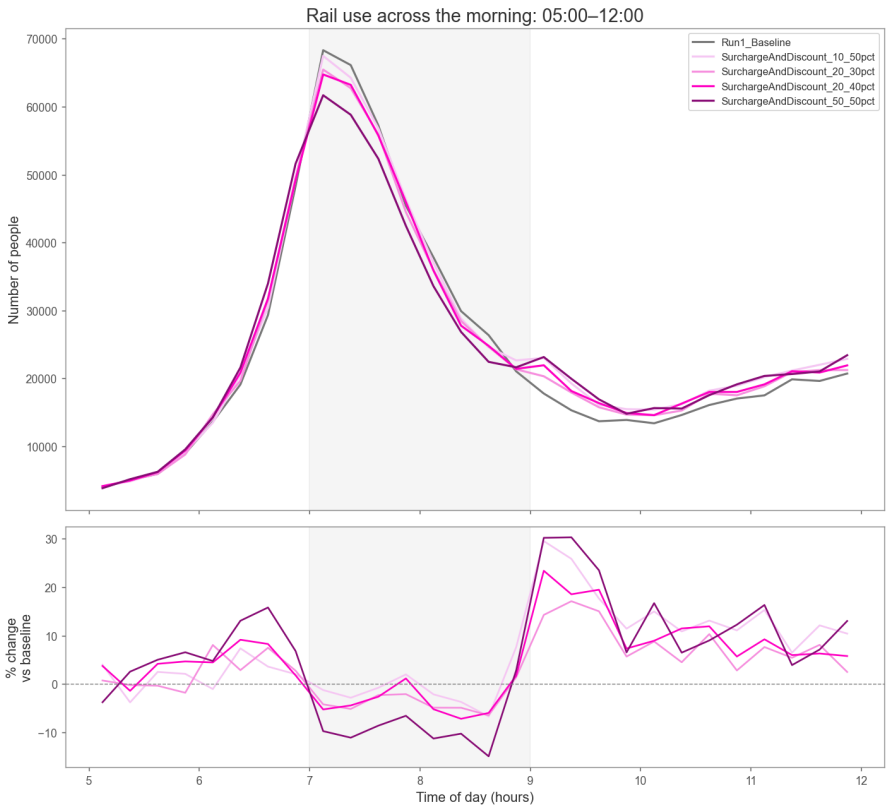


Figure 5.11: S3: Morning distribution of rail travel for various levels of peak surcharge and off-peak discount

Network demand

The combined surcharge and discount scenario is shown in Figure 5.12, with the pre-, post-peak and national maps located in Appendix Sections D.3 and D.4.

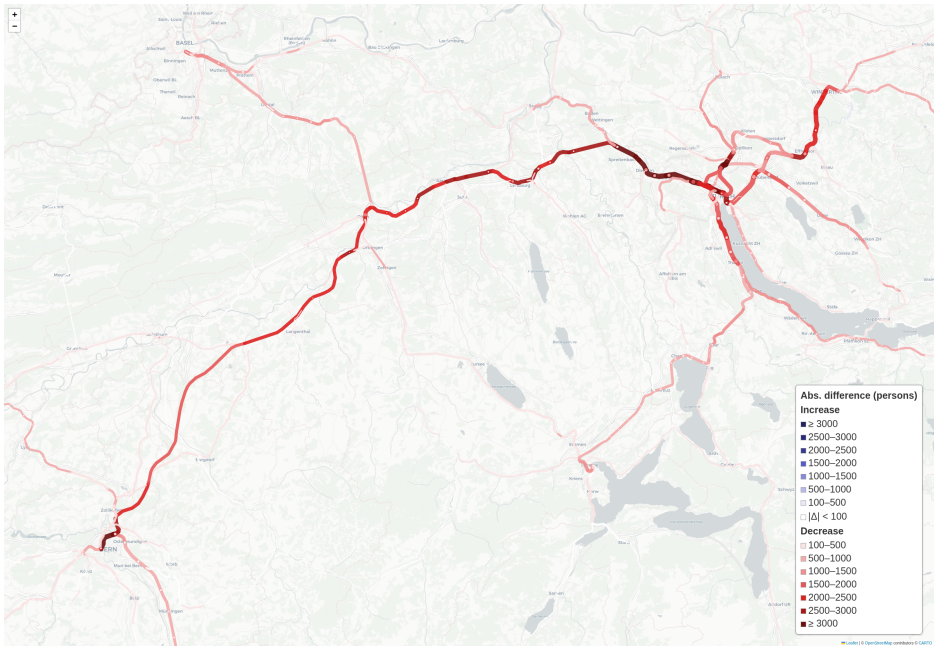


Figure 5.12: S3 (50&50% surcharge & discount): Change in network demand during the peak (07:00-09:00) period compared to baseline

The scenario's induced change in network demand closely resembles the surcharge-only scenario (S1), showing a strong decrease on the busiest corridors and around Zürich and Bern, as well as no links having an increase in passengers. The response is again proportional to ridership, having the largest decrease on the busier links. The fact that S3 results resemble the S1, having a reduction of very similar scale, indicates that, within the peak window, the surcharge (rather than the discount) does almost all of the work, which is supported by the findings also in the single instrument scenarios.

The corridors showing the largest reductions coincide with those under S1, so the same rolling-stock implications apply. The Zurich approaches and the segment immediately east of Bern are the clearest candidates for capacity review.

Rail peak trips

The results show that baseline rail peak trips generally stay the same (54.3%) in the scenario with peak surcharge 50% and off-peak discount 50%. This is the lowest percentage compared to just surcharge (54.6%) and just discount (56.5%). Approximately a third of the trips shift time more than the 15-minute tolerance (33.6%), but again the percentage is slightly higher than that of only surcharge (31.9%) and only discount (33.4%). Mode change is at 12.1% which is a bit less than for surcharge only and a bit more than for discount only, also as expected. The submodes for the mode switching follow a similar pattern.

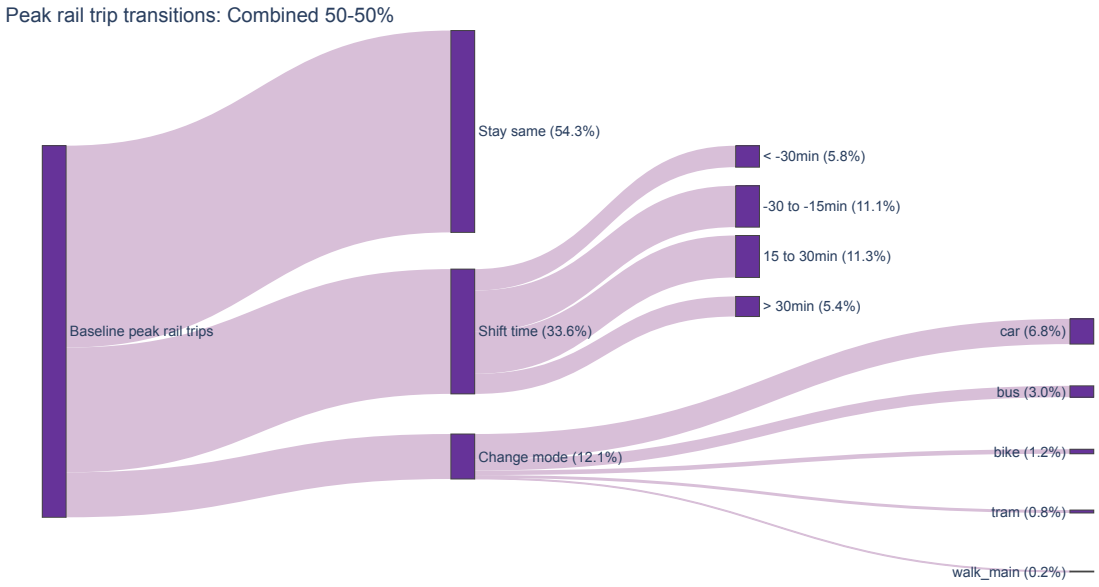


Figure 5.13: S3: Peak rail trips

The trip transitions show that both the surcharge and the discount are acting together. As one would expect, there are fewer trips unchanged and more shifted in time than for either of the single instrument policies, while the mode switch is lower than for surcharge and higher than for discount.

Distributional equity

Figure 5.14 below shows both the schedule delay and agent-executed score changes compared to baseline according to the policy. Similar to both the peak surcharge scenarios and the discount scenarios, across all socio-demographic variables the differences in SDE and SDL between the segments are minimal. SDE and SDL also appear to be symmetric. There is not a noticeable change in the effect with varying surcharge and discount amounts.

For the agent utility, the score is largely similar to baseline with a slight positive offset, with very few segment and pricing level combinations showing a decrease in score. This indicates that overall there is a benefit for the agents.

Since the scenarios in this set have two varying pricing amounts, it is not expected to have a linear or continuous trend across the scenario values. In terms of PT subscription, over all the pricing levels the gain in score is similar, with *GA* again having a slightly larger gain and *none* having almost no increase except for the 20-40% scenario, which is likely due to stochasticity. For the age categories, most categories have similar increases except 0-17 has a stronger increase for 20-40 and 20-30, and the 25-44 category is more or less around 0 change in score.

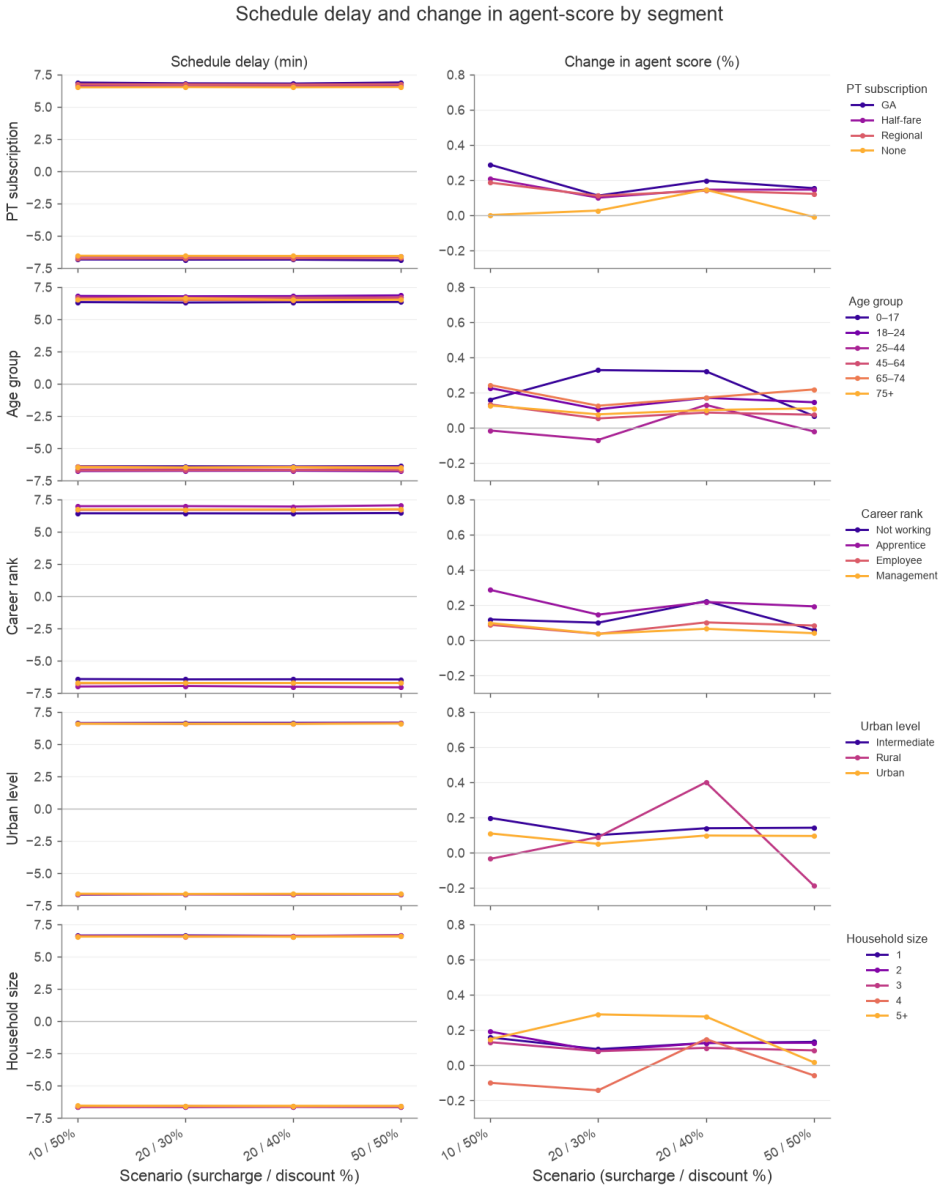


Figure 5.14: Schedule delay and agent score change compared to baseline for population segments based on the combined peak surcharge and off-peak discount policies

For career rank, the lowest score gain is for the highest ranks (employee and management) while the *not working* segment experiences a higher score for 20-40% and *apprentice* has an overall higher score increase. For urban level, again the intermediate and urban segments have quite similar effects, while rural is quite inconsistent. Finally, the score change for household size less than four is similar for all levels, while for four the changes are around zero and for more than five there is a higher positive increase for 20-30% and 20-40%.

Since multiple of the described effects do not have a solid interpretation and vary seemingly inconsis-

tently, it suggests that there may be a significant amount of simulation noise and results should be perceived with caution.

Overall, the score increases generally are similar across these scenario levels, indicating that the amounts of surcharge and discount do not strongly affect them. There are minor differences between the segments. Several are likely due to randomness, however, some show a logical reaction and thus might show a genuine effect. In these cases, the policy benefits the ”less advantaged” groups more (e.g. career rank *not working* or *apprentice*, and household size 5+).

Summary of effects

Looking first at **demand redistribution**, the combination both lowers the peak demand and increases the demand in the off-peak periods. This results in cutting peak trips by up to 9.21% at the 50&50 level and reducing the peak share of daily rail trips to as low as 17.19% (by 2.41%). Additionally, the reduction of peak trips seems to be generally governed by the surcharge level.

In terms of the **modal split**, every combination sways the share towards PT and away from car. This produces a favourable outcome as the off-peak discount is able to negate the surcharge influence on the modal split. It should be noted that the discount is, however, applied across a much longer period of the day compared to the surcharge.

For **revenue**, all four combinations are profitable, with the change in ticket revenue the dominant term rather than the surcharge or discount themselves. Notably, the most profitable pairing is the one with the largest discount and smallest surcharge.

For **welfare and equity**, scores are marginally positive across the tested levels and, because two prices vary together, no clean trend with the level is observed. Differences between socio-demographic groups are minor and, where present, appear to slightly favour less advantaged groups. However, given the size of the effects and the simulation noise, this should be interpreted cautiously. Schedule delay is again relatively small and symmetric.

Overall, the fact that the surcharge and discount combination yields a very similar peak reduction is relatively surprising. A switch from the peak to the off-peak at the 50-50% level means avoiding the surcharge and gaining the discount. Thus, the effective difference between travelling in and out of the peak amounts to a full fare, a significant financial incentive to switch. It would be expected that this notably increases the number of trips retiming, however, the reduction (−9.21%) is actually marginally smaller than for the surcharge alone (−9.73%). There are two plausible reasons why the off-peak discount is not successfully shifting peak travellers. First, the discount alone (S2) produced no peak reduction, for which one possible explanation was that the financial incentive was too small to draw peak travellers into the off-peak. The combined policy makes that incentive considerably larger, yet peak trips still do not reduce any further, which suggests that incentive size alone is not the restricting factor. This points to the second explanation, which suggested that agents may face a too large shift or have strict constraints on activity start times, for example, strict work or school start times which they cannot miss, which pricing cannot overcome regardless of its level. Since the maximum replanning amount is one hour, travellers closer to the beginning of the priced period cannot reach the off-peak discount and, thus, remain mainly motivated by the surcharge. The relative importance of the two factors cannot be fully resolved from this scenario alone. Nevertheless, the discount’s main effect is thus not additional peak reduction but the attraction of new off-peak trips. This is consistent with what was already suggested in the single-instrument scenarios, namely that the surcharge and the discount primarily act upon two different groups of agents, which are peak and off-peak travellers respectively. Thus, when the two instruments are combined, the peak reduction is driven by the surcharge, while the discount mainly adds off-peak ridership rather than contributing to retiming.

5.2.5. S4: Rail & Road peak surcharge

The fourth scenario pairs the rail peak surcharge with a road peak surcharge. The rail surcharge is held fixed at 30% while the road surcharge is varied (10%, 30%, 50%), so the results are compared not only to the baseline but also to the equivalent rail-only surcharge, in order to isolate the effect of adding a car charge.

Table 5.5: Comparison of peak surcharge and combined rail-car surcharge scenarios

		Peak surcharge	Rail & Car surcharge		
	Baseline	**30%**	**30% & 10%**	**30% & 30%**	**30% & 50%**
Total rail passenger trips [M]	2.03	2.00 (-1.5%)	2.01 (-1.0%)	2.02 (-0.5%)	2.02 (-0.5%)
Total rail passenger-km [M]	76.70	75.80 (-1.2%)	76.01 (-0.9%)	76.38 (-0.4%)	76.82 (+0.2%)
Long-distance rail passenger-km (FV) [M]	41.94	41.48 (-1.1%)	41.65 (-0.7%)	41.93 (-0.0%)	42.14 (+0.5%)
Regional rail passenger-km (RV) [M]	27.11	26.73 (-1.4%)	26.75 (-1.3%)	26.83 (-1.0%)	26.98 (-0.5%)
Profit from surcharge [K]	0.00	64.46	64.69	65.95	66.85
Revenue change for tickets [K]	0.00	-179.23	-137.26	-62.83	24.99
Discount loss [K]	0.00	0.00	0.00	0.00	0.00
Balance [K]	0.00	-114.77	-72.58	3.12	91.84
Peak share of day (rail) [%]	19.60	18.61	18.63	18.76	18.89
Change in peak rail trips [%]	0.00	-6.13	-5.74	-4.72	-3.79
Mean agent score	50.03	50.01	50.01	50.00	49.99
Car [%]	48.1	48.1	48.1	48.1	48.0
PT [%]	18.5	18.4	18.5	18.5	18.5
Walk [%]	26.2	26.2	26.2	26.2	26.3
Bike [%]	7.2	7.3	7.2	7.2	7.2

Table 5.5 places the combined rail-and-car scenarios alongside the equivalent 30% rail-only surcharge and the baseline. The main observation is that adding a car charge softens the effects of the rail surcharge. As the road surcharge increases, the modal share, rail trips and kilometres recover towards the baseline, reaching approximate baseline values at the highest road surcharge. At the same time, the reduction in peak rail trips weakens from -6.13% to -3.79%. Since the rail surcharge is unchanged across these scenarios, this recovery in rail ridership can mainly come from travellers who, under the rail-only surcharge, had switched to car, and who now remain on rail once the car is also charged. The peak rail reduction weakens with increasing road charge as well, because these retained travellers include ones who had left the peak by leaving rail altogether rather than by retiming. With the peak reduction roughly 40% smaller once rail ridership returns to its baseline level, a notable proportion of the surcharge's peak-spreading effect, thus, is a diversion to car.

The financial balance improves with increasing road surcharge, turning from negative to positive once the road surcharge matches or exceeds the rail surcharge. Furthermore, agent scores decrease below baseline, with the mean agent score for the highest surcharge levels having the lowest value out of all tested scenarios. This is expected since the surcharge affects more agents and is harder to avoid since mode switch to car no longer allows escape from it.

Time distribution of travel

Figure 5.15 shows the rail use distribution for the morning hours for the tested combined surcharge amounts for both rail and car surcharge. In this scenario set, the results are not only compared to the baseline, but also to the equivalent rail-only surcharge to directly observe the effects of introducing a car surcharge.

Overall, the change in traveller numbers is between approximately -8% and +9% compared to baseline. Compared to the equivalent rail-only surcharge, the distribution seems to follow a similar effect, with a slight increase in travel in the shoulder periods as well as in the peak period. The increase in travel in the peak period also seems to show that the car charge reduces the mode switch away from rail, thus lifting the whole curve towards baseline relative to the rail-only case. This results in the shape of the redistribution to be retained but its magnitude dampened, more so as the road surcharge increases. In general, the rail demand is reduced during the peak time while increased in both of the shoulder periods (6-7 am and 9- 10 am) and returning to baseline levels as it gets further from the peak period.

