Integrating ordinal work-from-home choice into Switzerland's national Activity-Based Model

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Abstract

The growing prevalence of working from home (WFH) presents a significant challenge for transport modellers: the long-standing convention of modelling a representative typical weekday is increasingly unable to capture day-to-day variations in commuter demand. Activity-based models (ActBMs) offer a behaviourally consistent framework for addressing this, yet WFH representation in operational ActBMs has typically remained coarse; limited to a binary possibility model specified on static sociodemographic and distance-based variables, and therefore insensitive to changes in transport networks or service provision.

This paper makes three contributions to address these limitations. First, we develop a novel WFH model two-stage sequential structure: (i) a binary *possibility* component to determine whether an individual can work from home, followed by (ii) an ordinal *intensity* component that determines the number of days per week they do so. Both components are estimated using data from the Swiss Mobility and Transport Microcensus (MTMC). Second, we move from distance-based to level-of-service-based model specification, making both model components sensitive to the transport network. Third, we integrate the updated model into the Swiss Federal Railway's (SBB) nationwide activity-based model, SIMBA MOBi, and validate it against a real-world case study: the closure of the Fribourg-Bern rail line in summer 2025 and its replacement bus service. The updated model produces aggregate WFH responses consistent with observed passenger and traffic counts, demonstrating a capability that the previous distance-based WFH possibility model cannot replicate.

Keywords

Activity-based modelling; travel behaviour; demand modelling; choice modelling

Preferred citation

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1 Introduction

The prevalence of working from home (WFH) has grown substantially over the past decade, reflecting both general trends towards flexible working arrangements and policies, as well as the external shock caused by the COVID-19 pandemic. In Switzerland, as elsewhere, this has had clear implications for travel demand: fewer commuters at peak hours, increased variability in day-to-day trip generation, and a increased dependence of commuting patterns on individual circumstances and employer policies.

These changes present both new challenges and opportunities for transport modellers. Crucially, there is a growing need to move from modelling a *typical weekday* to more complex models that can capture day-to-day variations in passenger behaviour for demand forecasting, including effects of infrastructure changes, service disruptions, and policy interventions.

Activity-based models (ActBMs) are particularly well suited to this challenge. By modelling the full scheduling process of daily activities, including the decision of whether to WFH, ABMs can represent these changes in a behaviourally consistent way. Despite this potential, typical WFH representation in operational ABMs is often either non-existent or coarse. This is a limitation of both:

1. the travel diary surveys themselves, which typically (i) only capture a single day of household trips/activities, (ii) treat *home* as an activity-type without capturing what individuals actually do at home, and (iii) (if included at all) include only basic infomration about working from home; and
2. the resulting models, which typically only capture this possibility as a binary outcome modelled on static sociodemographic variables (e.g. employment status and distance-from-the-workplace), and are therefore not sensitive to policy and transport network changes.

This paper addresses these limitations through three contributions. First, we develop a new sequential WFH model for Switzerland using new variables in the Swiss Mobility and Travel Microcensus (MTMC) that captures both the binary *possibility* to WFH as well as the ordinal *intensity* of home working in terms of days-per-week. Secondly, we move from distance-based to travel-time-based specifications for both model components, therefore making them sensitive to the transport network and so capable of evaluating induced changes in WFH behaviour resulting from timetable changes or disruptions. Finally, we incorporate the new model into the Swiss Federal Railway's (SBB) nationwide activity-based model, SIMBA MOBi (Scherr *et al.*, 2020), and validate our approach through a real-world case study: the closure of the rail line between Fribourg and Bern in summer 2025, with a replacement bus service substantially increasing travel times for affected commuters. We demonstrate that the updated model produces an increase in aggregate WFH levels consistent with observed passenger and traffic counts, where the previous distance-based model, being insensitive to timetable changes, is unable to do so.

This work is explicitly framed as a first methodological step in an ongoing research programme. The longer-term goal is to investigate hybrid machine learning choice models (in particular RUMBoost and ParamBoost (Salvadé and Hillel, 2025, 2026)), for both the possibility and intensity components, enabling automated/assisted specification of non-linear utility functions and comparison with manually specified models though this is not yet part of the results presented here. This output is part of a continued collaborative research effort to continuously improve behavioural representations in SIMBA MOBi, including optimisation-based scheduling (Manser *et al.*, 2022a) and mobility-tool ownership (Hillel *et al.*, 2021).

The remainder of the paper is structured as follows. Section 2 reviews the literature on WFH modelling in transport and on hybrid choice model specification. Section 3 outlines the modelling framework and its integration into the ActBM pipeline. Section 3.3 describes SIMBA MOBi, the MTMC data, and the Fribourg-Bern case study. Section 4 presents the estimation and simulation results. Finally, Section 5 concludes and sets out the direction for future work.

2 Modelling work-from-home in travel demand

Initial WFH modelling research recognised that teleworking is not a single decision but a structured process involving feasibility, preference, and realised behaviour (Mokhtarian and Salomon, 1994, 1997). Subsequent empirical work formalises this distinction by jointly modelling adoption and frequency, showing that treating these outcomes independently leads to inconsistent inference due to shared unobserved factors (Pouri and Bhat, 2003; Sener and Bhat, 2011). Extensions further decompose the process into option, choice, and frequency components, demonstrating that the determinants of having the option to telecommute differ substantially from those governing whether and how often that option is exercised (Singh *et al.*, 2013).

Across this literature, WFH behaviour is primarily explained by occupational and sociodemographic characteristics, with consistent effects for professional and managerial occupations, education, and household structure. Attitudinal factors have also been shown to play an important role, either directly or through latent constructs (Mokhtarian and Salomon, 1997). However, most specifications estimated prior to the COVID-19 pandemic treat WFH as largely independent of transport conditions, with commute characteristics either excluded or represented only indirectly through static proxies such as distance (Mokhtarian and Meenakshisundaram, 2002; Paleti, 2016). As a result, WFH is effectively modelled as a supply driven phenomenon, determined by fixed employment characteristics rather than as a behavioural response to travel conditions.

More recent work has begun to relax this assumption, including incorporating work-home travel time (Shabanpour *et al.*, 2018). Studies conducted during and after the COVID-19 pandemic further incorporate perceptions of risk, productivity, and commuting conditions, and show that WFH interacts with mode choice and travel behaviour (Balbontin *et al.*, 2022; Hensher *et al.*, 2022). At the same time, emerging evidence highlights structural interdependencies between WFH and longer term decisions: teleworking intensity and commute distance are jointly determined, with implications for how residential location and network conditions interact with WFH propensity (Asmussen *et al.*, 2024). These findings point to the importance of representing WFH within a framework that allows feedback with travel conditions.

Despite these advances in behavioural modelling, the representation of WFH in transport models remains limited. In traditional four step models, WFH is typically handled implicitly as a reduction in work trip generation rates, an approach that assumes invariance with respect to network conditions. This assumption has been challenged by recent evidence showing that trip generation responds to accessibility, and that ignoring this dependency is increasingly untenable (Heinitz, 2025). Agent-based modelling also often misses an explicit representation of WFH. Castro and Ford (2026) underline than in MATSim, agents' trips cannot be cancelled in the context of disruptive events, even if "disappearing traffic" is observed in reality.

ActBMs provide a more suitable framework, since the decision to work from home can be embedded directly within daily activity patterns. However, existing implementations, including microsimulation approaches and operational platforms, typically adopt a single modelling stage of a binary choice (i.e. whether WFH or not) on the modelled day (RSG, 2023) or a multinomial frequency of WFH (e.g. mainly, occasionally, never in Moeckel (2017)). Additionally, these models continue to rely predominantly on sociodemographic and distance based variables, and therefore are not sensitive to changes in travel time, service levels, or network disruptions.

In the context of modelling day to day variability in travel demand, these limitations are critical. While the literature has established appropriate behavioural structures for representing WFH decisions, there remain gaps in ActBM practice of (i) representing the true complexity of WFH decisions, and (ii) linking these decisions to transport level-of-service (LoS). In particular, existing implementations are not well suited to capturing short-to-medium term responses to network changes or service disruptions, which are central to the analysis of non representative weekdays. In addition, the majority of the identified literature draws on North American or Australian data and context; European, and in particular Swiss, implementations have received comparatively little attention, despite the availability of high-quality national travel diary data and operational national-scale ActBMs.