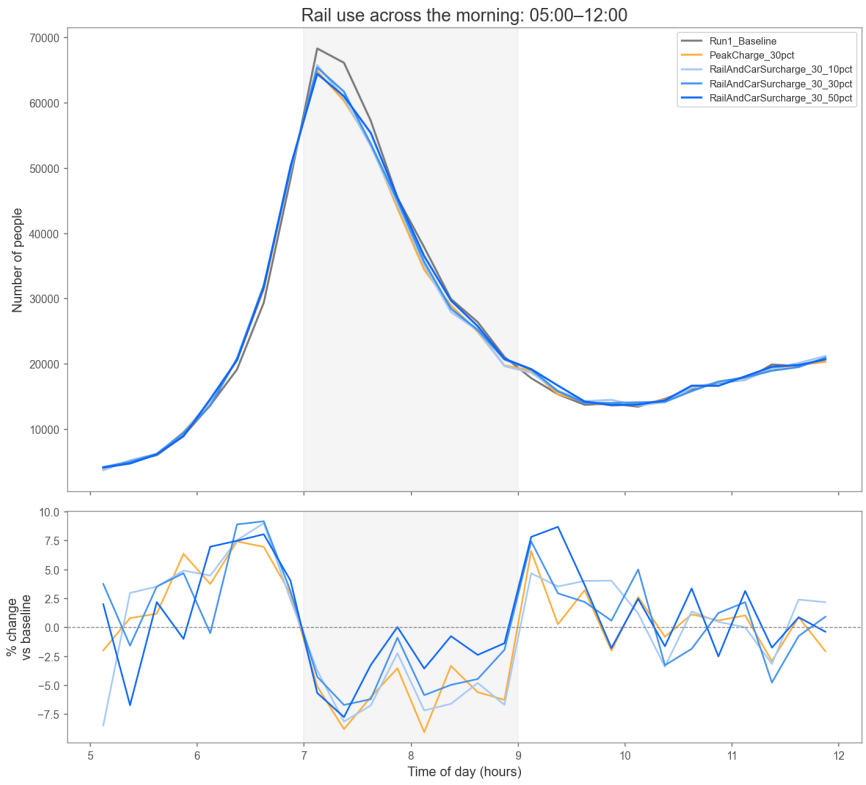


Figure 5.15: S4: Morning distribution of rail travel for rail and car peak surcharge

Network demand

The spatial effect of the combined rail and road policy is shown in Figure 5.16, relative to baseline, with the shoulder-period and national maps in Appendix Sections D.3 and D.4.

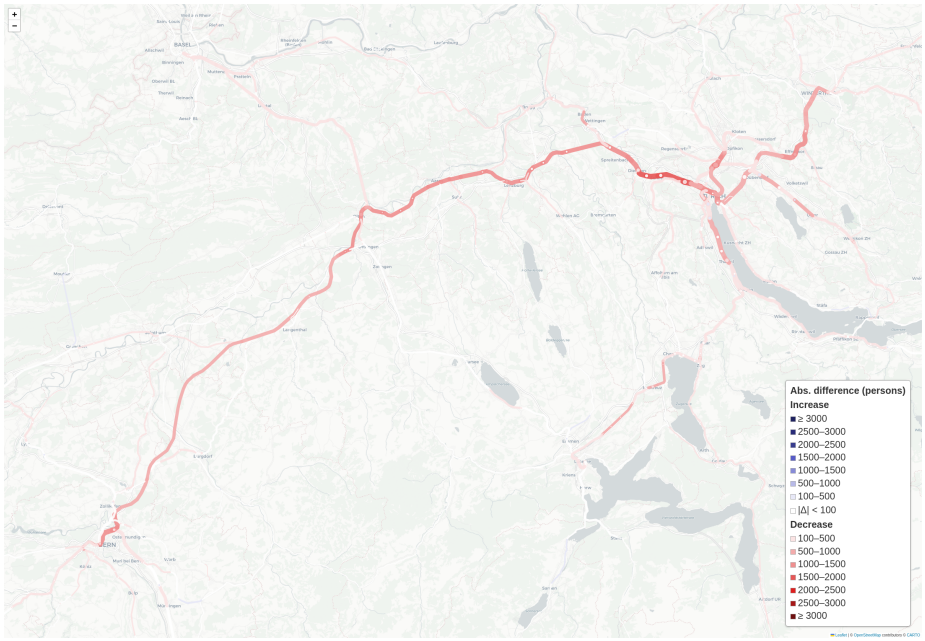


Figure 5.16: S4 (30&50% rail & road surcharge): Change in network demand during the peak (07:00-09:00) period compared to baseline

Relative to baseline, the decrease in passenger numbers occurs on the same corridors as for the surcharge-only (S1) scenario. These are the main corridors and the approaches to Zurich and Bern, however, the reduction is at a smaller scale than shown in the map for S1 (Figure 5.4). Part of this smaller reduction can be attributed to the lower rail charge (30% in this scenario against 50% in S1), and part to the car surcharge retaining travellers on peak rail who would have otherwise switched to car.

To isolate the road surcharge from the price-level effect, Figure 5.17 shows S4 against the equivalent 30%-rail-only surcharge. In this comparison, the rail price is held fixed so that any differences in passenger demand are due to the addition of road pricing. The map, therefore, essentially shows the number of passengers who would leave peak rail due to a 30% surcharge and switch to road instead of retiming as well as some agents who would leave road switching to rail.

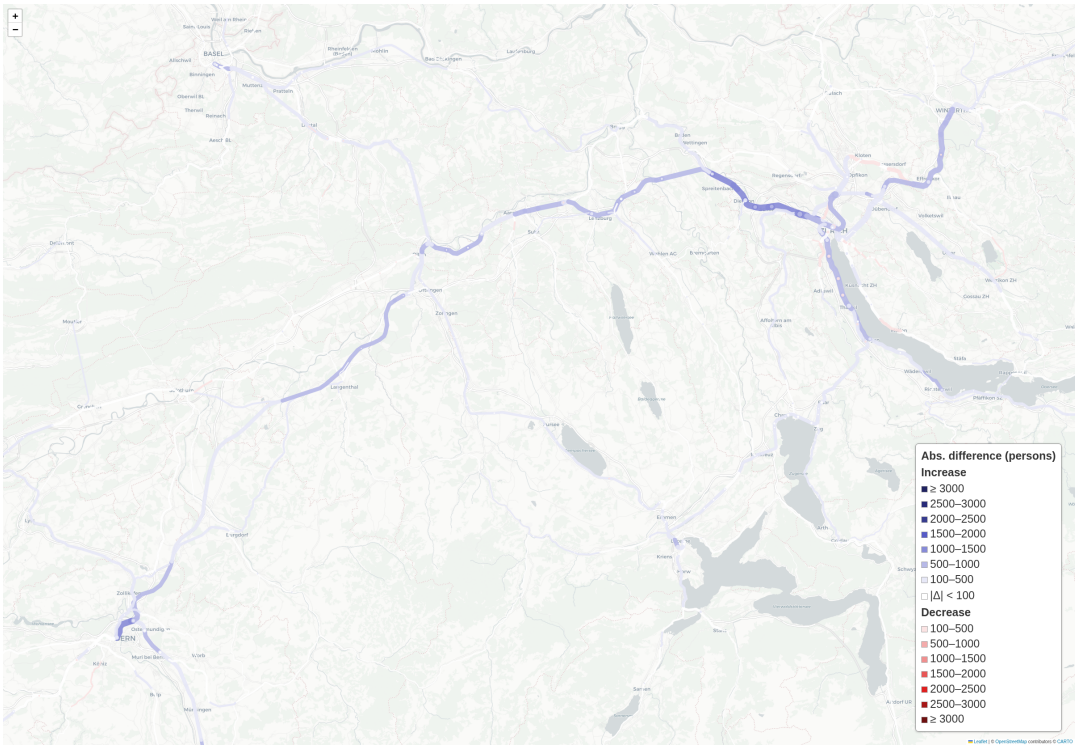


Figure 5.17: S4 (30&50% rail & road surcharge): Change in network demand during the peak (07:00-09:00) period compared to S1 (rail surcharge 30%)

It can be seen that the map is blue across essentially the entire network. Every major corridor that the rail surcharge relieved shows fewer passengers removed once car travel is also priced, confirming that the car charge shifts peak demand back onto rail. A small number of links show a slight decrease (in the lowest band), but these are scattered and do not occur in a single corridor. Most likely, it is a result of route reassignment within the rail network rather than a genuine effect.

Crucially, this effect is not confined to corridors with an obvious competing road but appears uniformly across the network. This implies that the mode switch to car in response to a rail peak surcharge is itself network-wide, not a corridor-specific side effect. This matters for how the rail surcharge's effects should be interpreted: a portion of the peak demand reduction is a switch to car rather than retiming, and would not occur if road travel were priced in parallel or if attractive car alternatives did not exist. The network-wide effect also suggests that the mode switch is driven by a general propensity to switch modes when only rail is penalised, rather than by specific corridors where the road happens to compete well.

Operationally, the reductions under S4 are smaller than under S1 but not negligible. A reduction of this scale due to a 30% rail surcharge on the busiest corridors is large enough that it could support

shortening trains by a coach. On the lighter segments and regional lines, the reductions are smaller and unlikely to motivate any change.

Rail peak trips

The results show that baseline rail peak trips in the scenario with peak rail surcharge 30% and peak road surcharge 50% largely remain unchanged (56.1%). This is a higher proportion than most of the other policies except the 50% off-peak discount (56.5%). This follows expectations as the car surcharge reduces trips that switch mode to car.

Furthermore, 32.6% of trips shift time more than the 15-minute tolerance and 11.2% change mode. Interestingly, compared to S2 and S3, which are the scenarios that involve a discount, fewer trips shift in time, while compared to the rail surcharge only (S1) it is slightly more. The latter again could be attributed to the road surcharge reducing mode switches, and thus more people are choosing the time shift option. It should be noted that the rail surcharge here is 30% rather than 50% in S1, thus part of the differences could be attributed to that.

To continue, compared to the rail surcharge of 50%, there are 2.3% point fewer trips where mode is switched away from rail, most of which comes from not switching to car, where there is a 2% point reduction. Similarly, for surcharge and discount its 0.9% fewer mode switches overall, of which 0.7% points are reduced in switching to car. Nevertheless, the off-peak discount still has a lower mode switch percentage. Therefore it can be reasoned that the car surcharge effectively decreases the rail-to-car mode switch response of a rail surcharge, while a discount is still the more effective instrument for avoiding mode switching altogether.

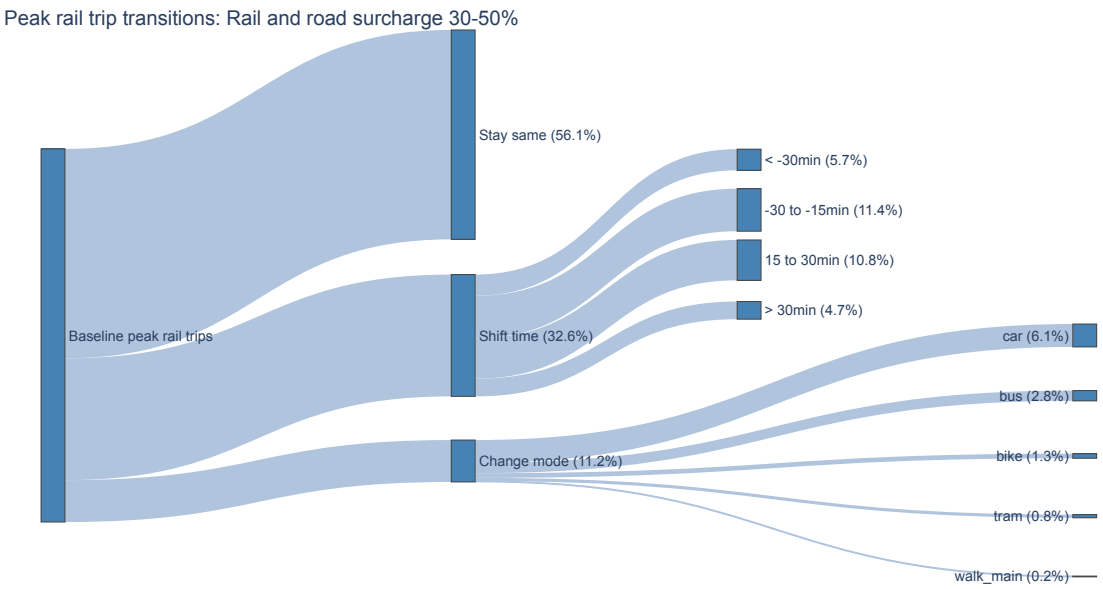


Figure 5.18: S4: Peak rail trips

Distributional equity

Figure 5.19 below shows both the schedule delay and agent-executed score changes compared to baseline according to the policy. Similar to scenarios S1-S3, across all socio-demographic variables, the differences in SDE and SDL between the segments are minimal. SDE and SDL also seem to be symmetric. There is no noticeable change in the effects with varying car peak surcharge amounts.

For the agent utility, the score is largely similar to baseline with a slight negative offset, which is expected since both rail and car are obtaining an extra charge. In general, scenarios show a decrease in score with increased car surcharge, which is also as expected. However, since the peak road surcharge could be creating benefits in travel time due to lowered congestion, increases in score are also plausible.

In terms of PT subscription, most segments are approximately at zero percent change, except GA has a slight negative offset. This could again be due to the higher rail ridership and thus bigger exposure to the rail surcharge. It can also be observed that the score is not meaningfully decreasing with increased car surcharge, again confirming dominant rail use.

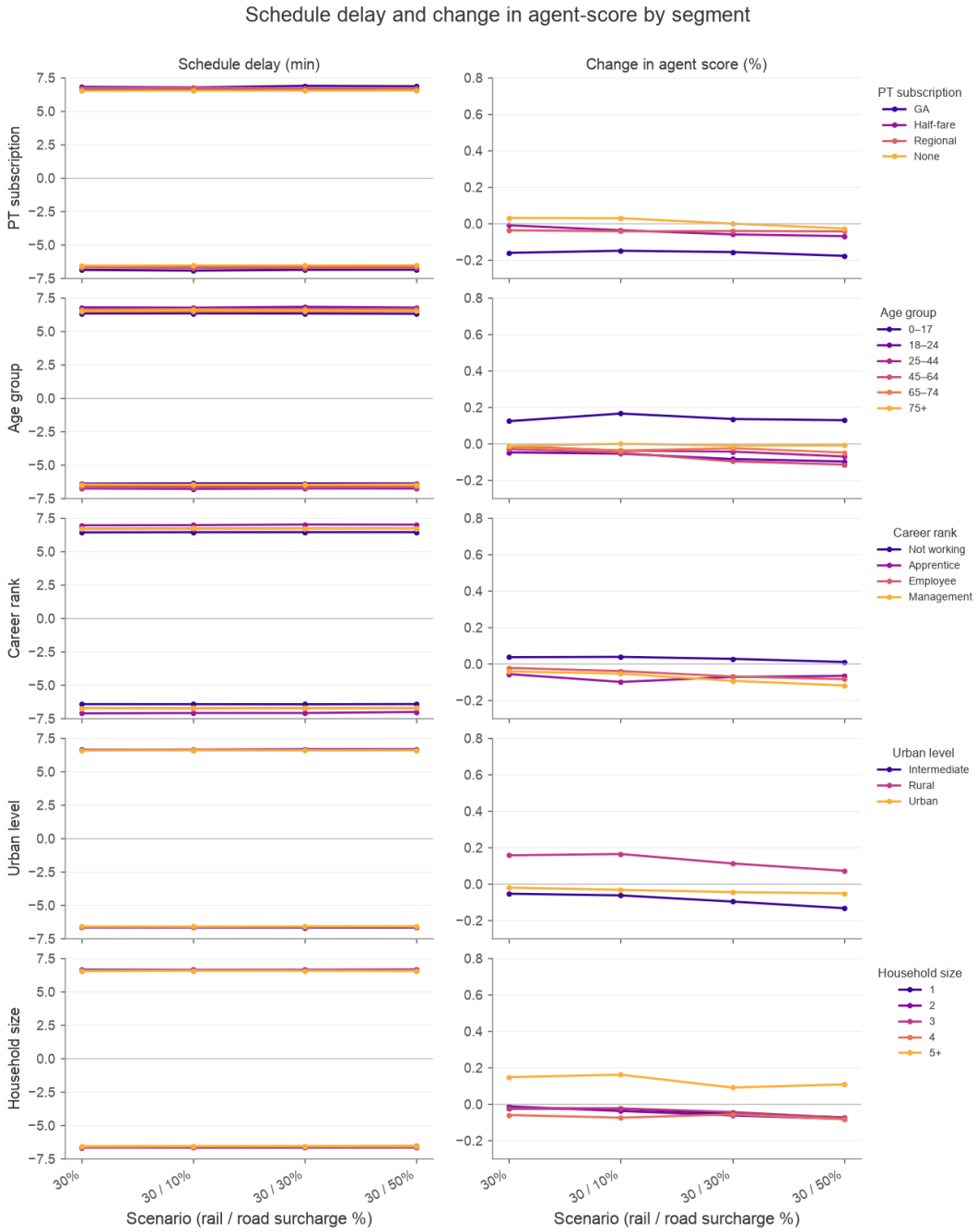


Figure 5.19: Schedule delay and agent score change compared to baseline for population segments based on the combined rail and car peak surcharge policies

In terms of age categories, most have a score change slightly below zero. It can be noticed that some are not affected by the road surcharge level: for example, 0 to 17, 75+ and 65 to 74. This could indicate less car use, while the middle age categories are decreasing in score slightly more with the higher car surcharge, possibly due to higher car use.

For the career rank, *apprentice, employee and management* have a slight negative score, while *not working* is slightly positive. In general, they don's show much change with increased road charge, except for *management* which reduces slightly in score. This also could be explained by whether rail or car is the more popular mode in this segment, since higher-rank professionals could have more car availability/ridership.

For urban level, the results also hint that urban and intermediate residents might be more dependent on rail, as indicated by the negative offset and only slight decrease in score with increasing car surcharge. At the same time, rural residents show a small decrease in score as the surcharge of the road increases, hinting at car use.

Finally, for household size, all segments are slightly negative and decreasing, with the only exception of very big households (5+) having a benefit.

Overall, while SDE and SDL are not greatly affected by the car surcharge or differentiated across socio-demographic groups, the agent score change is more varied than for pure rail pricing scenarios. This is likely because in this scenario group the population affected is a lot greater and we can see some distributional effects present, yet they are still not very significant.

Summary of effects

In terms of **demand redistribution**, the policy flattens the peak, but adding the car surcharge weakens the rail peak trip reduction, from -6.13% under the rail-only surcharge down to -3.79% at the highest road charge, which is about a 40% smaller effect. This is the expected direction: as driving becomes more expensive, some travellers who would otherwise have left rail for car now remain during the peak. The road charge therefore results in a smaller rail peak reduction, but protects rail ridership.

On the **modal split**, adding a car surcharge reduces the switching from rail to car that a rail-only surcharge induces. Rail ridership recovers towards its baseline level as the car charge increases, indicating that travellers who would otherwise divert to car remain on rail once it is also charged, and the public-transport modal share returns to its baseline accordingly. This supports the idea that pricing the competing mode can keep the modal split intact, at the cost of weakening the peak reduction. It should be noted, however, that on the background of the full day, the change in modal split (0.1%) is still small.

For **revenue**, the financial balance improves as the car charge rises and turns positive once the road surcharge reaches the rail level, since fewer riders are lost from rail. The amounts involved remain small relative to SBB's overall revenue, and it is worth noting the car-surcharge income itself is not credited to the rail operator.

For **welfare and equity**, the score changes in general are slightly negative and, unlike the pure rail scenarios, slightly more varied across groups. This follows expectation since pricing the road increases the affected population. The differences, however, remain small. Schedule delay is again minimal and even across segments.

5.3. Interpretation

Overall, the scenarios tested show that the most preferable form of policy is a surcharge combined with a discount. Peak surcharge alone is successful at reducing peak trips, but does so at the cost of the agent score, overall ridership and losing passengers to the road. The combination with a discount negates some of these effects by attracting ridership during the off-peak, increasing agent scores and the public transport modal share. It can also be seen that the combination scenario is the one that obtained the smallest peak share of the day, indicating a more balanced rail demand. In terms of instrument value, in general effects scale smoothly with the instrument level, without an abrupt threshold at which behaviour shifts. This is consistent with the choice model estimation, in which switching behaviour depends on person and trip characteristics, so that individual switching levels are distributed across price levels rather than concentrated at a single one.