This paper addresses this gap by developing a two-stage WFH model that captures both the feasibility and intensity of WFH as functions of travel-time-based LoS attributes, enabling WFH behaviour to respond endogenously to changes in the transport system, and incorporating it within SBB's operational nationwide ActBM, SIMBA MOBi (Scherr *et al.*, 2020).

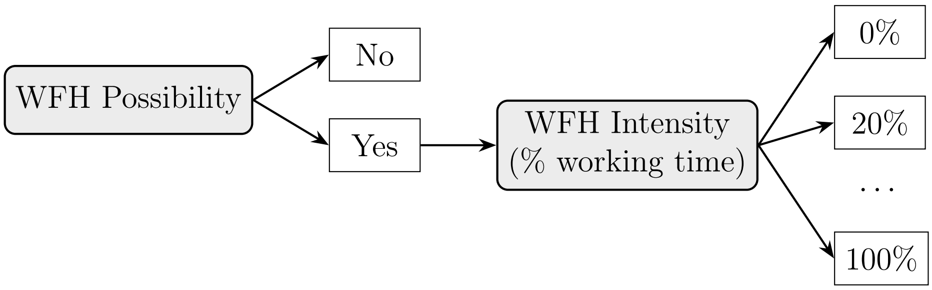
3 Methodology

This section describes the two-stage sequential WFH model, its estimation, and its integration into the SIMBA MOBi pipeline.

3.1 Modelling approach

We adopt a two-stage sequential model structure, illustrated in Fig. 1, motivated by the conceptual distinction between two qualitatively different dimensions of WFH behaviour identified in the literature (Singh *et al.*, 2013; Pouri and Bhat, 2003): (i) the *possibility* to WFH, and (ii) the *intensity* of WFH, i.e. the percentage of working time actually worked from home. The two stages are estimated sequentially and independently: the possibility model is estimated on the full working population, whilst the intensity model is estimated on the sub-sample of individuals who report having the possibility to WFH.

Figure 1: Two-stage sequential representation of WFH behaviour with binary possibility choice followed by ordinal intensity choice.



The first stage is specified as a binary logit model, with a latent utility V_{poss} determining whether individual n can work from home:

$$P(\text{WFH possible}_n) = \frac{\exp(V_{\text{poss},n})}{1 + \exp(V_{\text{poss},n})} \tag{1}$$

The second stage is specified as an ordered logit model, capturing the percentage of WFH on an ordinal scale from zero to five. The ordered structure is preferred over a multinomial logit because it imposes a natural monotone ordering on the outcomes, reducing the number of free parameters whilst improving behavioural interpretability. The probability of individual n working from home $20 \cdot k\%$ per week is given by:

$$P(Y_n = k) = F(\tau_{k+1} - V_{\text{int},n}) - F(\tau_k - V_{\text{int},n}), \qquad k \in \{0, 1, \ldots, 5\} \tag{2}$$

where $F(\cdot)$ is the logistic CDF, $\tau_0 = -\inf$, $\tau_6 = \inf$, and $\tau_1 < \tau_2 < \cdots < \tau_5$ are estimated threshold parameters. Note that this can be interpreted as the number of days working from home, assuming a full time equivalent job.

Both model components draw on four broad categories of explanatory variables. To ensure sensitivity of WFH behaviour to the transport network, we include travel-time-based LoS attributes including a weighted travel time (across PT and driving modes), PT access/egress time and number of transfers, and finally a zone-based multimodal accessibility metric. This enables WFH rates to respond endogenously to changes in timetables, service levels, or disruptions. Employment characteristics include sector of employment, employment percentage, schedule flexibility, free workplace parking, and whether the individual holds an executive position. Individual-level sociodemographic characteristics include age, language region, educational attainment, nationality, and ownership of PT subscriptions/discount cards. Finally, household structure is captured through household composition, the number of children, and car ownership and availability.

The models are estimated using data from the 2021 wave of the Swiss Mobility and Transport Microcensus (MTMC; Bundesamt für Raumentwicklung (ARE) & Bundesamt für Statistik (BFS) 2023), a nationwide travel diary survey conducted every five years by the Federal Statistical Office (FSO) and the Federal Office for Spatial Development (ARE). Note, that 2021 represented a peak in home-working post-COVID, and WFH rates have since declined (Guillaume-Gentil *et al.*, 2025, Fig. 3, p.44). The 2021 wave includes dedicated questions capturing both dimensions of WFH behaviour: respondents are asked (i) whether they have the possibility to work from home, and (ii) what percentage of their working time they do so. These questions were administered to all employed respondents, yielding estimation samples of 28,135 individuals for the possibility model and 12,977 for the intensity model (the latter restricted to those reporting WFH possibility). In order to evaluate the impacts of modelling LoS-based WFH choice, we also estimate a distance-based *benchmark model* based on prior work (Danalet *et al.*, 2021), which models possibility to WFH based on the distance between the workplace and home locations with the other LoS variables omitted. All models are estimated by maximum likelihood using Biogeme (Bierlaire, 2023).

3.2 Rationale for a travel-time-based possibility model

The inclusion of travel time in the possibility model warrants careful justification, since WFH possibility is often framed as an employer-determined policy rather than a function of individual travel conditions. As such, a travel-time-based specification may appear counter-intuitive: an employer's decision about which roles can be performed remotely is unlikely to be directly influenced by how long a given employee takes to commute.

However, in practice, the *realised* possibility to WFH, as observed in survey data, combines both the employer's *structural* policy constraint (primarily driven by whether a role is compatible with home working or not) as well as whether an individual has successfully negotiated or been granted flexibility to WFH. In other words, longer or more difficult commutes increase the incentive for employees to request remote-working arrangements(Asmussen *et al.*, 2024; Hensher *et al.*, 2022). This results in a positive expectation on the travel time parameters for both possibility to and intensity of WFH.

A related concern is endogeneity of WFH possibility and commute travel times. In practice, these may be jointly determined: individuals who know they can WFH may choose to live further from their workplace, whilst those who cannot may choose to live closer. As such, distance- or travel-time-based specifications risk conflating the causal effect of travel conditions on WFH with the reverse effect of WFH availability on residential location choice. Note that both distance-based and travel-time-based models face this limitation, and addressing this endogeneity rigorously would require a joint model of residential location and WFH possibility, which is beyond the scope of both this paper and the current state of travel demand modelling practice.

3.3 Integration and scenario evaluation

We integrate the LoS-based two-stage WFH model into SBB's nationwide microscopic activity- and agent-based transport model, SIMBA MOBi (Scherr *et al.*, 2020). Starting from a synthetic resident population of Switzerland, SIMBA MOBi constructs individual 24-hour activity and travel plans for each agent across all modes and trip purposes, combining sequential discrete choice models for long-term and daily decisions with a rule-based scheduling algorithm that enforces time-budget and spatial constraints (Scherr *et al.*, 2019). The model is applied by SBB to evaluate scenarios including timetable changes, new infrastructure, and service disruptions.

The new WFH model replaces the existing distance-based binary possibility model (i.e. the *benchmark* model) in the activity scheduling component, MOBi.plans (Scherr *et al.*, 2019; Manser *et al.*, 2022b). The binary possibility model is first applied to all employed agents; those for whom WFH is possible are then passed to the ordinal intensity model to determine their weekly WFH frequency. WFH status is assigned stochastically for the simulated (typical) weekday, consistent with the predicted intensity distribution. Agents assigned WFH have their work activity integrated into the *home* activity, and are rescheduled accordingly, allowing downstream mode choice and trip generation to adjust endogenously.

To validate the travel-time sensitivity of the updated model, we use the complete closure of the Fribourg–Bern rail line from 28 June to 24 August 2025 as an observed counterfactual. Replacement buses added delays to journeys on the corridor (e.g. 30 minutes between Bern and Fribourg), substantially degrading LoS for commuters. By observing both PT passenger counts and overall traffic counts between the regions, two key effects were observed from the disruption: (i) a shift from PT to private vehicle modes; and (ii) a reduction in overall demand at peak times, reflecting an increase in WFH rates.