Lack of peak trip reduction from the off-peak discount: While comparatively the scenario results follow general expectations, the lack of peak trip reduction by even a 50% discount is surprising. The review performed by Liu and Charles [29] does suggest that discounts have a smaller influence than surcharges, however, the obtained results imply that the discount manages to only attract off-peak trips. This hints at two likely causes. The first is that the reduced costs are not sufficiently large to attract peak travellers. This might be an effect of the higher schedule delay and peak arrival valuations implemented from the choice model stage, or also simply a consequence of a comparatively low cost sensitivity of the population. The second relates to the fact that the discount is applied only outside of the peak period and is only applied after the peak and not before. This means that agents can only shift later to obtain the discount. Since many of the rail peak trips occur early in the peak, this would require a large motivator for the significant time shift to post-peak. To continue, for agents travelling early enough, the shift might even not be possible due to the limit of maximum one hour replanning set in the simulation. Additionally, activity start times might also prohibit (or strongly disincentivise) such a large shift, based on strict work or school start times. Therefore, some agents might only be able to shift earlier, since that is not restricted by a strict boundary, yet this time has no discount.

Which of the two explanations governs is not clear. The literature does, however, offer some indication regarding the first. Lovrić et al. [30] used an agent-based model to explore public transport off-peak discount policies for Singapore. For a 50% pre-peak discount, they found a change in peak ridership of -2.29%, an increase in off-peak ridership of 2.07%, and an increase in public transport modal share of 0.81%. In the present study, the corresponding values for a 50% off-peak discount are a change in peak ridership of +0.57%, a total ridership increase of 4.9%, and a 0.4% increase in PT modal share. While the results are not directly comparable, differing in the applied timings and the transport system modelled, both show off-peak attraction and relatively little to no peak reduction. Notably, however, Lovrić et al. [30] see an increased reduction of peak trips with increasing levels of discount, reaching a 4.21% reduction at a 100% discount. This suggests that larger discounts might shift more peak trips, meaning the incentive size could be too low rather than schedule rigidity alone being responsible. Testing higher discount levels would be a logical next step to confirm this.

Beyond the discount level, the application window offers a way to improve the peak reduction. Since the discount here is applied only after the peak, agents can obtain it only by shifting later, missing those who could shift earlier. Multiple real-life pre-peak price reduction policies have shown success in shifting peak travel: Currie [8] analyses Melbourne's free-before-07:00 travel policy, estimating that it reduced inbound peak demand by 1.2–1.5%. As another discount-based approach, this reinforces the finding that such measures produce a real but relatively moderate peak reduction and that the application window is something that needs to be explored further.

Combined instrument results: Moreover, Douglas, Henn, and Sloan [12] modelled fare incentives in Australia and found a 10.8% reduction in peak loads for a combined 30% surcharge and 30% discount. They also reported that for the 30% surcharge alone the reduction is 7.7% and for a 30% discount it is 3.1%. While the exact 30%-30% value combination was not tested in this study, the combined 20%-40% scenario produced a 3.62% reduction and the 50%-50% scenario a 9.21% reduction. The individual instruments at 30% produced a 6.13% reduction for the surcharge and a 0.61% increase for the discount. Although the specific values differ, both the study and this thesis find that the two

instruments have notably different individual effects, with discounts having a considerably weaker effect than surcharges, as well as overall the magnitudes fall within a comparable range.

Mode shift to road: The combined rail-and-road scenario (S4) confirms that part of the rail surcharge's peak reduction comes from travellers switching to car, and shows that pricing the competing mode reduces this loss, but does not eliminate it. As the road charge increases, rail ridership recovers towards baseline, indicating that travellers who would have switched to car under the rail surcharge alone instead remain on rail. This recovery is only partial, however. The off-peak discount (S2) achieves a lower rate of mode switch (5.5% compared to 6.1%). This is because the two policies act differently: the road charge suppresses mode switch indirectly, by making the car less attractive, and so cannot prevent it completely as long as the car remains a viable option for some travellers. The discount, however, never raises the rail cost and, thus, does not push travellers towards the car in the first place. This suggests that discouraging mode switch by pricing the competing mode is less effective than avoiding it by not penalising rail at all — reinforcing that a surcharge, even when paired with a road charge, carries an inherent tendency to lose passengers to the road that a discount does not. Nevertheless, differences are relatively small, thus, the choice mainly depends on the exact goals and priorities of the operator.

Medium and long-term effects: Finally, the results should be interpreted in light of the time horizon represented by the simulation. The simulated behavioural responses correspond to relatively immediate adaptations following the introduction of pricing, whereas longer-term responses are likely to be larger. In their review, Liu and Charles [29] describe the "medium term growth effect" as an effect which arises from passengers needing to adjust life activities, for example, to enable earlier commuting. This suggests that some adjustments to travel increase over time and, thus, their effects are delayed rather than appearing immediately. Similarly, Litman [28] reports how fare elasticities increase over time from approximately -0.3 to -0.5 in the short-term (first year) compared to -0.6 to -0.9 over the long-term (five to ten years). Furthermore, if a nationwide off-peak travelling policy is applied, there may be even longer-term adaptations occurring through cultural changes. Meaning, if off-peak travel and/or arrival becomes more common and normalised, changes might occur in workplace flexibility, organisational policies, or social norms surrounding flexible working hours. As any of these longer-term adjustments are not represented in the current modelling framework, the long-run effectiveness of time-of-day pricing may be greater than estimated in this study.

6

Discussion and Conclusion

This thesis aimed to understand how time-of-day pricing would even out the spread of Swiss rail passengers across the day, what side effects it would cause, and how different forms of application compare. It does so through a full methodological pipeline from survey data to simulation: first understanding travellers' sensitivities and preferences, then integrating these into a simulation where various forms and levels of pricing are tested. This chapter answers each of the posed research questions, reflects on the findings and contributions, presents the limitations of the study, and proposes directions for future work.

6.1. Conclusion

SQ 1: How sensitive are Swiss rail travellers to time-of-day pricing and to shifts in their departure time?

The estimation shows that the peak-surcharge coefficient is not significantly different from the general cost coefficient, meaning that travellers respond to a time-of-day surcharge in the same way as to any other increase in fare. Sensitivity to time-of-day pricing therefore equals the general cost sensitivity, estimated at -0.077 at the sample mean, which corresponds to a value of travel time of 19.9 CHF/h.

Sensitivity to departure-time shifts is captured by the schedule-delay valuations as well as the arrival-time preference dummy. Regarding the former, at the sample mean, the schedule-delay valuations are 24.55 CHF/h for a shift earlier (SDE) and 16.94 CHF/h for a shift later (SDL). Departing earlier is valued above the value of travel time (19.9 CHF/h), while departing later is valued below it, implying that travellers are particularly reluctant to shift their departure earlier. Both valuations are at the higher end of the range reported in comparable studies (Table 4.7), which suggests that Swiss rail travellers show a comparatively strong reluctance to shift their schedules. This may be influenced by the sample composition and should be investigated further to confirm the sensitivities. For the arrival-time preference dummy, the valuation is at 5.52 CHF. This means that travellers are willing to pay 5.52 CHF to arrive between 7:00 and 7:40 in the morning compared to an otherwise equivalent trip. While this is an early arrival time, the observed travel patterns and sample composition support this finding.

The results do not indicate notable hypothetical bias due to the stated nature of the data nor a bias against peak pricing incentives based on the answer pattern and comparison with the national VTT. It is, however, important to acknowledge that the schedule delay early exceeds the late valuation, so earliness is penalised more heavily than lateness, which is an asymmetry that opposes the more common pattern in literature. Nevertheless, this finding is shared by some other rail studies estimated on similar data.

SQ 2: To what extent do these sensitivities vary across population segments?

Sensitivity variations across population segments were captured through covariate interactions in the departure-time choice model, with four retained based on significance and behavioural grounding. The

two cost interactions act in opposite directions. Household size reduces cost sensitivity. This is a less common interaction, but still plausible. A likely explanation is that larger households have more contributors to household income. Additionally, larger household size may indicate that the household contains children, which might require a larger financial incentive to adjust schedules. The effect is capped at a household size of four, after which no further change in cost sensitivity is supported by the data. Half-fare subscription, however, increases cost sensitivity, which is consistent with half-fare holders being occasional rail users who still pay a fare on each trip and are accustomed to checking prices — unlike GA holders, whose travel is largely covered by the subscription, or non-subscribers, who rarely travel by rail. On the scheduling side, the study trip purpose sharply increases the penalty for lateness (SDL), reflecting the strict start times of classes and lectures. Meanwhile, managers and directors (socio-professional category 4) show a stronger penalty for earliness (SDE), plausibly because senior roles carry the autonomy to keep a preferred schedule rather than shift earlier and lose valuable sleep or morning at-home time.

Several interactions which were expected were tested but not retained. Household income showed no significant interaction with cost sensitivity, which is notable given how commonly income is found to influence price sensitivity. Its influence may be partly absorbed by the half-fare and household-size terms, or limited by the sample's income variation. Age and general PT subscription were also insignificant, and although an education-level interaction was significant once tested on its own, it did not remain that way once combined with the other interactions. This indicates that, in this sample, price response is governed mainly by subscription type and household structure, while schedule-delay sensitivity appears to be influenced by the rigidity of a traveller's arrival constraints.

SQ 3: How do different forms of time-of-day pricing differ in their effects?

Four forms of time-of-day pricing policies were tested: peak surcharge, off-peak discount, a combination of both, and rail and road peak surcharge. The four pricing forms notably differ in their effects, revealing a trade-off between reducing peak demand and preserving (or improving) the other network outcomes.

Rail peak surcharge is effective at reducing peak trips, but it lowers revenue, ridership, mean agent score, and PT modal share. Rail off-peak discount has an opposite effect: it improves revenue, ridership, agent score, and PT modal share, yet fails to reduce peak trips, even producing a small increase. It does, interestingly, reduce the daily peak share of rail trips. This indicates that additional off-peak travel is attracted rather than peak trips being removed. In this way, the redistribution of demand is achieved by growing the off-peak, not shrinking the peak. Therefore, neither instrument alone is completely satisfactory for an operator that must relieve the peak without driving demand away.

The two combined policies (S3, S4) each address this trade-off in a different way. Combining a rail surcharge with a car surcharge keeps most network outcomes close to baseline, with rail ridership returning to approximately baseline levels once the car surcharge exceeds the rail surcharge, as pricing the car reduces the shift from rail to road. However, the policy reduces mean agent score the most of all four policies (although differences are small). This is a likely outcome since travellers are charged across both modes with limited options for avoidance. In contrast, the rail surcharge combined with an off-peak discount raises mean agent score and PT modal share, while substantially reducing peak trips (especially for the highest level tested), and performs well in terms of revenue and ridership. Out of all scenarios, thus, it is the most well-rounded. It combines the peak-reducing effect of the surcharge with the ridership-attracting benefits of the discount, offsetting each instrument's weakness. This highlights that the combined policies each address the trade-off in a different way: the discount attracts off-peak ridership, while the road charge reduces the attractiveness of the "escape route".

All policies, however, aligned in how they affected the network: evenly in terms of spatial distribution, with reduction in peak demand generally acting as a share of the original demand. In terms of high peak demand, this is a favourable result as the busiest corridors also received the most peak relief.

Nevertheless, the findings should be used as an indication rather than a definitive outcome. In general, the policies should be compared with caution since the results may be dependent on the specific start and end times of application, the length of each period and the value level of the pricing incentive.

SQ 4: How does the level of time-of-day pricing affect the redistribution of passenger de-

mand?

The effect of pricing level on demand redistribution is measured in two ways: the share of daily total trips occurring in the peak, and the percent reduction in the number of peak trips. The change in levels has a different effect for each policy.

For the peak surcharge, the higher its level is, the greater is both the redistribution of travel and the reduction in peak trips. For the off-peak discount, the peak share of daily trips decreases with higher discount levels, yet this comes with no reduction in the number of peak trips. The discount even slightly increases peak trips, however, the increase is small and does not have a clear pattern across levels. This reinforces the finding that the off-peak discount is having a marginal effect on trips performed in the peak, mainly attracting more off-peak trips.

For the combined surcharge and discount policy, the peak share and peak trips generally decrease with increasing levels. The effects seem to be compounded from what is found for the surcharge and the discount separately, with the reduction of peak trips mainly governed by surcharge levels. For the combined rail and car surcharge, the effect is opposite to the rail-only surcharge. For this policy, higher road surcharge levels produce less redistribution and less trip reduction within rail, since charging road disincentivises switching to the car for peak travel. Overall, for all policies, an increase in policy level results in increased intensity of the effects.

In terms of the effect pattern, no threshold effects were observed as the responses scaled mostly smoothly with the level. Although some studies report a staggered or threshold response, the results follow expectations if the modelling set-up and choice modelling estimates with heterogeneous price and scheduling sensitivity are considered. The lack of an effect threshold can be explained by the differing price boundary for changing plans per population segment. This effect is further exacerbated by differences in agent plans and in each traveller's distance from the off-peak period, such that segments cross their thresholds gradually rather than all at once.

SQ 5: What are the wider effects on modal split, ridership, revenue, and welfare?

The wider effects vary considerably across the policies, governed mostly by whether the instrument is based on a surcharge or a discount.

In terms of modal split, as expected, a rail surcharge decreases the public transport modal share. The modal split can be preserved, or even shifted in favour of public transport, if either a surcharge on road is also applied, or an off-peak discount is applied. However, although both have a desired effect on the PT modal share, they have different underlying mechanisms. The added road surcharge prevents peak trips from switching to the road, while an off-peak discount attracts off-peak trips, therefore, both are mostly acting on a different set of trips.

The rail surcharge also decreases both ridership and revenue, while the off-peak discount increases them. Both are interlinked since the surcharges and discounts themselves contributed comparatively little to the total balance, which was determined mainly by passenger-kilometres. Since the effects of destination change, trip cancellation or activity reordering are not possible in the simulation, the results should be taken as an indication and not as an accurate prediction.

The welfare effects are moderate, but still suggest effects from the pricing policies. First, mean agent SDE and SDL values remained largely unchanged across all policies and all population segments, indicating that the policies do not worsen travellers' scheduling outcomes and that this effect is distributionally even. Mean agent scores did differ depending on whether a policy charged or discounted travellers, with the former decreasing overall scores and the latter increasing. These effects are difficult to fully separate from stochastic variance between simulation runs, however, as the changes were mostly consistent, in the expected direction, and scaled with the policy level, they suggest that an underlying effect was captured. Nevertheless, it was of very small scale. To continue, some variation across population groups was present, but it was relatively small and was likely driven by differences in how much each group uses rail rather than by the policy itself. Overall, the results show that either the distribution of effects is equitable, or the effects are not strong enough to be detected at this level of simulation analysis.

To what extent could time-of-day pricing on Swiss rail spread passenger demand across time, and what would its impacts be on modal split, welfare, ridership and revenue?

Overall, the thesis shows that time-of-day pricing has potential as a demand-management tool for Swiss rail. Depending on its form, it could effectively reduce peak trips and even increase overall ridership. Taking the best-performing policy - combined 50% peak surcharge and 50% off-peak discount - as an example, it is possible to reduce peak trips by 9.21%, while increasing agent score, improving public transport's modal share and increasing ridership and revenue. The welfare effects were small against the scale of the whole population, showing no evidence of the strongly negative or inequitable outcomes sometimes assumed in public debate. These findings are, however, only an indication of the effects of such a policy, with the simulation not including responses such as activity reordering or trip suppression. Additionally, the estimated behavioural response for timing is based on a single stated-preference sample which is not population representative. Thus, the results demonstrate that time-of-day pricing can be a promising demand-management strategy, while still encouraging further study.

6.2. Contributions and reflections of the approach

While the findings of the thesis were presented in the previous section, this section presents the main contributions of the thesis in terms of the approach as well as reflections for future studies planning to implement a similar methodology.

6.2.1. Contribution

The applied approach of linking an estimated discrete choice model to an agent-based simulation offers three main advantages. First, it captures behavioural heterogeneity by allowing estimated socio-demographic interactions to influence individual responses within the simulation, instead of representing all travellers with a single average sensitivity. Second, it enables policy-specific behavioural parameters to be estimated. In this study, for example, the estimation identified a peak arrival preference that could be incorporated into the simulation. It also tested whether people have a different sensitivity to a peak surcharge cost instead of the general cost. Third, many of the policy implications analysed in this thesis, such as the trade-offs between peak reduction, financial outcomes, and welfare, are only accessible when the estimated behavioural model is embedded within a system-wide simulation. To the knowledge of the author, previous studies of public transport time-of-day pricing have focused primarily on departure-time shifts and peak reduction, with comparatively little attention paid to such effects as welfare and distributional equity. This thesis shows how multiple facets of the response can be explored, leading to better supported policy-making.

To state concretely, the thesis differs from previous studies in that the framework was used to compare four distinct pricing strategies rather than a single instrument, and to separate demand that is retimed within public transport from demand lost to other modes. The findings show the value of this distinction: evaluated on peak reduction alone, the peak surcharge (S1) appears effective, yet by comparing the rail-only surcharge against the joint rail-and-road scenario and analysing the peak trips across scenarios it can be concluded that a notable part of the peak reduction is from travellers leaving rail rather than retiming. This is a finding invisible in an aggregate result, but highly important for public transport demand management. It is these kinds of trade-offs that the methodology of this thesis allows to identify.

6.2.2. Reflection

This approach does require additional effort compared to applying either model independently, since consistency needs to be ensured between the behavioural model, the simulation inputs, and the simulation framework. For example, parameters need to be scaled, and some also need to be constrained to realistic ranges. For instance, the household size interaction parameter had to be capped since price sensitivity would not decrease endlessly with increasing household size. This barely affected the choice-model fit, but prevented implausible values in the simulation. Moreover, it is also necessary to match available variables between the choice model and the simulation/synthetic population. Therefore, if possible, a backward approach would be recommended, where the behavioural mecha-

nisms required by the simulation are identified and then a stated-preference experiment is designed specifically to estimate those parameters. However, it is not a hard requirement.

To continue, applying estimated parameters to a synthetic population implicitly assumes that the estimation sample is representative of that population. If the sample varies drastically, the simulated responses may become biased. In this thesis, for example, the estimation sample contained a relatively high proportion of higher-income respondents, which may have influenced the willingness to pay for departure-time changes and, thus, the effectiveness of the pricing policies. Thus, the estimation sample should correspond as closely as possible to the target population, unless the parameters are deliberately estimated for specific traveller segments.

6.3. Practical recommendations

There are practical recommendations that can be learned from this research as well. To do this, the results have to be considered in the context of the current system, especially taking in account the highly prevalent subscriptions present in Switzerland.

Fare structure: The results suggest that the best overall policy is the combined peak surcharge paired with an off-peak discount. In practice, generally Swiss train tickets are valid for a whole day, and it does not matter at which time the train is taken. An exception is the Supersaver ticket, which is a discounted ticket valid only for a specific, low-occupancy train. Therefore, it is recommended that single tickets are offered in an off-peak and peak (effectively all-day) version. This preserves the flexibility of rail travel, as passengers are not tied to a specific train and need to only be aware of the priced periods. Similarly, subscriptions should follow the same split: an off-peak variant and a peak-inclusive variant, applied to the GA, Half-fare and Regional travel card. Supersaver tickets should remain as they are. Since they discount specific low-demand trains rather than a time window, they serve occasional and tourism travellers without conflicting with the peak/off-peak division.

Price level: The results show that in general incentives must be substantial to shift behaviour, although the exact threshold differs across population segments. To achieve the approximately 9% peak trip reduction, a 50% surcharge and 50% discount were applied. In practice, this means an off-peak single ticket priced about half the current fare and a peak ticket approximately 50% more expensive. For the subscriptions, there is no direct translation in what the price increase and decrease should be, since a per-trip percentage does not transfer directly to a flat-rate subscription, thus warranting more investigation. Nevertheless, there are two possible ways to apply the incentive to subscriptions. The first is to increase the peak-inclusive subscription cost and decrease the off-peak subscription cost compared to the current subscription cost. This would preserve the idea of an all-inclusive travel card, however, it would likely require a large cost increase to an already expensive subscription. The second is to keep the price constant, but change the discount amounts. For example, the GA 100% discount could be changed to a 100% discount on off-peak trips and a 50% discount on peak trips, while the half-fare 50% discount could become a 75% discount off-peak and 25% for peak trips. Regardless, a thorough economic analysis should be performed to ensure successful implementation.

Time periods: The results indicate that rail travellers in Switzerland like to travel early. This is supported both by the choice modelling results where there was a preference to arrive between 7:00-7:40 in the morning as well as from the simulation and microcensus data that show a very early morning peak. Therefore, it is recommended that the pre-07:00 morning period is not counted as off-peak. If a morning discounted off-peak is wanted, its boundary should preferably sit earlier, before 06:00 or even 05:00.