4 Results

We first present and analyse the WFH model estimation across the two model components and the distance-based benchmark model, followed by the integration into SIMBA MOBi and scenario evaluation.

4.1 Model estimation results

Parameter estimates for all three model components are shown in Table 1. Replacing commute distance with travel time in the possibility model leaves estimates stable across all other variable groups, with signs, magnitudes, and significance levels consistent between the two specifications. Both the distance parameter in the benchmark model (0.009***) and the travel time parameter in the updated model (0.322***) are positive and highly significant, consistent with the behavioural rationale set out in Section 3.2: longer commutes increase the incentive to negotiate WFH arrangements. The implied effect of an additional minute of travel time on WFH possibility is approximately 35 times larger than that of an additional kilometre of distance. In the possibility model, PT access time, egress time, and number of transfers are all insignificant, suggesting that WFH possibility is driven by in-vehicle time rather than overall journey time.

Across the sociodemographic, household, and job characteristic variables, the possibility and intensity components are broadly consistent in sign. Two notable reversals are worth highlighting. Executive position is positively associated with WFH possibility (0.776***) but negatively with intensity (-0.111***), consistent with executives having formal flexibility whilst facing greater demands for in-person presence. Similarly, number of children is positive for possibility (0.070***) but negative for intensity (-0.113***). PT egress time is positive and significant in the intensity model (0.579***) but insignificant in the possibility model, suggesting that this component of the commute is most directly associated with the frequency of home working rather than its availability.

Table 1: Parameter estimates for the benchmark (i.e. distance-based WFH possibility), WFH possibility, and WFH model components. *, **, *** indicate estimates significant at the 90%, 95% and 99% levels respectively.

	Benchmark	WFH possibility	WFH intensity
Accessibility / transport			
Travel time	-	0.322***	0.258***
Travel time NA	-	0.406***	0.863***
PT access time	-	-0.219	0.074
PT egress time	-	-0.090	0.579***
N. transfers	-	-0.007	-0.007
Accessibility	0.050***	0.052***	0.044***
Distance (0–150km)	0.009***	-	-
Distance NA	0.254**	-	-
Job information			
Sector: Business	1.504***	1.508***	0.471***
Sector: Production	0.974***	0.957***	0.337***
Sector: Wholesale	1.127***	1.142***	0.741***
Sector: NA	1.390***	1.382***	0.701***
Executive position	0.796***	0.776***	-0.111***
Work percentage	0.039***	0.041***	0.042***
Fixed working hours	-	-	-0.572***
Flexibility NA	-	-	-0.215***
Free parking	-	-	-0.216***
Urban workplace	-	-	0.173***
Socio-demographics			
Education: No education	-2.555***	-2.578***	-0.047
Education: Secondary	-1.345***	-1.364***	-0.208***
Education: Tertiary	-0.783***	-0.797***	-0.307***
Age (18–35)	0.046***	0.045***	0.024***
German speaker	0.316***	0.317***	0.181***
Swiss	-	-	-0.252***
GA or HT	0.355***	0.384***	0.029
Household			
Composition (Single)	-0.095**	-0.093**	-0.186***
N. children	0.072***	0.070***	-0.113***
N. children NA	-1.458**	-1.442**	-
N. cars	-	-	-0.055***
Car availability	-	-	-0.104*
Constants			
Constant (Yes)	-2.156***	-2.194***	-
τ_1	-	-	-1.559***
τ_2	-	-	0.400***
τ_3	-	-	0.952***
τ_4	-	-	1.547***
τ_5	-	-	1.981***

4.2 Integration and simulation results

All constants (i.e. the *yes* constant in the possibility model and the thresholds τ_1–τ_5 in the intensity model) are recalibrated to reproduce market shares from 2021, following Train (2009), with final values shown in Table 2. As noted above, 2021 represented a peak in home-working following the COVID pandemic.

Table 2: Constants recalibrated to reproduce market shares. For convenience, the original value of the constants is shown in brackets next to the recalibrated constants.