Employers: From reviewed literature, employer compensation of travel costs reduces price sensitivity and can hinder the effectiveness of the pricing policy, since travellers are exposed to less or none of the travel costs. Therefore, before implementation, the operator should engage with employers and coordinate, if possible, how such compensation will apply under the policy to not work against the demand management objective. An option would be that the employer covers an employee's subscription, as it's already offered at many workplaces, however, the covered subscription should be the off-peak

variant, with the employee free to pay the upgrade to all-day travel if they desire. This keeps the price signal intact for peak travel while leaving the choice with the traveller. Coordination may also support demand management through awareness, hopefully normalising and inspiring more flexible start times - a requirement for shifting departure time.

Communication: Finally, positive communication is necessary to ease public acceptance. This analysis found no evidence of the strongly negative or inequitable welfare effects often assumed in debate around time-of-day pricing. Such evidence should be presented transparently, supported by a more detailed welfare and distributional analysis, as it addresses directly the equity and fairness concerns most likely to be raised. Communication, however, should not stop once the policy is implemented. Studies such as Eliasson and Jonsson [13] show that the acceptability of road pricing often increases after implementation, as the positive results of the policy are experienced and communicated, rather than being judged on people's prior perceptions and beliefs. Continued communication of positive outcomes is therefore important both before and after implementation, in order to create initial acceptance, and then sustain and increase the support once the policy is in place.

6.4. Limitations

6.4.1. Behavioural data

Small sample and estimates: The behavioural parameters in this thesis are estimated from a relatively small sample (180 respondents and 1,076 observations). The sample also has a high proportion of high-income travellers, which could reduce the estimated cost sensitivity and, thus, inflate the willingness-to-pay values. This does not appear to affect the value of travel time, which aligns closely with the national benchmark, but the schedule-delay valuations (VSDE and VSDL) do sit at the upper end of the comparable literature, suggesting some upward bias may be present for these. This has two consequences. First, the monetary interpretation of the schedule-delay results in particular should be read with this potential upward bias in mind. Second, because all utility parameters are scaled relative to the estimated cost coefficient, stronger pricing incentives are required in the simulation before behavioural changes occur, meaning the simulated response to pricing may be conservative. Additionally, a notable share of respondents did not report an ideal arrival time, so the reference departure time was used as a proxy, weakening the schedule-delay estimates.

Data filtered to morning travellers: A further limitation is that the parameters are estimated on a morning peak-hour PT subsample but applied to the whole-day population in the simulation. The schedule-delay and time-of-day sensitivities of a morning commuter are not necessarily those of a midday or evening traveller, so applying them universally risks misrepresenting off-peak behaviour. This matters less for the conclusions of this study, which concern mainly the morning peak, but it does mean the whole-day totals and the mode-switch behaviour should be treated as indicative rather than precise.

Influence of Covid-19: Additionally, the data was collected in 2021, and Covid-19 effects were not accounted for. Travel behaviour in that period was atypical – most notably affected by increased working from home. Thus, the estimated preferences may partly reflect the pandemic situation rather than typical behaviour.

6.4.2. Choice model

Base ticket cost: In the choice modelling phase, the influence of the base ticket cost could not be identified in the final model and was thus excluded. This is likely due to collinearity with travel time, which limited the ability to estimate its effect separately. The dataset also contains limited mode-choice and no trip-suppression alternatives, so these responses to pricing are not captured in the estimation.

Panel data: To continue, the dataset used for the choice model estimation has a panel format, meaning one person answered several choice situations. Commonly, in the choice model, the correlations between answers of the same respondent are captured by using the panel likelihood trajectory, which

multiplies the choice probabilities across all observations belonging to the same respondent, treating each person's sequence of choices as a single joint outcome so that the estimated taste parameters are shared across their answers. However, due to the fact that the choice model in this thesis was formulated as an MNL model, which has no unobserved error component, this was not applied. While answers were still grouped, ensuring that the standard errors were corrected, the estimates still do not fully account for this panel structure. This means the model still treats all respondents as sharing identical taste parameters, capturing the panel structure only through corrected standard errors rather than by acknowledging genuine preference variation between individuals.

Hypothetical bias: Finally, one could argue that the emotional resistance to peak pricing as well as the hypothetical nature of the survey may have led to biased survey answers. While the results suggest that this has not occurred at a significant level, as explained in Section 4.2 and Section 4.4 respectively, this is a possibility.

6.4.3. Simulation

Scenario design: There are two main limitations to the scenario design. The first is that the peak surcharge does not perfectly align with the peak of rail travel. The highest point of the rail morning peak occurs approximately 15 minutes earlier than that of public transport overall, and about 30 minutes earlier than that of car. As a result, the 07:00–09:00 window — conventionally treated as the peak by the operator and government — is not centred on the rail peak but instead covers it and its later side. This may lead the effects to be underestimated, since the surcharge is not applied precisely where rail demand concentrates.

The second is that the off-peak discount is applied from 09:00–15:00 and from 19:00 onwards, so it spans considerably more hours than the two-hour peak surcharge and covers periods across the whole day rather than only the morning. This asymmetry reflects the different roles of the two instruments: the surcharge is targeted narrowly at the peak it aims to relieve, whereas the discount is applied broadly to provide travellers with a wider range of alternative times to shift into. Exclusion of the pre-peak period in this case was motivated by the operator preference, as the earlier hours before the peak already have a relatively significant number of travellers and it's more preferable to shift people later. Nevertheless, this asymmetry needs to be acknowledged when comparing daily metrics and warrants further research into what the application window for the off-peak discount should actually be.

Simulation model structure: The most significant structural limitation lies in how time-of-day pricing enters the simulation. Pricing is applied only in the MATSim stage, where agents can adjust departure time, route, and mode. However, many of the choices that shape a traveller's day, such as the order of activities, activity start times, destinations, and the number of trips made, are determined earlier, in the preprocessing step, and are held fixed before pricing is introduced. As a result, the simulated response to pricing is confined to the limited responses MATSim controls, while the upstream choices that a real traveller would also reconsider under a price change remain fixed. This suggests that the peak-reduction and rescheduling effects reported in this thesis are likely a lower bound. A traveller facing a morning surcharge might, in reality, reorder their activities, change a destination, or cancel a trip — responses likely leading to even more reduced peak demand yet the pipeline cannot represent. The relatively modest shifting observed, and the weak response to the off-peak discount in particular, may therefore partly reflect this structural rigidity rather than genuine behavioural inelasticity. For the pricing signal to produce a fully realistic response, it would need to propagate through the entire pipeline rather than the final stage alone. Additionally, quantifying these effects is difficult, since reported results for public transport studies are often in the form of demand elasticity and do not distinguish how much each choice dimension contributes to the overall result.

6.5. Recommendations for future research

6.5.1. Choice modelling

A valuable improvement to the estimation would be a larger, more representative sample, which would directly address the biases described above. Estimating the model on full-day travellers rather than

the morning subsample would remove the mismatch between the estimation sample and the simulated population. It would also allow testing if preferences differ between morning and evening trips, and if so, differentiated values could be implemented in the simulation. Using post-2021 data would provide a behavioural basis free of pandemic effects. The stated-preference experiments from the Swiss 2025 Mobility and Transport Microcensus could be considered for such a future estimation. It would also be worth exploring non-linear formulations of the schedule-delay terms, such as quadratic SDE and SDL, which the literature suggests may improve fit, as the disutility of a large shift may grow faster than proportionally. These extensions would most likely require a larger dataset to estimate reliably. To continue, a larger dataset would also allow using, for example, a Mixed Logit formulation, thus accounting for the panel nature of the data and heterogeneity between individual preferences. Similarly, some socio-demographics expected to be influential, such as income, could be tested again for significant interactions, since it's possible that with a larger dataset and different variable formulation, their effect might be captured. A combined RP–SP estimation would additionally anchor the stated responses to observed behaviour. Additionally, using population weights for the choice model estimation could also aid in creating consistency between the choice model sample and the simulated population. Finally, a tour-based design would capture scheduling interactions across the day that a single-trip experiment cannot. This would allow the sensitivities for, for example, activity duration, already present in the MATSim scoring function, to be estimated and refined rather than taken as given.

6.5.2. Simulation development

A difficult yet substantive improvement would be integrating time-of-day pricing into the whole decision pipeline of the simulation, however, it would require large structural changes in the current model framework. This is because one choice is dependent on others, and while some decisions upstream would be affected by public transport pricing, at the point they are made the departure time is not yet determined, thus, it is unclear whether the peak or off-peak price should apply. One possible way forward would be to perform agent plan creation multiple times instead of once. The suggestion is to iterate through the whole MOBi.plans choice pipeline multiple times, starting with the mobility tool ownership choice until the daily plan creation and to do this under different pricing assumptions, applying peak prices in some iterations and off-peak prices in others. This would produce, for each agent, several complete and internally consistent decision chains, each carrying its own upstream choice alongside the travel plan they imply. These candidate chains could then be scored, with the agent selecting one, for example, probabilistically according to the higher score. The resulting daily plan might still be adapted in the network simulation and influenced by the network conditions. In this way, most of the choice dimensions could be accounted for. Alternatively, the choice model infrastructure could also be replaced by an optimisation algorithm encompassing all decisions in one. Nevertheless, the best-fitting approach has not yet been found, and thus would be an exciting direction for future work.

To continue, from a simulation perspective, the stochastic variability of MATSim should also be quantified by repeatedly running the baseline scenario with different random seeds, establishing the magnitude of random variation and allowing policy effects to be interpreted relative to the inherent simulation noise.

6.5.3. Policy analysis

In terms of policy analysis, since income information was unavailable for the synthetic population, the welfare analysis could not assess the distribution of costs across income groups. Incorporating income into the synthetic population and extracting the exact fare paid by each traveller would enable a much richer equity analysis, making it possible to identify which travellers bear the costs of pricing policies and whether the burden differs across socio-demographic groups.

The policy scenario designs could also benefit from further exploration. The sensitivities regarding time windows for which the policies are applied should be investigated. Similarly, a larger range of policy instrument levels could be tested, especially for the off-peak discount, to observe whether at some level it begins to also reduce the peak demand. Future studies could also investigate pricing during the evening peak and extend pricing to all public transport rather than rail only. Finally, a more in-depth analysis of specific train loads could allow quantification of the savings for the operator due to reduced peak load, or necessary extra cost to accommodate off-peak increased ridership.

Overall, there are many directions for future research spanning the improvement of model realism as well as depth and breadth of the policy evaluation. It is hoped that the framework and findings presented in this thesis provide a useful basis for that continued work, and a step towards more comprehensive evaluation of public transport policy.

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A

Appendix A: Scientific Paper

Time-of-Day Pricing on Swiss Rail: From Departure-Time Choice Modelling to MATSim Simulation

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August 28, 2026

Abstract

Swiss rail is renowned for its high 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 choice model with person and trip covariates, obtaining policy-specific and socio-demographically heterogeneous sensitivities to price and scheduling. The results show a general preference for departing at the peak period, captured through an off-peak dummy variable. Furthermore, there is significance of socio-demographic interactions, namely household size and public-transport subscription with cost sensitivity, study trip purpose with schedule delay late and career category manager or director with schedule delay early. Furthermore, the sensitivities are integrated within an agent-based model simulating four different pricing policies. Beyond their effect on peak demand, the policies are assessed on how the response divides between retiming within public transport and switching mode, as well as on operator revenue, ridership, agent welfare, and distributional equity across socio-demographic groups. The peak surcharge proves to be the most effective at reducing peak demand, but does not perform well in other criteria, as many trips switch mode rather than retime. The off-peak discount does not reduce peak trips but is favourable otherwise. A combination of both surcharge and discount proves to be most advantageous, although the discount does not prevent modal shift, but rather attracts new rail trips in the off-peak. Beyond informing SBB and general transport policy, the paper aims to inspire comprehensive evaluation of public transport policies using agent-based modelling, while demonstrating the method of integrating segment-based estimated parameters from a policy-relevant stated preference experiment in a simulation model.

Keywords

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

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 [25]. This concentration has negative impacts on both passengers and operators. For passengers, overcrowding reduces comfort and can raise safety concerns [11] or lead to longer travel times due to reduced reliability of train travel [23]. For operators, meeting the peak demand requires large investments in infrastructure, rolling stock, and high service frequencies. This is a heavy financial burden even though this additional capacity is mainly used for a limited number of hours each day [11].

An alternative to capacity expansion is to redistribute demand away from the peak through time-of-day pricing. Time-of-day pricing can take the form of a surcharge during peak hours, a discount during off-peak hours, or a combination of both. In this way, operators can create a financial incentive for travellers to shift their departure times and spread out demand more evenly throughout the day [11, 18, 28]. Empirical evidence confirms that such methods can be effective: free early-bird tickets in Melbourne shifted more than 2,000 rail passengers out of the peak per day [5], and a large-scale peak avoidance experiment in the Netherlands reduced peak trips by 22% among participants [23].

Nevertheless, transport pricing interventions can be a controversial topic. Studies have found that respondents often do not support time-differentiated pricing in public transport [7, 18], with some perceiving it as unjust and not aligned with government policies aiming to reduce car usage [31]. Therefore, before such a policy can be brought to the public, there needs to be evidence not on a single outcome but on the full set of effects that jointly determine whether such a policy is both feasible and beneficial. On the demand side, this means understanding how effectively the pricing spreads travel across the day, how it affects mode choice, and how the resulting gains and losses are distributed across the population, since acceptability depends not only on the aggregate effect but on who is affected. On the operator side, it means knowing the effect it may have on ridership and the financial balance, which are decisive for a policy's viability. Assessing these effects side by side is what allows the trade-offs between them to be observed and analysed, which is essential for determining whether the policy is worth pursuing.

In practice, however, pricing studies largely report aggregate outcomes, such as fare elasticity or the reduction in peak trips [18]. Nevertheless, the same aggregate figure can arise from travellers retiming, changing mode, or forgoing the trip altogether, which have very different implications for the operator. Combining a behavioural model, which provides the policy-specific sensitivities that govern individual travel choices, with a network-wide simulation that translates them into system outcomes makes it possible to distinguish these responses. Few studies have applied this approach to public transport, and those that have focus on off-peak discounts and demand redistribution, leaving the comparison of pricing instruments, the resulting modal shifts, and the distributional and welfare effects across population segments largely unexamined.

This paper combines a departure-time choice model with an agent-based simulation to evaluate time-of-day pricing across a set of network effects. In order to estimate price and schedule sensitivities, a stated-preference experiment from the Swiss Mobility and Transport Microcensus is used. A departure-time choice model is formulated and estimated, with the inclusion of socio-demographic covariates. The behavioural parameters from the choice model are scaled and integrated into an existing agent-based model capable of simulating the Swiss population and transport system. Four pricing policy scenarios are designed and simulated, and their outputs are evaluated in terms of departure-time distribution, modal split, ridership, revenue, and welfare. While demonstrated here on the Swiss rail network used as a case study, the approach is general and transferable to other public transport systems and pricing contexts.

1.1 Research aim

The main research question is:

> *To what extent could time-of-day pricing on Swiss rail spread passenger demand across time, and what would its impacts be on modal split, welfare, ridership and revenue?*

This paper contributes to the literature on public transport time-of-day pricing in three ways. First, it estimates

a choice model that incorporates socio-demographic heterogeneity in price and scheduling sensitivity, together with an inherent peak arrival preference, contributing to the departure-time choice and public transport pricing literature. Second, it demonstrates how these estimated behavioural parameters, including their heterogeneity, can be integrated into an agent-based simulation to evaluate pricing policies. Third, it uses this framework to evaluate four distinct pricing instruments across a broad set of network outcomes, providing both conclusions about how the instruments compare and a demonstration of how agent-based simulation supports a full multidimensional evaluation.

The remainder of this paper is structured as follows: Section 2 presents the literature review, Section 3 describes the methodology, Section 4 presents the results, and Section 5 provides the discussion and conclusions.

2 Literature review

2.1 Effects of pricing interventions

A change in travel cost for specific times of the day can result in travellers responding in several different ways, from which changing departure time is only one. The most direct response for spreading peak demand is a departure-time shift, where travellers retime their trip to a cheaper period. Alternatively, travellers may also switch mode. Thus, a common practice is to model departure-time choice together with mode choice [9]. Furthermore, travellers may also abandon the trip altogether. To represent this option, several studies include a specific "no travel" alternative in the choice set [13]. Over longer time periods, responses may even extend to changes in destinations as well [29]. While this broader selection of responses jointly determines the aggregate response to pricing, the redistribution of demand across the day depends most directly on the departure-time response, which is discussed in more detail further in the review.

In general, studies show that pricing is an effective way to manage demand, whether done through peak surcharges or off-peak discounts. Beyond this, the following studies offer insights into how temporal demand shifts occur. Liu and Charles [18] provide a review of empirical evidence on spreading peak demand via differential fare policies. They find that passengers tend to shift to the nearest available cheaper time period rather than moving further away from their preferred departure time. As a result, this can concentrate demand in shoulder periods rather than distributing it evenly throughout the day, an effect also noted by Thommen and Hintermann [28]. The reviewed studies also confirm that peak surcharges are more effective in reducing crowding than equivalent off-peak discounts, while a combination of both produces the strongest behavioural response [18]. To continue, Weesie et al. [31] find that the behavioural response to discounts is non-linear, with diminishing marginal utility at higher discount levels, while Huber, Wallimann, and Meier [15] find that discounts of 30% or more raise the share of demand shift by approximately 3.8 percentage points relative to smaller discounts. Overall, these studies indicate that pricing reliably shifts temporal demand but does so unevenly in terms of its effects.

2.2 Influencing factors

Price levels alone do not determine departure-time choice. Many travellers face constraints in their schedules due to fixed work and school timings, intra-household interactions, and institutional factors such as business opening hours, all of which limit individual schedule flexibility [28, 11]. One variable shown to have significant influence in previous studies is trip purpose. For instance, business travellers are more likely to select unrestricted alternatives and show lower tolerance for schedule shifts, while leisure and shopping travellers have more flexibility [31, 4]. To continue, some studies estimate departure-time preferences separately for outbound and return trips or morning and evening trips, as behaviour is shown to be different between the two segments. For instance, Peer, Knockaert, and Verhoef [23] specify schedule delay separately for the morning and evening commute and find earliness to be valued more highly in the morning. In addition to these, a range of socio-demographic and trip characteristics have been found to influence departure-time choice, including age [30, 16], employer travel cost compensation [4], income [29, 6] and ticket subscription type [31]. In combination, these findings show that departure-time choice is not only influenced by price but also highly depends on the constraints and characteristics of a person. This implies that

any attempt to model pricing effects must account for this heterogeneity to capture behaviour realistically.

2.3 Discrete choice modelling

Discrete choice models are commonly used in transport economics and travel behaviour research to model individual decision-making. They allow to derive behavioural parameters, such as sensitivity to cost, and valuations, such as the value of travel time, directly from both revealed and stated choice data [3]. 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 [3]. 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. Regarding model formulation, Multinomial Logit (MNL) is widely utilised as a baseline specification. Improvements in fit are achieved through more advanced error structures, model segmentation or direct socio-demographic term inclusion, and non-linear functional forms [16, 29, 9]. A shift-based model, where alternatives are defined relative to a respondent's preferred departure time, compared to a time-period model, is appropriate when individual scheduling preferences are accessible [9].

2.4 System-wide modelling

While discrete choice models provide individual-level behavioural parameters, evaluating system-wide policy impacts requires embedding these responses within a network-level framework. A common limitation in peak pricing studies is that behavioural response is primarily analysed at the individual level without embedding in network assignment or simulation frameworks [4, 6, 16, 29, 15, 28]. Demand elasticity may indicate that ridership will reduce, but it does not show where these travellers are going instead, what mode they are switching to, and if this then impacts another corridor, mode or the riders themselves. These effects are especially important for public transport policy assessment since a peak surcharge that causes a modal shift to car is a very different outcome than a departure-time shift within rail, even if the demand elasticity might be the same.

Traditional four-step travel demand models treat the time-of-day distribution of trips as a fixed input determined outside the model, and work with aggregate origin-destination flows rather than individual travellers, making it impossible to capture the heterogeneous responses across population groups that pricing policies are likely to produce [24]. 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 acts according to their own preferences and constraints, and the collective behaviour of all agents produces network-level outcomes such as congestion and crowding, which in turn again influence the agents and their choices. It uses an iterative co-evolutionary framework in which agents adjust their activity plans - including departure times, routes, and modes - until a stable equilibrium is reached [2, 22, 26]. The parameters in the scoring function can be taken from generic parameter presets [20] or estimated from discrete choice models [14, 22].

Several agent-based and activity-based models have been applied to simulate the effects of transport pricing policies. Meyer de Freitas, Schuemperlin, and Balać [21] apply MATSim to a cordon pricing scheme for Zurich, varying toll levels and analysing distributional outcomes of income groups. Müller et al. [22] embed terms with behavioural sensitivity parameters in the MATSim scoring function from a latent class mode choice model, showing that class-specific parameters can be used to represent preference heterogeneity within the simulation. In terms of public transport pricing policy simulations, Lovrić et al. [19] apply the SimMobility activity-based simulation platform to evaluate Singapore's free pre-peak travel policy. Adnan et al. [1] use the same model to simulate multiple off-peak discount pricing scenarios, analysing them in terms of revenue, ridership and modal split. Lastly, Kaddoura et al. [17] test public transport fares in a MATSim-based simulation on a synthetic corridor, optimising the general fare level. Together, these studies demonstrate the capabilities of agent-based models for transport policy analysis.

2.5 Literature gap

The application of agent-based models to public transport time-of-day pricing remains limited, particularly in terms of the pricing policies considered (predominantly off-peak

discounts), the analysis of distributional equity, and the representation of socio-demographic heterogeneity in behavioural sensitivities. The most closely related work is that of Zhao et al. [32], which combines a stated-preference departure-time choice model with an agent-based simulation framework to evaluate public transport pricing. However, it focuses on variations in off-peak discount cut-off times for a single pricing instrument, rather than comparing alternative pricing strategies or examining their broader behavioural and welfare implications.

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 [10]. 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. 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).

The report by the Federal Office for Spatial Development [10] also estimated choice models on the SP4 data, but with different variable definitions, without socio-demographic covariates or a separate time-of-day term, combining morning and evening travellers, and mostly as joint time-and-mode models. This study retains the same shift-based structure, including the schedule-delay variables, but re-estimates it on a narrower, policy-relevant sample: morning travellers only, to avoid return-leg trips whose sensitivities may differ [23], and public-transport travellers only, as the policy's target group. It further adds a time-of-day period term and socio-demographic covariates to capture sensitivities across population segments, which the official report did not pursue.

The choice model specification followed a stepwise procedure. Each model is formulated as a shift-based Multinomial Logit (MNL). Furthermore, observations are grouped by the respondent identifier and robust standard errors are reported. This does not capture taste heterogeneity across respondents in the way a mixed logit specification would, but it accounts for the correlation between the repeated choices of the same individual when assessing the significance of the estimates. 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. All statistically significant interaction terms are incorporated in a single model. After an iterative process of removing interaction terms that become insignificant or have negligible magnitude or lack a behavioural explana- tion, the final model is obtained.

3.3 Agent-Based Simulation

To assess system-wide impacts, the estimated behavioural parameters are integrated into SIMBA MOBi, the national activity-based transport model developed by SBB [27]. This is achieved by introducing the estimated behavioural parameters into the model's scoring function, as done by He, Chow, and Zhang [12]. To scale them to fit with existing parameters, parameters are converted into willingness-to-pay space based on cost sensitivity. To reflect heterogeneity, parameters are differentiated across subpopulations based on sociodemographic characteristics.

Following model integration, a baseline scenario is run with no peak charge to validate and calibrate the parameter integration. Furthermore, four pricing scenarios are simulated: peak surcharge, off-peak discount, combined peak surcharge and off-peak discount, and rail and road surcharge. For each of these, multiple simulation runs are performed at different instrument price levels to test sensitivity and observe any trends. The resulting outputs are examined in terms of demand redistribution, modal split, revenue, welfare and equity.

4 Results

4.1 Choice model estimation

The final estimated choice model results are presented in Table 1. The estimation results show that all parameters carry the expected sign and are significant at the 0.01 level, with the exception of crowding, which closely misses the 0.05 level (B_{CRHIGH} p = 0.08). All four interaction terms are significant with expected signs.

The results show that cost sensitivity decreases with household size. This may be explained by larger households having more contributors to household income, resulting in greater financial capacity. Additionally, it could compound with the presence of children, which could motivate households to keep their schedule more fixed, thus responding less to pricing. Both together could result in a lowered cost sensitivity. Furthermore, half-fare subscription holders are more sensitive to cost. Plausibly, they are more likely to be occasional rail users who still pay a fare on each trip and are accustomed to checking prices, which could explain their higher cost sensitivity. To continue, study-purpose trips are more sensitive to lateness, a reasonable effect since educational institutions generally have strict program start times where even a small delay can be perceived very negatively. Finally, people whose job position falls into the management or director category are more sensitive to earliness. This is plausible since these roles are relatively senior and those holding them are likely to have the autonomy and resources to keep their preferred schedule rather than shift earlier.

To continue, the off-peak arrival parameter ($B_{OFFPEAK}$) shows the dis-preference to arriving off-peak compared to during the peak. The peak here is taken from what provided the best model-fit for this data, which is the period between 7:00 to 7:40 in the morning. While 7:00 to 7:40 is a very early arrival time, there are two observations that could explain this result. First, the sample has a high proportion of rail trips. Rail trips are often only a part of the full journey, with another trip leg following afterwards, such as a walk or bus. For this reason, arrival at the station might be preferred to be between 7:00 and 7:40, however, arrival at the destination might be later. Second, the verification microcensus counts displayed in the full report show that the peak of rail travel is right after 7 am, aligning well with this finding of early rail travel.

The schedule-delay parameters, β_{SDE} and β_{SDL}, are both negative and significant, confirming that travellers experience disutility from earliness and lateness. The two are estimated separately, and the early penalty is larger than the late one. This asymmetry indicates that travellers are more reluctant to bring their departure forward than to push it back, which is relevant for peak-spreading, since encouraging earlier travel might be more difficult or require stronger pricing incentives.

The estimated parameters can be expressed in willingness-to-pay space. These valuations express, in monetary terms

Table 1: Final departure-time choice model with socio-demographic and trip variable interactions

Parameter	**Interpretation**	**Estimate**	**Rob. t-stat.**	**Rob. p-value**
β_{TR}	Nr of transfers	−0.2227	−3.45	0.0006
β_{COST}	Cost sensitivity	−0.1505	−4.90	< 0.0001
β_{SDE}	Schedule delay early (hr)	−1.6297	−6.68	< 0.0001
β_{SDL}	Schedule delay late (hr)	−1.1236	−4.15	< 0.0001
β_{TT}	Travel time (min)	−0.0254	−3.36	0.0008
$\beta_{\text{CR HIGH}}$	High crowding (ref. low)	−0.3136	−1.75	0.0800
β_{OFFPEAK}	Off-peak arrival (ref. peak)	−0.4251	−2.94	0.0033
Interactions				
$\gamma_{\text{COST}\times\text{NbHH}}$	Cost × Household size	0.0309	3.92	0.0001
$\gamma_{\text{COST}\times\text{AboDT}}$	Cost × Half-fare subscription	−0.0385	−2.23	0.0256
$\gamma_{\text{SDL}\times\text{MotifStudy}}$	Late delay × Study trip purpose	−1.4453	−2.40	0.0166
$\gamma_{\text{SDE}\times\text{CSP4}}$	Early delay × CSP category 4	−1.1495	−2.20	0.0275
ASC_2	Alternative-specific constant (time-shift)	0.2744	1.65	0.0992
ASC_3	Alternative-specific constant (mode-switch to car)	−0.9658	−4.08	< 0.0001

Sample size: 180; Observations: 1076; Final log-likelihood: −913.272; AIC: 1852.543; BIC: 1894.052; ρ^2: 0.169; $\bar{\rho}^2$: 0.157

and at the sample mean, how travellers value the timing and comfort of a trip. The valuations are presented in Table 2. The results show that a traveller experiences departing one hour earlier than preferred as equivalent to a cost of 24.6 CHF, and departing one hour later as 16.9 CHF, compared with a value of travel time of 19.9 CHF/h. The order $V_{SDL} < V_{TT} < V_{SDE}$ is itself informative: schedule delay late being valued less negatively than travel time implies that, for the same amount of time, a traveller would rather accept a later departure than additional time in the vehicle. This is contrary to the common finding that lateness is the most heavily penalised outcome [8]. The switched order here suggests that, for this morning sample, late arrival is not as strongly constrained, whether because start times are flexible or because travellers have an arrival buffer. Additionally, the high V_{SDE} indicates a strong reluctance to depart earlier, and the positive value placed on arriving within the 7:00–7:40 window shows a tendency to travel very early in the morning. One possible interpretation is that travellers are already near the earliest departure they are willing to make, thus leaving little room to move earlier while being able to move later, thus explaining the variable order and the early preference window.

This order, however, is not uniform across the sample. Study-purpose trips are significantly more averse to lateness, consistent with the fixed start times of classes and lectures, while sensitivity to earliness is stronger for travellers in managerial or director positions. Consequently, the direction in which a traveller can most easily be shifted is segment-dependent, since the groups least able to arrive later are not those least able to depart earlier.

Table 2: Parameter valuations at the sample mean

Parameter	**Description**	**Valuation**
Rates (CHF/h)		
V_{SDE}	Value of schedule delay early	24.6
V_{SDL}	Value of schedule delay late	16.9
V_{TT}	Value of travel time	19.9
Per-unit penalties (CHF)		
V_{TR}	Value of a transfer	2.89
V_{OFFPEAK}	Off-peak arrival penalty	5.52
$V_{\text{CR_HIGH}}$	High crowding penalty	4.07

Note: Obtained by dividing the parameter by β_{COST} at sample mean equal to -0.0771. The high crowding penalty is derived from an insignificant coefficient.

The estimated VTT (19.9 CHF/h at the sample mean) is comparable to the value (21 CHF/h) reported in the Swiss microcensus of the same year for public transport in the 10–50 km distance band [10]. The alignment suggests the estimate is consistent with observed behaviour and shows no sign of strong upward hypothetical bias. The reversed schedule-delay ordering is shared with several rail and public transport studies and, because the estimates are large,

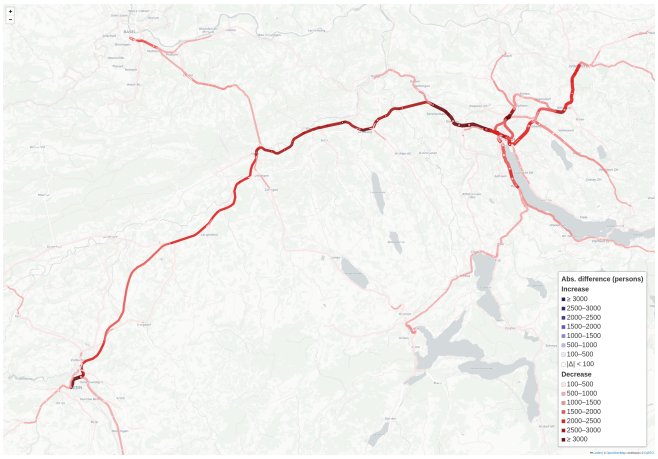
stable and significant, and because the microcensus's own analysis found the same ordering, this appears to reflect the data itself rather than the model formulation.

4.2 Simulation

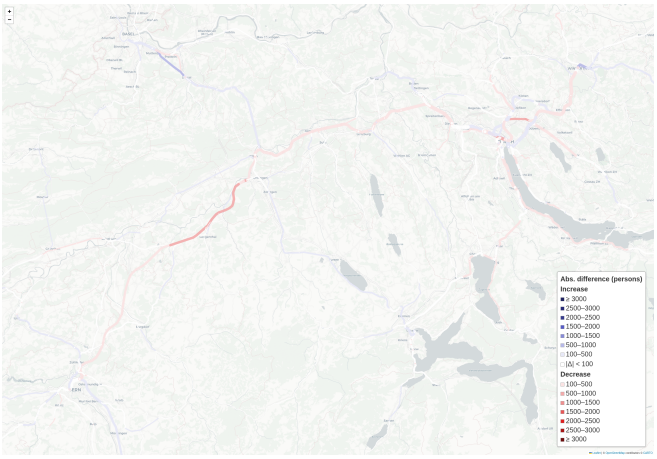
Using the agent-based model, four pricing scenarios are simulated: a peak surcharge (S1), an off-peak discount (S2), their combination (S3), and a combined rail-and-road surcharge (S4). The full per-scenario results are reported in the full report of this study. The change in network demand during the peak period for each scenario is shown in Figure 1, and the key metrics across all facets are compared in Table 3.

Demand redistribution. The two policies that achieve the largest peak-trip reduction are the 50% surcharge (-9.73%) and the 50% surcharge and 50% discount combination (-9.21%), which are almost equal, indicating that the peak reduction is driven by the surcharge component and that adding the discount does little to reduce peak trips. This is further confirmed by the maps in Figure 1 that show that the combined scenario (S3) closely resembles the surcharge-only scenario (S1), again signalling that within the peak window the surcharge, rather than the discount, does almost all of the work. The off-peak discount in reality is ineffective in reducing peak trips. Working in the other direction, it is an outlier as it increases peak trips (+0.57%). Nevertheless, the discount scenarios still lower the peak share, redistributing trips by adding off-peak demand rather than by reducing the peak demand. Spatially, although the surcharge is applied uniformly across the network, the resulting reductions concentrate on the busiest corridors and on the approaches to Zurich and Bern.

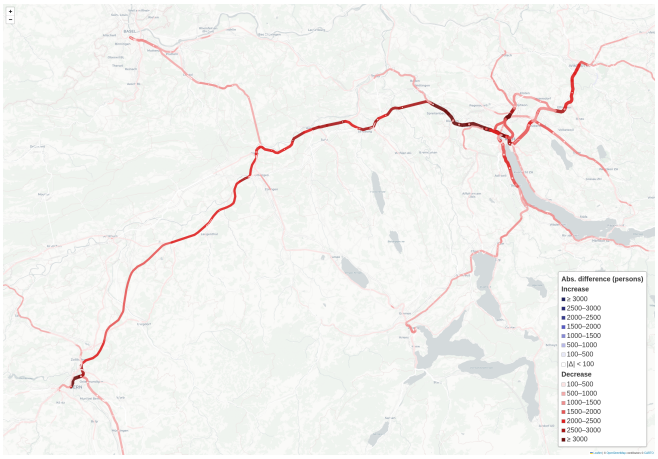
Figure 1: Change in network demand during the peak (07:00–09:00) period compared to baseline, for the four pricing scenarios.



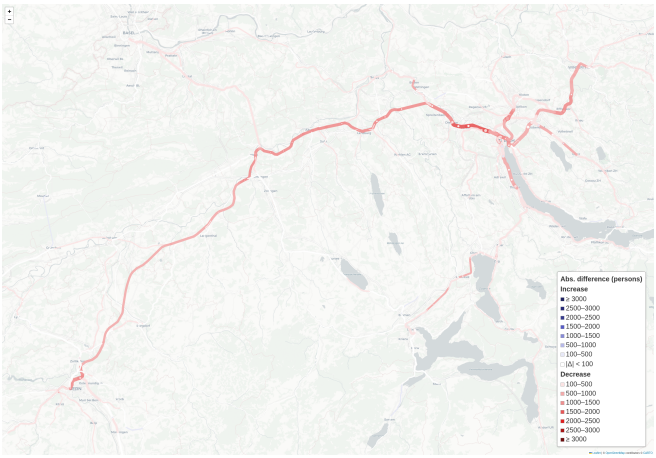
(a) S1: Peak surcharge (50%)



(b) S2: Off-peak discount (50%)



(c) S3: Surcharge & discount (50% & 50%)



(d) S4: Rail & road surcharge (30% & 50%)

Table 3: Comparison of representative pricing policy scenarios

		Peak surcharge		Off-peak discount	Surcharge & Discount	Rail & Car surcharge
	Baseline	**30%**	**50%**	**50%**	**50% & 50%**	**30% & 50%**
Total rail passenger trips [M]	2.03	2.00 (-1.5%)	1.99 (-2.0%)	2.13 (+4.9%)	2.09 (+3.0%)	2.02 (-0.5%)
Total rail passenger-km [M]	76.70	75.80 (-1.2%)	75.22 (-1.9%)	81.16 (+5.8%)	79.71 (+3.9%)	76.82 (+0.2%)
Profit from surcharge [K]	0.00	64.46	102.51	0.00	103.14	66.85
Revenue change for tickets [K]	0.00	-179.23	-295.42	893.18	603.39	24.99
Discount loss [K]	0.00	0.00	0.00	391.89	390.84	0.00
Balance [K]	0.00	-114.77	-192.91	501.29	315.69	91.84
Peak share of day (rail) [%]	19.60	18.61	18.04	18.68	17.19	18.89
Change in peak rail trips [%]	0.00	-6.13	-9.73	0.57	-9.21	-3.79
Mean agent score	50.03	50.01	50.00	50.08	50.06	49.99
Car [%]	48.05	48.11	48.15	47.72	47.82	48.03
PT [%]	18.51	18.40	18.39	18.89	18.74	18.51
Walk [%]	26.23	26.24	26.24	26.23	26.21	26.25
Bike [%]	7.20	7.25	7.22	7.15	7.23	7.20

This means that the response mainly scales with baseline ridership - reducing most on the most travelled routes. In terms of operational significance, this is a satisfactory finding as the busiest routes, according to these findings, should have the largest reduction in peak demand, and these are also the routes where it is most needed.

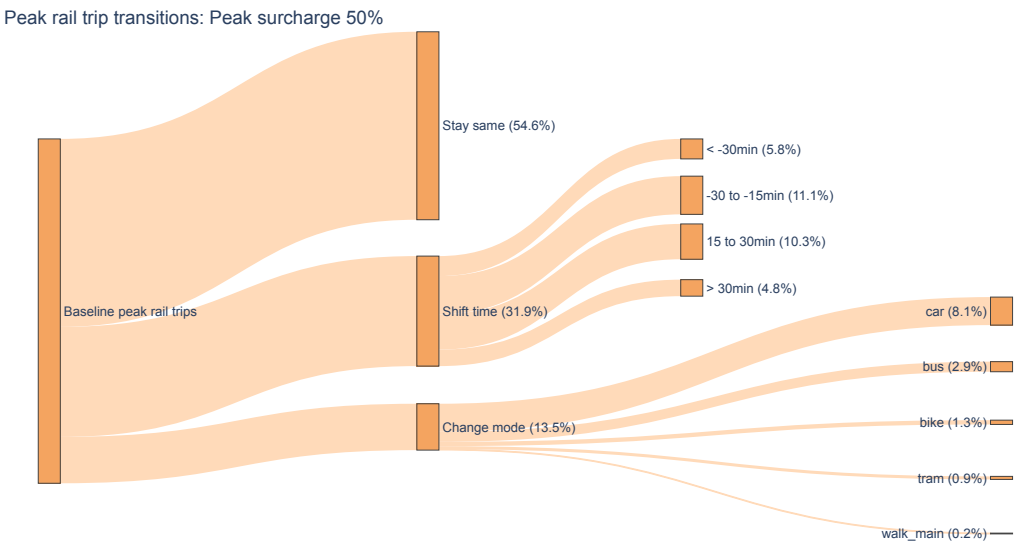
Modal split and behavioural decomposition.

For the peak surcharge scenario (S1), a breakdown of what happens to baseline peak rail trips under the policy is shown in Figure 2 (for other scenarios the diagrams are available in the full report). The figure shows that under the surcharge roughly a third of trips shift in departure time and about 14% change mode, most of which switch to car.

This illustrates the nuance that an agent-based model is able to provide for an analysis. While for road transport a reduction in traffic is the goal, for public transport not only is it necessary to reduce peak demand, but also to preserve the modal split, which is why such an analysis is crucial.

Furthermore, since some of the peak rail trips might have been replanned simply due to the stochastic nature of the simulation, the S4 (rail and road surcharge scenario) comparison addresses the effect of mode change due to surcharge. Table 3 shows that while a 30% rail surcharge alone is able to reduce peak trips by 6.13%, once a 50% road surcharge is applied, the reduction in peak rail trips is -3.79%. Since with a 50% road surcharge the modal split

Figure 2: Peak rail trips change from baseline scenario to peak surcharge 50% scenario



is effectively the same as for the baseline scenario, this suggests that -3.79% is approximately the actual percentage of peak rail trips that are retimed rather than switched to another mode. This confirms that a breakdown of effects is necessary for public transport demand analysis to show crucial differences relevant for policy success that are otherwise hidden in aggregate values.

Lastly, from the map comparison in Figure 1, every major corridor that the rail surcharge relieved shows fewer passengers removed once car travel is also priced, confirming that the car charge prevents peak demand shifting onto road, and this effect appears uniformly across the network. This implies that the mode switch to car in response to a rail peak surcharge is itself network-wide, and the effect would not occur if road travel were priced in parallel. Importantly, the difference is largely even across the whole network, indicating that the switch to road is not a specific corridor effect but a general one occurring along the whole network.

Revenue. In terms of revenue, the surcharge-only scenarios are the only ones with a negative balance, whereas every policy involving a discount is strongly positive. This is driven by passenger-kms, showing that the instrument costs, at least as defined in this study, are not the main contributors to the financial balance. A reduction or increase in the passenger-kms is creating a stronger effect than any earnings from a surcharge or losses from a discount. It should, however, be noted that the revenue calculations are a simplified approximation and do not account for removed trains due to lesser demand or more trains added to service due to increased off-peak ridership. Nevertheless, the conclusion from the results is that the instruments themselves are not having as big a financial impact as the resulting ridership, which again reinforces how important it is to preserve rail ridership when trying to redistribute demand.

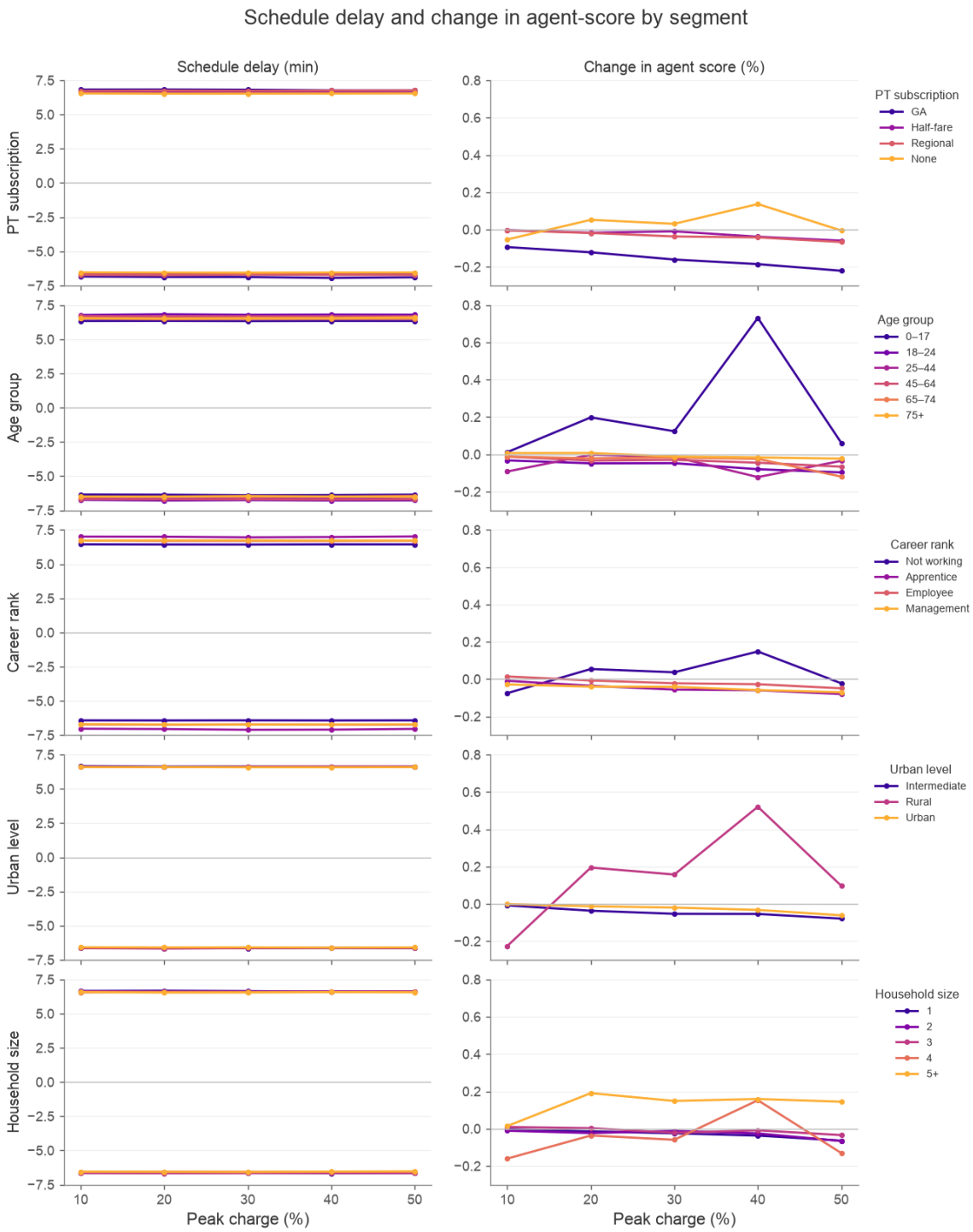
Welfare and equity. Across all policies, the schedule delay and changes in agent score are limited and, for the pure rail scenarios, show no strong or systematic pattern across socio-demographic groups. The results for S1 are shown in Figure 3, while for the other scenarios they can be viewed in the full report. A slightly different effect emerges for GA subscription holders, who see a slightly larger decline in their score under the surcharge. However, this can be explained by their higher likelihood of rail use and thus greater exposure to the policy requiring higher expenses. Some segments that are less likely to travel by rail show inconsistent and seemingly random effects, including score increases that have no plausible cause under a peak surcharge, and are therefore most likely due to stochasticity. The segments that do follow a consistent pattern show only very small effects, especially relative to these noise-driven fluctuations. Otherwise, the effects are even and small. Schedule delay is similarly small (approximately 7 minutes on average) and symmetric across population segments. Combined with possible simulation noise, the results should be interpreted cautiously, but show no clear signs of distributional inequity or significant effects on welfare.

Policy comparison. The four pricing forms notably differ in their effects, revealing a trade-off between reducing peak demand and preserving (or improving) the other network outcomes. Rail peak surcharge is effective at reducing peak trips, but it lowers revenue, ridership, mean agent score, and PT modal share. Rail off-peak discount has an opposite effect: it improves revenue, ridership, agent score, and PT modal share, yet fails to reduce peak trips, even producing a small increase. Combined rail and car surcharge preserves most network outcomes relatively close to baseline levels, avoiding the modal shift that the rail-only surcharge induces, though it reduces mean agent score the most of all four policies since travellers are charged across both modes with limited options for avoiding it. Rail surcharge combined with off-peak discount is the most well-rounded: it raises mean agent score and PT modal share, while substantially reducing peak trips, and performs well in terms of revenue and ridership, combining the peak-reducing effect of the surcharge with the ridership-preserving benefits of the discount, offsetting each instrument's individual weakness.

5 Discussion

This study set out to assess to what extent time-of-day pricing could redistribute Swiss rail demand and what its wider impacts would be. Beyond answering this for the Swiss case, the aim was to demonstrate an evaluation approach capable of looking past peak reduction alone. This is achieved by pairing an estimated departure-time choice model with an agent-based simulation, which translates

Figure 3: Mean schedule delay and change in agent scores across population segments for peak surcharge 50% scenario.



individual, socio-demographically dependent preferences into network-wide outcomes across demand redistribution, mode choice, revenue, and welfare.

The four pricing forms notably differ in their effects, revealing a trade-off between reducing peak demand and preserving (or improving) the other network outcomes. The most consequential of these results, however, is one that a peak-reduction figure alone would conceal. The peak surcharge, evaluated on peak reduction alone, appears effective, yet the trip analysis across scenarios and the comparison with the rail and road surcharge scenario reveals that a notable part of this peak reduction stems from travellers leaving rail rather than retiming. For public transport, it is not only necessary to reduce peak demand

but also to preserve the modal split, contrary to road policies, which is why such a distinction and analysis matters. The fact that an equal peak reduction can represent either outcome is precisely why the response has to be decomposed rather than read from an aggregate value.

This is where the approach itself contributes. It provides an example of integrating an estimated departure-time choice model into an activity-based simulation, enabling policy-specific behavioural parameters to be estimated and incorporated. In this study, for example, the estimation identified an off-peak arrival preference that could be carried into the simulation. It also captures behavioural heterogeneity by allowing estimated socio-demographic interactions to influence individual responses within the simulation, instead of representing all travellers with a single average sensitivity. Combining behavioural modelling with an agent-based approach further makes it possible to observe changes in network performance, mode shares, passenger kilometres, revenues, and welfare simultaneously that would not be attainable from behavioural estimation alone. It additionally reveals where relief concentrates spatially, with the response mainly scaling with baseline ridership and reducing most on the busiest corridors. To continue, this study contributes to the discourse on welfare within the time-of-day pricing topic. The welfare effects were found to be modest and distributed relatively evenly across socio-demographic groups. Where any variation across groups did emerge, it was small and likely driven by differences in how much each group uses rail rather than by the policy itself, showing either that the distribution of effects is equitable or that the effects are not strong enough to be detected at this level of simulation analysis.

The approach does, however, require additional effort compared to applying either model independently, since consistency needs to be ensured between the choice model, the simulation inputs, and the simulation framework. Parameters need to be scaled and some also constrained to realistic ranges. For example, the household size interaction parameter had to be capped since price sensitivity would not decrease endlessly with increasing household size, which barely affected the choice-model fit but prevented implausible values in the simulation. It is also necessary to match available variables between the choice model and the synthetic population. Therefore, if possible, a backward approach would be recommended, where the behavioural mechanisms required by the simulation are identified and then a stated-preference experiment is designed specifically to estimate those parameters.

Several limitations within this study should also be acknowledged. The behavioural parameters are estimated from a relatively small sample with a high proportion of high-income travellers, which could reduce the estimated cost sensitivity and inflate the willingness-to-pay values. Since all utility parameters are scaled relative to the cost coefficient, stronger-than-in-reality pricing incentives would thus be required in the simulation before behavioural changes occur, meaning the simulated response to pricing may be conservative. The parameters are also estimated on a morning peak-hour subsample but applied to the whole-day population, so the whole-day totals and the mode-switch behaviour should be treated as indicative rather than precise. Moreover, the data was collected in 2021, so Covid-19 effects such as increased working from home are not accounted for, and a notable share of respondents did not report an ideal arrival time for which a proxy from the reference trip was used, weakening the schedule-delay estimates. On the model side, the base ticket cost could not be identified separately, most likely due to collinearity with travel time, and the dataset contains limited mode-choice and no trip-suppression or destination change alternatives. Most fundamentally, pricing is applied only in the MATSim stage, where agents can adjust departure time, route, and mode, while other choices such as the order of activities, activity start times, destinations, and the number of trips are determined before this stage and held fixed. As a result, the peak-reduction and rescheduling effects reported here are likely a lower bound, and the weak response to the off-peak discount in particular may partly reflect this structural rigidity rather than genuine behavioural inelasticity.

These limitations point to clear directions for future work. Valuable improvements include, firstly, a larger, more representative sample, estimated on full-day travellers rather than the morning subsample and using post-2021 data free of pandemic effects. This would also allow preferences to be tested for differences between morning and evening travel. Secondly, integrating time-of-day pricing into the whole decision pipeline of the simulation rather than the final stage alone would capture the upstream choices currently held fixed, though it would require large structural

changes to the framework. Thirdly, incorporating income for each agent or household into the synthetic population and extracting the exact fare paid by each traveller would enable a much richer equity analysis of how the cost burden falls across socio-demographic groups.

6 Conclusion

This paper evaluated to what extent time-of-day pricing on Swiss rail could spread passenger demand across time, and its impacts on modal split, welfare, ridership and revenue, through a full pipeline from stated-preference estimation to agent-based simulation.

The choice model showed that Swiss morning rail travellers are comparatively reluctant to shift their schedules, with a marked preference to arrive early, and that this sensitivity varies across traveller segments. Carried into the simulation, the tested instruments differed considerably: a surcharge reduced peak trips but at the cost of ridership, revenue, welfare and PT modal share; a discount improved these but did not reduce the peak; and the combination of the two proved the most well-rounded, reducing peak trips by 9.21% at the highest level while improving the other outcomes. Across all policies, the welfare effects were small and distributed relatively evenly across socio-demographic groups, with no evidence of the strongly negative or inequitable outcomes sometimes assumed in public debate. A central finding, visible only through the multimodal simulation, is that a notable part of the surcharge's peak reduction reflects travellers leaving rail for the car rather than retiming — a distinction important for a policy aiming to manage rail demand instead of driving it away.

The strength of the approach is that it captures not just the size of the peak reduction, but its composition and its wider effects on modal split, revenue and equity. It also allows policy-specific, socio-demographically heterogeneous sensitivities to be integrated, improving the realism of the results. These findings are an indication rather than a definitive outcome, but they suggest that time-of-day pricing can be a promising strategy for Swiss rail, while still warranting further study.

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B

Appendix B: Literature Review Supplement

B.1. Literature review framework

The literature review was performed using Google Scholar and Scopus searching for research in the concepts outlined in Table B.1.

Table B.1: Framework for literature review

Concept groups	Time-of-day pricing; departure-time choice; agent-based simulation
Keywords	**Time-of-day pricing:** • peak pricing • tariff differentiation • public transport fares • time-of-day pricing • demand management • rail demand • public transport demand **Departure-time choice:** • departure time choice • departure time model/modelling • time-of-day choice • time-period choice • schedule delay (SDE/SDL) • value of travel time **Agent-based simulation:** • agent-based model/modelling • activity-based model/modelling • MATSim • transport simulation • public transport simulation

B.2. Reviewed choice modelling studies

Table B.2: Overview of reviewed discrete choice modelling studies for tariff differentiation (Part 1: Model specification)

Paper	Model specification	Choice dimension	Model separation	Sociodemographic variables included
Weesie & Hofker (2009)	Unspecified DCM (implied standard logit)	Ticket type (TOD restriction)	Season ticket holders / VDU card holders / infrequent travellers	Frequency of rail use; trip purpose (business vs education vs other)
Vrtic et al. (2007)	MNL (joint SP model with scale parameters per experiment)	Route $\times$ mode $\times$ TOD	None	Car ownership; annual km driven; age; PT subscription (GA / half-fare / none); language region (French / German / Italian)
Peer et al. (2016)	MNL + panel latent class MNL (3-class)	TOD	None	None in model
Vrtic et al. (2011)	MNL (joint SP model with scale parameters per experiment)	Route $\times$ mode $\times$ TOD	None	Car ownership; annual km driven; age; GA / half-fare ownership; language region (French / German / Ticino); full-time employment (not significant)
De Jong et al. (2003)	ECL (MNL and NL as benchmarks)	TOD $\times$ mode	4 travel purposes; education estimated as MNL	Age ($<$40 dummy); part-time employment; single worker (train); education level (low); works from home regularly; employer travel cost compensation; flexible and fixed working hours
Daly et al. (2005)	ECL (MNL and NL as benchmarks)	TOD $\times$ mode	London / Dutch / West Midlands; commute, business, other	Age; part-time employment; works from home; education level; income; employer cost compensation; car availability; household size; gender
Van den Berg et al. (2009)	MNL, nested logit, mixed logit	Ticket type	None	Gender; trip purpose; car ownership; employer travel cost compensation (yes / partial / no)

Table B.3: Overview of reviewed discrete choice modeling studies for tariff differentiation (Part 2: Variables included)

Paper	Travel cost	Travel time	Crowding	Peak element	SDE	SDL	Time period	Reliability	Transfers
Weesie & Hofker (2009)	x			x	x	x	x		
Vrtic et al. (2007)	x	x		x	x	x		x	x
Peer et al. (2016)		x	x	x	x	x		x	x
Vrtic et al. (2011)	x	x		x	x	x		x	x
De Jong et al. (2003)	x	x		x	x	x			
Daly et al. (2005)	x	x			x	x	x		
Van den Berg et al. (2008)	x	x		x	x	x			

Table B.4: Overview choice dimensions and model types of departure-time choice modelling studies. Entries marked † are adapted from the review performed by Fox et al. [16] Table 8.

Author(s)	Year	Choice dimension	Model type
Bajwa, S. †	2008	Dep Time X Mode	MNL, NL, MxL
Ben-Akiva, M. and M. Abou-Zeid †	2013	Dep Time X Arr Time	not stated
Bhat, C. †	1998	Dep Time X Mode	MNL, MxL
Bowman, J. and M. Ben-Akiva †	2001	Daily activity pattern	MNL
Daly et al.	2005	TOD $\times$ mode	ECL (MNL and NL as benchmarks)
Day, N. †	2008	Dep Time X Mode	MNL and other
de Jong, G., A. Daly, M. Pieters, C. Vellay, M. Bradley and F. Hofman	2003	Dep Time X Mode	ECL, MxL (MNL and NL as benchmarks)
Ettema, D., F. Bastin, J. Polak, and O. Ashiru †	2007	Activity timing and duration	MNL, MxL
Hess, S., A. Daly, C. Rohr and G. Hyman †	2007	Dep Time X Mode	MNL, NL
Holguín-Veras, J. and B. Allen †	2013	Time period X Mode X Route X Frequency	MNL
Holyoak, N. †	2007	Dep Time	MxL
Knockaert, J. †	1995	Dep Time X Mode	MNL, NL, MxL
Lizana, P. †	2014	Dep Time X Mode	MNL, MxL
Noland, B. and K. Small †	1995	Dep Time	not stated
Nurul Habib, K. †	2012	Work start time X Work duration X Mode	not stated
Paleti, R., P. Vovsha, and D. Givon †	2014	Dep Time X Mode	Other
Peer et al.	2016	TOD	MNL and panel latent class MNL
Saleh, W. and S. Farrell †	2005	Dep Time	MNL
Sikder, S., B. Augustina, A. Pinjaria and N. Elurub †	2014	TOD	MNL
Small, K. †	1982	Work arrival time	MNL
Tringides, C. and R. Pendyala †	2004	Dep Time X Mode	Other
Van den Berg et al.	2008	Ticket type	MNL, NL, MxL
Vovsha, P. and M. Bradley †	2004	Tour scheduling	MNL
Vrtic et al.	2007	TOD X Mode X Route	MNL
Vrtic et al.	2011	TOD X Mode X Route	MNL
Weesie & Hofker	2009	Ticket type (TOD restriction)	not stated
Willigers, J. and M. de Bok †	2009	TOD X Mode X Destination	NL
Williams, I. and J. Bates †	1993	TOD X Mode	NL

B.3. System-wide model studies

Table B.5: Overview of reviewed simulation studies

Title	Authors	Year	Model	Modes	Objective	Metrics
Modelling the impact of alternative fare structures on train overcrowding	Whelan & Johnson	2004	Fare/demand model (not agent-based)	Rail	Effect of peak surcharges and off-peak discounts on train overcrowding	Peak load factor, ticket-type demand, operator revenue
SimMobility Mid-term Simulator: a state-of-the-art integrated agent-based demand and supply model	Lu et al.	2015	SimMobility Mid-term (ABM + DTA)	All	Present integrated agent-based demand–supply simulator	Activity-pattern prediction vs. observed, computation time
Agent-based optimisation of public transport supply and pricing: impacts of activity scheduling decisions and simulation randomness	Kaddoura et al.	2015	MATSim, synthetic corridor	Car, bus	Joint optimisation of PT fare and headway; effect of departure-time adaptation	Social welfare, operator profit, bus mode share, waiting time, optimal fare/-headway
Evaluating off-peak pricing strategies in public transportation with an activity-based approach	Lovrić et al.	2016	SimMobility pre-day	All	Evaluate free pre-peak travel and off-peak discounts	Peak/off-peak ridership, PT mode share, PT trips, average fare, operator revenue
Road pricing: an analysis of equity effects with MATSim	Meyer de Freitas et al.	2016	MATSim, Zurich	Car, PT	Equity effects of a cordon peak-hour toll	Cordon crossings, VKT, agent score change, mode share, score change by income group
Activity rescheduling within a multi-agent transport simulation framework (MATSim)	Balać & Axhausen	2017	MATSim, Zurich (0.1% sample)	All	Implement activity re-scheduling (insert/remove/swap) in MATSim	Mean agent score, number of activities, distinct activity chains, computation time
Pairing discrete mode choice models and agent-based transport simulation with MATSim	Hörl et al.	2019	MATSim, Zurich	All	Pair a discrete mode choice model with network simulation in the loop	Mode share fit to reference data, travel-time prediction error, runtime
Agent-based microsimulation of a passenger rail system using customer survey data and an activity-based approach	Makinde et al.	2019	MATSim, passenger rail operator	Rail	Predict impact of fare pricing strategies on peak rail demand from operator survey data	Peak arrival/departure volumes, correlation with passenger counts
Examining impacts of time-based pricing strategies in public transportation: a study of Singapore	Adnan et al.	2020	SimMobility Mid-term	All (PT focus)	Evaluate nine time-based pricing strategies (free pre-peak MRT and off-peak discounts)	Peak/off-peak PT ridership, PT mode share, operator revenue, denied boardings, PT trips; by income, person type and gender
SIMBA MOBi: microscopic mobility simulation for corporate planning	Scherr et al.	2020	SIMBA MOBi (MATSim-based)	All	Present SBB's national microscopic demand model for corporate planning	Calibration and validation against counts, travel diaries and rail OD surveys
A validated multi-agent simulation test bed to evaluate congestion pricing policies on population segments by time-of-day in New York City	He et al.	2021	MATSim-NYC	Car, PT	Evaluate cordon congestion pricing by population segment and time of day	Car trip reduction, consumer surplus per capita by segment, share negatively affected, departure-time distribution, revenue
Integration of different mobility behaviors and intermodal trips in MATSim	Müller et al.	2022	MATSim, Vienna	All	Represent heterogeneous mode preferences via latent-class parameters and intermodal trips	Mode share and trip distance validation

C

Appendix C: Choice Modelling Supplement

C.1. Wald test results

Table C.1: Wald test results for parameter consolidation: PT and Car separated parameters

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 C.2: 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 $= 0.012$				
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 $= 0.106$				

C.2. Microcensus 2015 counts: rail trip daily distribution

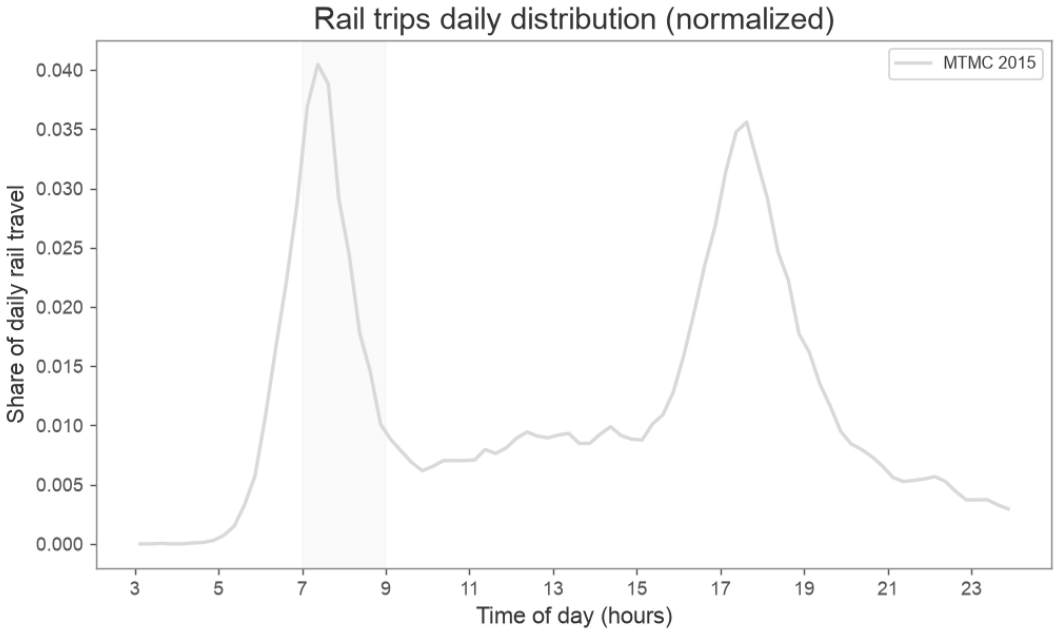


Figure C.1: The daily distribution of rail trips as counted in the 2015 Swiss Mobility and Transport Microcensus

C.3. Final choice model variable correlation matrix

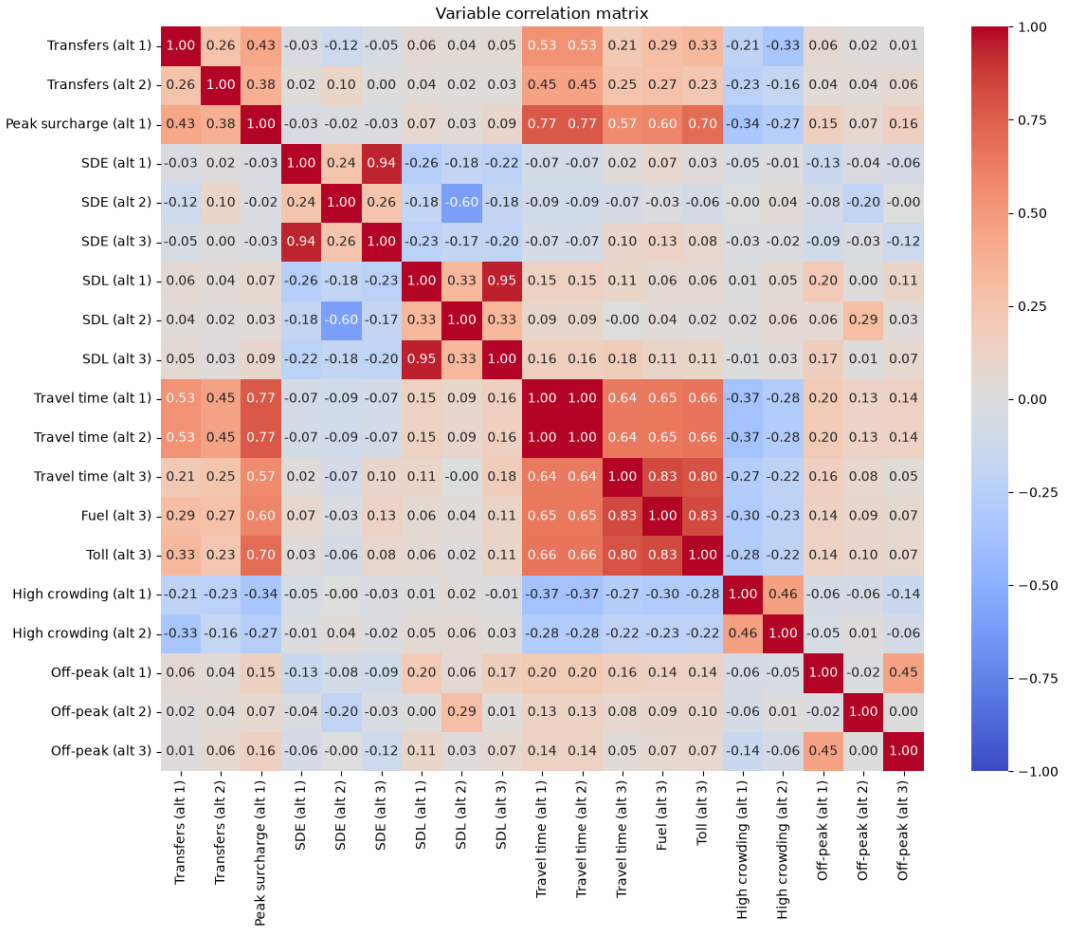


Figure C.2: Final model: variable correlations

C.4. Results of interaction variable testing

Table C.3: Overview of sociodemographic and trip variables considered for interaction testing (bolded variables are included in the final model)

Variable	Description	Format	Tested / Note
RP_langue_num	Language region	Dummies (German, French, Italian)	Tested; Italian excluded (low coverage)
RP_UrbLevel	Urbanisation level of residence	Dummies (Urban, Suburban, Rural)	Tested; not significant
RP_Genre	Gender	Dummy (Female=1)	Tested; not significant
RP_Age	Age	Continuous + quadratic term	Tested; not significant
RP_AboTP	Any PT subscription	Dummy	Tested; not significant
RP_AboAG	General travelcard (GA)	Dummy	Tested; not significant
RP_AboDT	**Half-fare travelcard**	**Dummy**	**Tested; significant (B_{cost})**
RP_AboCom	Regional travelcard	Dummy	Tested; not significant
RP_AboParcours	Modulat travelcard	Dummy	Tested; excluded (low coverage)
RP_AboSeven25	Seven25 travelcard	Dummy	Excluded (no variation in sample)
RP_NbHH	**Household size**	**Linear and piecewise**	**Tested; significant (B_{cost})**
RP_hhIncome	Household monthly income	Linear and Piecewise linear (1-9)	Tested; not significant
RP_regionID	Residence region	Dummies (7 regions)	Tested; not significant (Region 7 excluded - low coverage)
RP_licence	Driving licence	Dummy	Tested; not significant
RP_ebike	E-bike in household	Dummy	Tested; significant (B_{TOD}, excluded due to lack of behavioural grounding
RP_educationlevel	Education level	Dummies (4 levels + missing)	Tested; lvl 1 significant, but becomes insignificant once combined in the model with other interactions
RP_CSPagr	**Socio-professional category**	**Dummies (5 levels; levels 0,1 excluded)**	**Tested; CSP 4 significant (B_{SDE})**
RP_Motif_num	**Trip purpose**	Dummies (Work, **Study,** Other; merged: to/from)	Tested; Work significant (B_{SDL}), **Study significant (B_{SDL})**, Other significant (B_{TOD}), Study and B_{SDL} retained in the model; Work lacked behavioural grounding; Other was unstable
domicile_travail	Declared work trip	Dummy	Tested; not significant
RP_classdist	Distance class	Dummies ($<$10km, 10–30km, $>$30km)	Tested; $>$30km significant (B_{SDL}) excluded due to lack of behavioural grounding
RP_distTP	PT trip distance	Continuous	Tested; not significant
RP_TypeOrig	Origin territorial type	Dummies (Urban, Suburban, Rural)	Tested; not significant
RP_TypeDest	Destination territorial type	Dummies (Urban, Suburban, Rural)	Excluded (low coverage suburban/rural)
RP_TPs_tot_TP	Total PT trip time	Continuous	Tested; not significant
RP_Tps_trip_TP	In-vehicle PT time	Continuous	Tested; not significant
RP_Freq_TP	PT headway	Log-transformed	Tested; not significant
RP_Mode_TP	Main PT mode	Dummies (Bus, Local train, Intercity; others excluded)	Tested; not significant
RP_possVP	Car ownership	Dummy	Tested; significant (B_{TOD}, excluded due to lack of behavioural grounding
RP_Velo	Bike trip possible	Dummy	Tested; not significant
RP_Marche	Walking trip possible	Dummy	Tested; not significant
RP_Tps_Velo	Bike trip time	Continuous	Tested; not significant
RP_Tps_ele_Velo	E-bike trip time	Continuous	Tested; not significant

D

Appendix D: Simulation Supplement

D.1. Processing of model outputs

The following section describes the steps to transform model outputs into the evaluation metrics.

D.1.1. Submode classification

To enable the analysis of rail trips and more detailed mode-switching behaviour, the public transport main mode is split into its submodes using the following methodology.

The SIMBA MOBi output provides trip-level information. In terms of modes, each trip includes *main_mode*, *longest_distance_mode* and *modes*, where:

- *main_mode* is the main mode of the trip, grouped into car, public transport, ride, bike and walk.
- *longest_distance_mode* is the mode covering the greatest distance of the trip, including car, rail, ride, walk, bike, bus, tram, other and additional public transport access modes.
- *modes* gives the full mode chain.

For each trip, if the main mode is not public transport, the submode is set equal to the main mode. Public transport trips are otherwise classified according to the hierarchy below:

1. if the longest-distance mode is rail, or any leg contains rail, assign *rail*;
2. if the longest-distance mode is bus, assign *bus*;
3. if the longest-distance mode is tram, assign *tram*;
4. if only bus is present, assign *bus*; if only tram is present, assign *tram*;
5. if both bus and tram are present, use the longest-distance mode as a tie-breaker when it is bus or tram, and otherwise assign *busandtram*;
6. if the trip consists only of walking legs, assign *walk_pt*;
7. otherwise assign *PT_other*.

D.1.2. Peak trip classification

Since exact rail boarding and disembarking times are not available, filter using the trip departure and arrival time is used to obtain rail peak trips. The peak time filter is true if any of the three conditions below are true:

- The departure time of the trip is during the peak time;
- The arrival time of the trip is during the peak time;
- The departure time is before and the arrival time is after the peak time.

It should be noted that this likely overestimates the number of peak trips since access and egress time is ignored. This can both inflate the peak share of the day, while also reducing the agent reaction to pricing instruments. This is because a trip may be labelled as a peak trip, while its rail leg occurs, for example, before the peak and its egress part of the trip is in the peak. In this case the agent would not have to pay the surcharge even though the results analysis would perceive that they would.

D.1.3. Peak trip tracking

To observe policy response on the target agent group, the rail trips occurring during the baseline morning peak are tracked to observe how they change in the priced scenarios. Since *trip_id* remains consistent across simulations, the baseline trips are filtered for submode rail and peak time, then located in each scenario output data and categorised into four groups: remain the same, shift time, change mode, or lost trip.

A trip is classified as remaining the same if in the scenario results it is still a rail trip and its departure time has changed by no more than $\pm$15 minutes. This threshold is installed to avoid overstating the policy effect, since MATSim's stochasticity can produce small departure-time shifts due to agent replanning that do not reflect the policy effect.

Trips in the *shift-time* category are sorted into four bins to show the extent and direction of the change, with a negative sign indicating an earlier departure:

- more than 30 minutes earlier;
- 15 to 30 minutes earlier;
- 15 to 30 minutes later;
- more than 30 minutes later.

Trips in the *change mode* category are those that are no longer performed by rail. Their departure time is disregarded, as it is no longer relevant to rail demand, and the switch is reported at the level of submode. Lost trips are those that no longer appear in the scenario output. Since currently the model is set-up so that trip suppression is not possible, this category is always zero.

D.1.4. Population segmentation

For the equity analysis, agents are grouped by socio-demographic characteristics. Five variables are used: public transport subscription, age category, job rank, household size and urban level. The variables are selected for their availability in SIMBA MOBi and their relevance to the distributional analysis of who bears the costs and benefits of the policies:

- **Job rank** serves as a proxy for economic status, since neither individual nor household income is available in SIMBA MOBi. Job rank is the employment-position type categorised as: not currently working (0), apprentice (1), employee (2) and management (3).
- **Household size** is selected as it serves as a partial proxy for household resources, as larger households may combine more earners although also with more dependents. More directly, it reflects household composition and life stage, from single-person households to families with children, which shape travel needs and scheduling constraints such as escorting trips and reduced timing flexibility. It can also be associated with car availability and ownership.
- **Public transport subscription** indicates whether holders of different subscription types are advantaged or disadvantaged, and additionally proxies for how frequently an agent uses rail: regular rail users tend to hold a fuller-coverage subscriptions (e.g. GA), while those without a subscription typically travel by train less often.
- **Age category** is included as a basic demographic dimension along which effects may differ.
- **Urban level** refers directly to the equity of rail provision, since rail coverage, accessibility, service level and reliance differ between urban, intermediate and rural areas.

The first four variables are taken directly from the agent dataset, while urban level is coupled by using each agent's residence location. Each agent's residence *zone_id* is matched to the Swiss national

urban–rural typology, a three-level classification (urban, intermediate, rural) based on population density and commuter flows [41].

D.2. Agent score and schedule-delay processing

Both welfare metrics are computed by matching baseline and scenario run outputs at the agent or trip level, using identifiers that remain consistent across simulation runs.

For the **change in agent score**, the baseline and scenario person datasets are matched on the person identifier *person*. For each agent, the percentage change in executed score is

$$\Delta S_i = \frac{S_i^{\text{scenario}} - S_i^{\text{baseline}}}{S_i^{\text{baseline}}} \times 100, \tag{D.1}$$

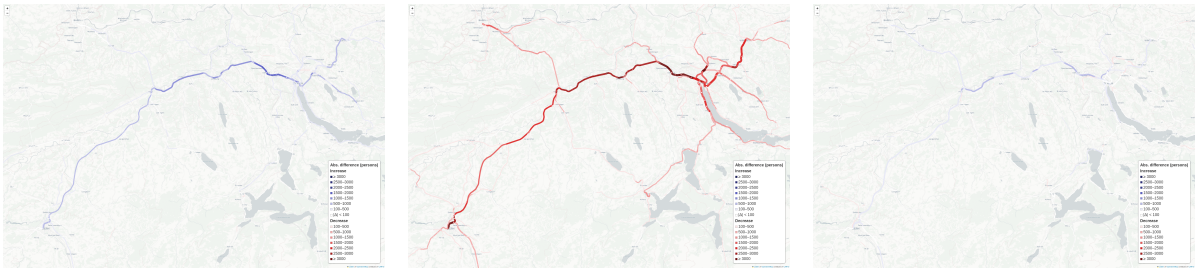
where S_i is the executed score of agent i. The percentage change is used rather than the absolute change to give a proportional measure. Agents are then grouped by the socio-demographic variable of interest and the mean ΔS_i per group is taken.

For **schedule delay**, baseline and scenario trips are matched on the trip identifier *trip_id*, and the departure-time difference is computed for each matched trip. Positive shifts are classified as schedule delay late (SDL) and negative shifts as schedule delay early (SDE):

$$\Delta t_j = t_j^{\text{scenario}} - t_j^{\text{baseline}}, \qquad \text{SDL} = \Delta t_j \text{ if } \Delta t_j > 0, \quad \text{SDE} = \Delta t_j \text{ if } \Delta t_j < 0. \tag{D.2}$$

Trip-level values are then aggregated to the person level by taking each agent's mean SDE and mean SDL separately across their trips. This data is then merged with the person dataset and averaged within each socio-demographic group.

D.3. Changes in demand across network per scenario and time period



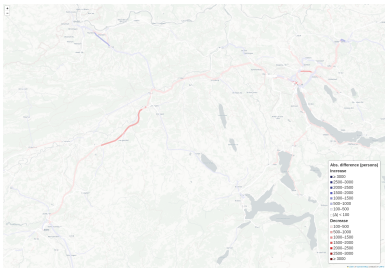
(a) Peak surcharge 50%: Pre-peak

(b) Peak surcharge 50%: Peak

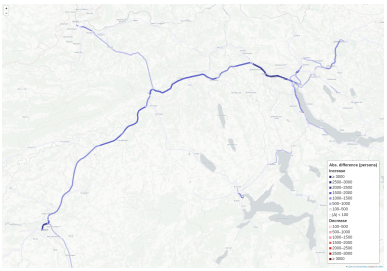
(c) Peak surcharge 50%: Post-peak



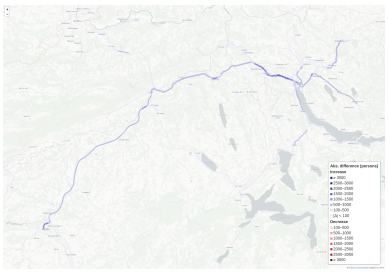
(d) Off-peak discount 50%: Pre-peak



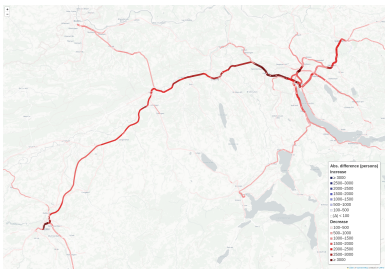
(e) Off-peak discount 50%: Peak



(f) Off-peak discount 50%: Post-peak



(g) Surcharge & discount 50&50%: Pre-peak



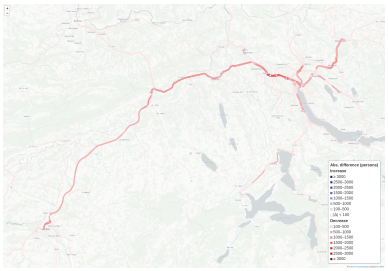
(h) Surcharge & discount 50&50%: Peak



(i) Surcharge & discount 50&50%: Post-peal



(j) Rail-and-road surcharge 30&50%: Pre-peak



(k) Rail-and-road surcharge 30&50%: Peak

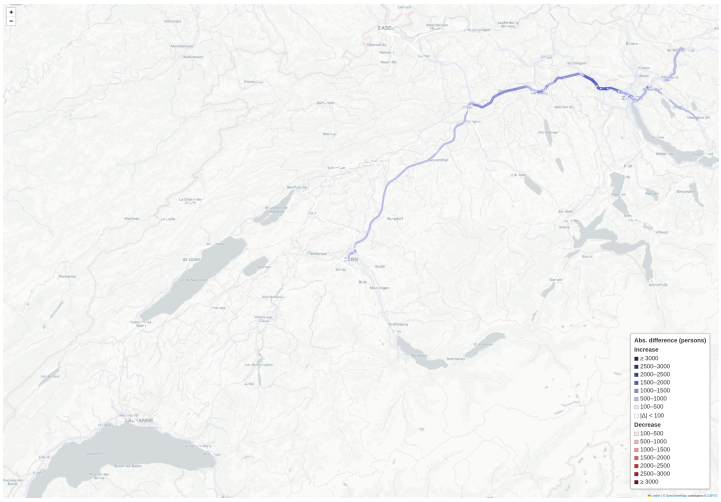


(l) Rail-and-road surcharge 30&50%: Post-peak

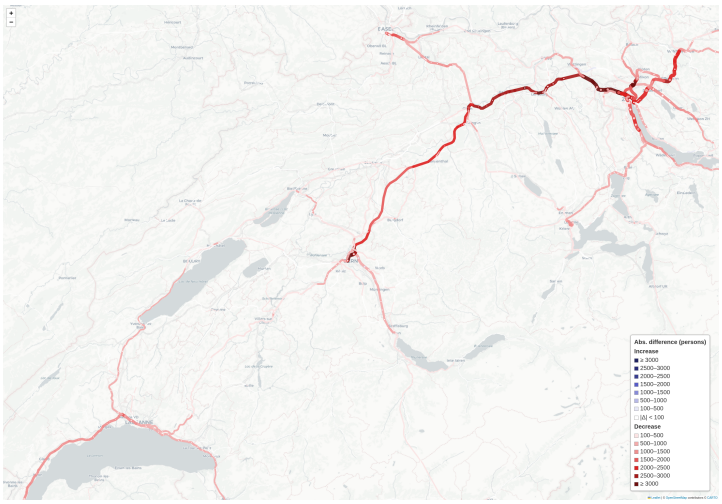
Figure D.1: Network demand differences relative to baseline by scenario (rows: S1–S4) and time window (columns: pre-peak 05:00–07:00, peak 07:00–09:00, post-peak 09:00–11:00).

D.4. Changes in demand: National maps

D.4.1. S1: Rail surcharge 50%



(a) 05:00-07:00: Pre-peak



(b) 07:00-09:00: Peak



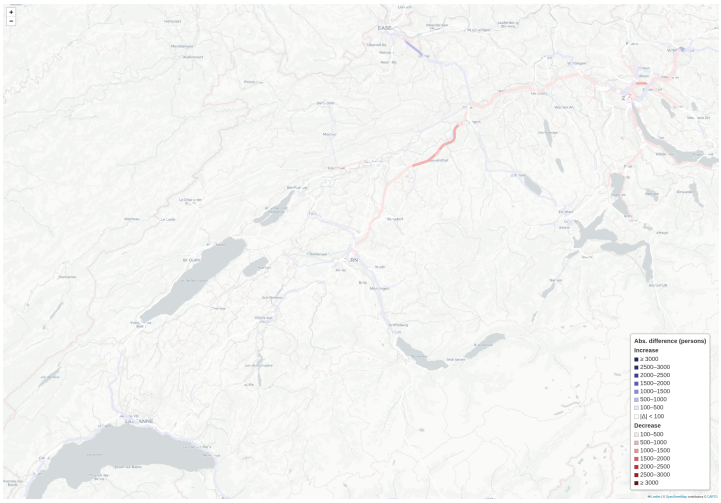
(c) 09:00-11:00: Post-peak

Figure D.2: Network demand differences relative to baseline for S1 by time window

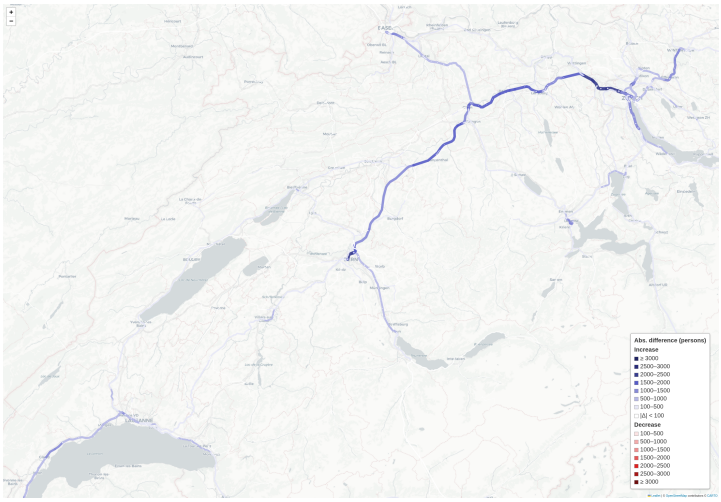
D.4.2. S2: Rail discount 50%



(a) 05:00-07:00: Pre-peak



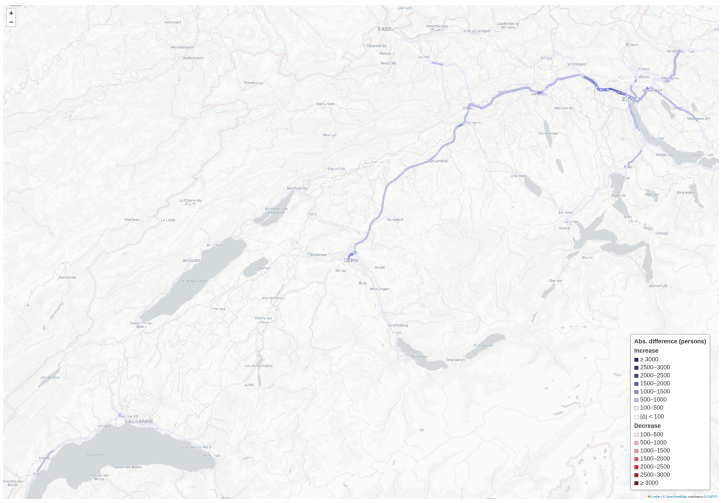
(b) 07:00-09:00: Peak



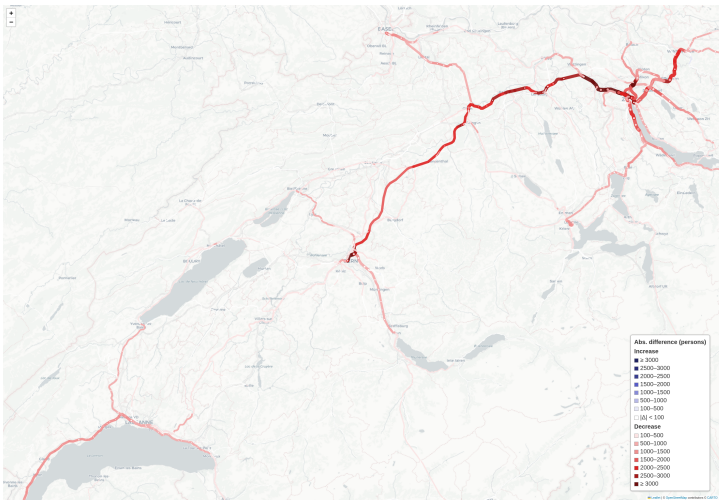
(c) 09:00-11:00: Post-peak

Figure D.3: Network demand differences relative to baseline for S2 by time window

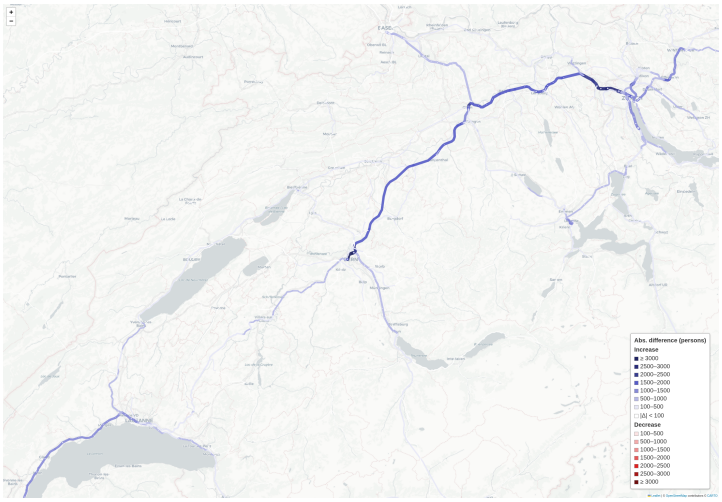
D.4.3. S3: Rail surcharge 50% and discount 50%



(a) 05:00-07:00: Pre-peak



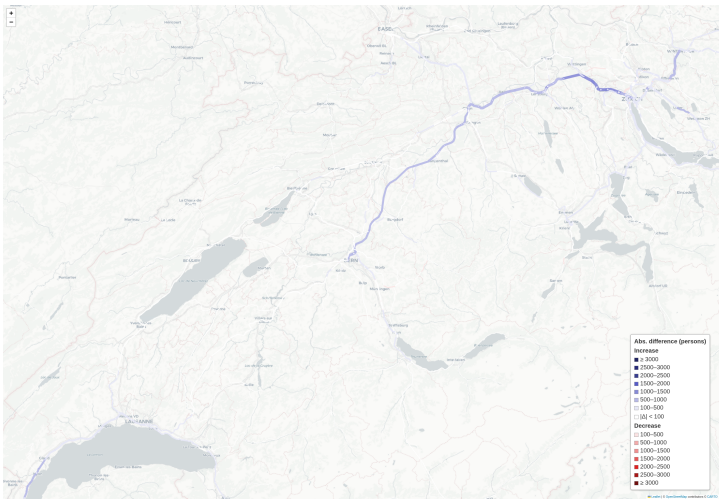
(b) 07:00-09:00: Peak



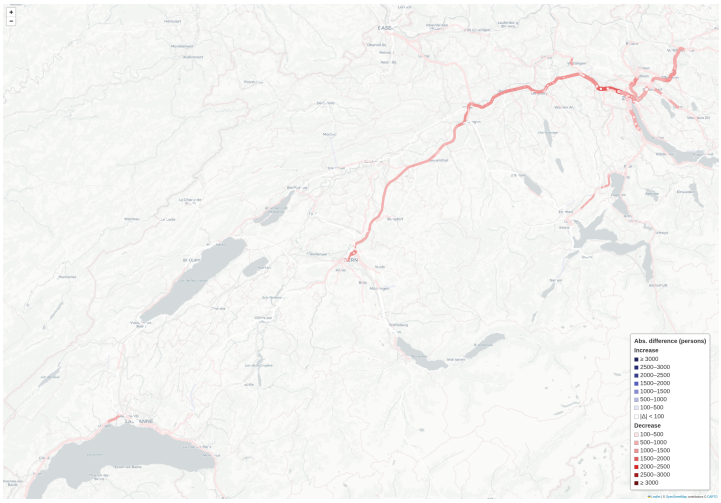
(c) 09:00-11:00: Post-peak

Figure D.4: Network demand differences relative to baseline for S3 by time window

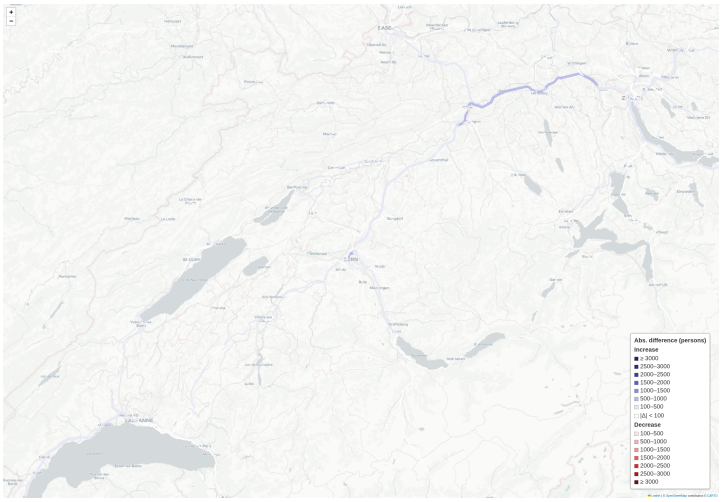
D.4.4. S4: Rail surcharge 30% and road surcharge 50%



(a) 05:00-07:00: Pre-peak



(b) 07:00-09:00: Peak



(c) 09:00-11:00: Post-peak

Figure D.5: Network demand differences relative to baseline for S4 by time window

D.5. Policy Comparison

The results are combined for the border values of all four scenario types to compare them alongside each other and see the effects of the scenario type.

D.5.1. Time distribution of travel

In figure D.6, the combination of the scenrio results can be seen. The main takeaways are that the discount seems to have no real effect on the peak trips. This can be seen as both green lines hover around 0 change during the peak window, with the exception of approximately 8:30 when the maximum discount (50%) gives a slight decrease. This is also notable in the fact that the 50% surcharge and 50-50% surcharge and discount lines are almost overlapping during the peak time. The time when they diverge is only slightly around 8.30 as well as at the post-peak shoulder period when the discounted scenarios have a steep increase. To continue, rail and car surcharge scenarios are simply dampened rail surcharge scenarios.

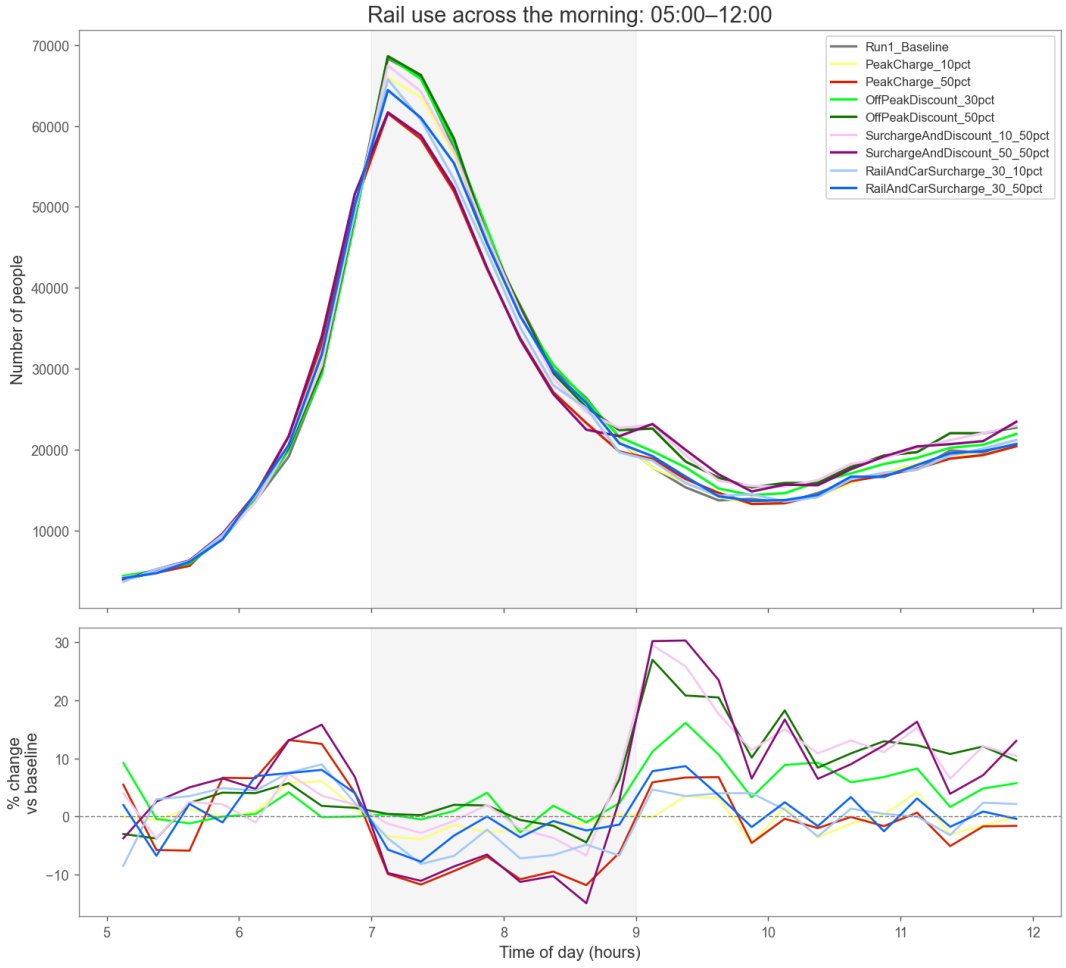


Figure D.6: Edge value scenario comparison for rail morning distribution

D.5.2. Key metrics

Table D.1 brings the representative scenarios of each policy type together for a side-by-side comparison. The comparison largely reinforces the conclusions already drawn for the individual scenarios rather than revealing new effects, but placing them next to each other makes the differences between policy types clearer.

Table D.1: Comparison of representative pricing policy scenarios

		Peak surcharge		Off-peak discount		Surcharge & Discount		Rail & Car surcharge	
	Baseline	**10%**	**50%**	**30%**	**50%**	**10% & 50%**	**50% & 50%**	**30% & 10%**	**30% & 50%**
Total rail passenger trips [M]	2.03	2.02 (-0.5%)	1.99 (-2.0%)	2.09 (+3.0%)	2.13 (+4.9%)	2.12 (+4.4%)	2.09 (+3.0%)	2.01 (-1.0%)	2.02 (-0.5%)
Total rail passenger-km [M]	76.70	76.44 (-0.3%)	75.22 (-1.9%)	79.30 (+3.4%)	81.16 (+5.8%)	80.90 (+5.5%)	79.71 (+3.9%)	76.01 (-0.9%)	76.82 (+0.2%)
Long-distance rail passenger-km (FV) [M]	41.94	41.83 (-0.3%)	41.24 (-1.7%)	43.67 (+4.1%)	44.86 (+7.0%)	44.64 (+6.4%)	44.06 (+5.1%)	41.65 (-0.7%)	42.14 (+0.5%)
Regional rail passenger-km (RV) [M]	27.11	26.95 (-0.6%)	26.41 (-2.6%)	27.96 (+3.1%)	28.63 (+5.6%)	28.61 (+5.5%)	28.03 (+3.4%)	26.75 (-1.3%)	26.98 (-0.5%)
Profit from surcharge [K]	0.00	22.62	102.51	0.00	0.00	22.86	103.14	64.69	66.85
Revenue change for tickets [K]	0.00	-52.31	-295.42	520.54	893.18	840.32	603.39	-137.26	24.99
Discount loss [K]	0.00	0.00	0.00	225.50	391.89	392.24	390.84	0.00	0.00
Balance [K]	0.00	-29.68	-192.91	295.04	501.29	470.94	315.69	-72.58	91.84
Peak share of day (rail) [%]	19.60	19.19	18.04	19.11	18.68	18.40	17.19	18.63	18.89
Change in peak rail trips [%]	0.00	-2.40	-9.73	0.61	0.57	-1.21	-9.21	-5.74	-3.79
Mean agent score	50.03	50.02	50.00	50.06	50.08	50.08	50.06	50.01	49.99
Car [%]	48.05	48.05	48.15	47.82	47.72	47.71	47.82	48.09	48.03
PT [%]	18.51	18.50	18.39	18.71	18.89	18.86	18.74	18.48	18.51
Walk [%]	26.23	26.25	26.24	26.27	26.23	26.23	26.21	26.24	26.25
Bike [%]	7.20	7.20	7.22	7.21	7.15	7.20	7.23	7.20	7.21

Reading across the table, a few points stand out. The two policies that achieve the largest peak-trip reduction are the 50% surcharge (-9.73%) and the 50 & 50 % combination (-9.21%), which are almost equal, indicating that the peak reduction is driven by the surcharge component and that adding the discount does little to reduce peak trips. The off-peak discount is the outlier here. It is the only policy that increases peak trips (+0.57% to +0.61%) while still lowering the peak share, confirming that it redistributes by adding off-peak demand rather than by cutting the peak.

In terms of revenue, the surcharge-only columns are the only ones with a negative balance, whereas every policy involving a discount is strongly positive. The rail-and-car surcharge sits in between, moving from negative to positive as the road surcharge increases.

The modal split is affected, but the public transport share stays within roughly 18.4-18.9%, which can be considered a relatively small range. Thus, at these levels none of the policies drastically shift mode choice, at least on the scale of the whole day travel.

Agent scores are also relatively flat across all policies (49.99-50.08), with the discount policies marginally positive and the surcharge policies marginally negative, consistent with cost decrease or increase for the travellers. Nevertheless, since this is an average across the whole population, the changes were not expected to be drastic. The fact that clear trends are present, even for policies that only affect two hours of the day and only around a part of the population that use rail, indicates that this influence on agent utility might be influential.

Overall, the scenarios tested show that the most preferable form of policy is a surcharge combined with a discount. Peak surcharge alone is successful at reducing peak trips, but does so at the cost of the agent utility, overall ridership and losing passengers to road. The combination with a discount negates some of these effects by attracting ridership during the off peak, increasing agent utility and the public transport modal share. It can also be seen that the combination scenario is the one that obtained the smallest peak share of the day, indicating a more balanced rail demand.

E

Appendix D: Code Sharing

The main code used for this thesis can be found in this repository. Please note that the data files are not shared due to access restrictions.

https://github.com/ameelijaanca/MasterThesisCode_Time-of-Day-Pricing-on-Swiss-Rail.git