	Benchmark	WFH possibility	WFH intensity
Constants			
Constant (Yes)	-2.189 (-2.156)	-2.229 (-2.194)	-
τ_1	-	-	-1.325 (-1.559)
τ_2	-	-	0.418 (0.400)
τ_3	-	-	0.946 (0.952)
τ_4	-	-	1.529 (1.547)
τ_5	-	-	1.963 (1.981)

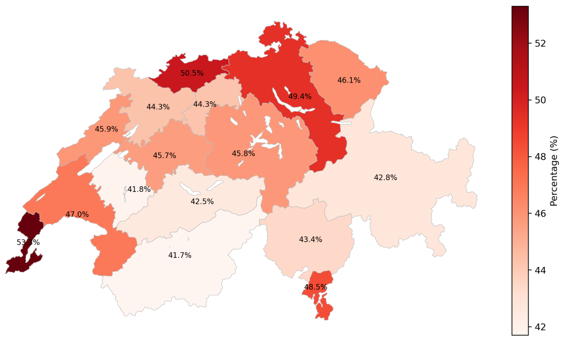
Fig. 2 shows simulated WFH possibility and occurence rates (from SIMBA MOBi with the new LoS-based sequential WFH model), aggregated by large labour market region, by both home and work location. Across Switzerland, approximately 42–53% of employed agents are assigned WFH possibility, with the highest rates in Geneva (53.4%) and the lowest in alpine regions. Of those with possibility, roughly half actually WFH on the simulated day, yielding realised WFH rates of 20–28% of the employed population. The spatial pattern is consistent between home- and work-location aggregations, with regions containing major cities showing the highest rates in both dimensions.

4.3 Case study: Fribourg–Bern line closure

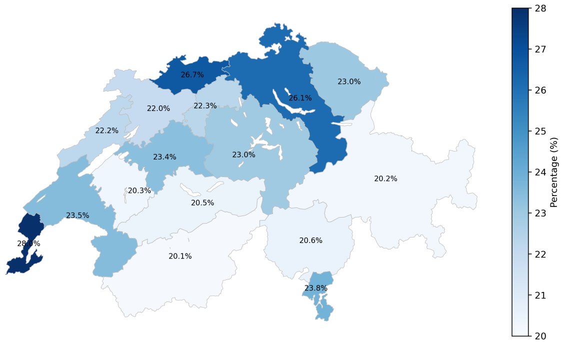
In the summer of 2025, the rail line between Fribourg and Bern was closed for 8 weeks for maintenance work. The closure affected regional and long-distance services and required replacement bus operations. Using the GTFS timetables for Tuesday before the interruption (24.06) and the first Tuesday during the interruption (1.07), we have simulated the change in WFH rates induced by the line closure.

Fig. 3 shows the change in WFH rates induced by the closure, expressed in percentage

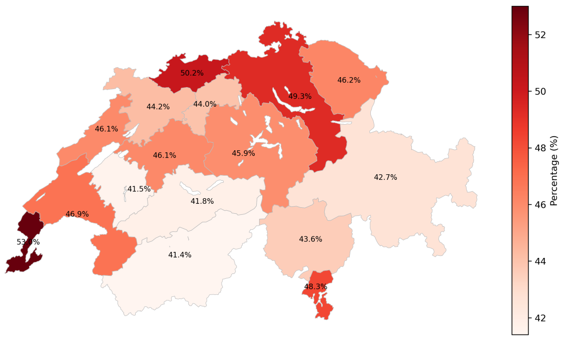
Figure 2: Simulated WFH possibility and realised WFH rates by large labour market areas under the updated travel-time-based model.



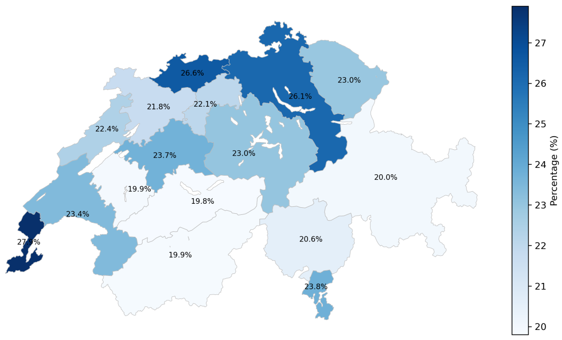
(a) WFH possibility, by home location.



(b) WFH occurrence, by home location.



(c) WFH possibility, by work location.

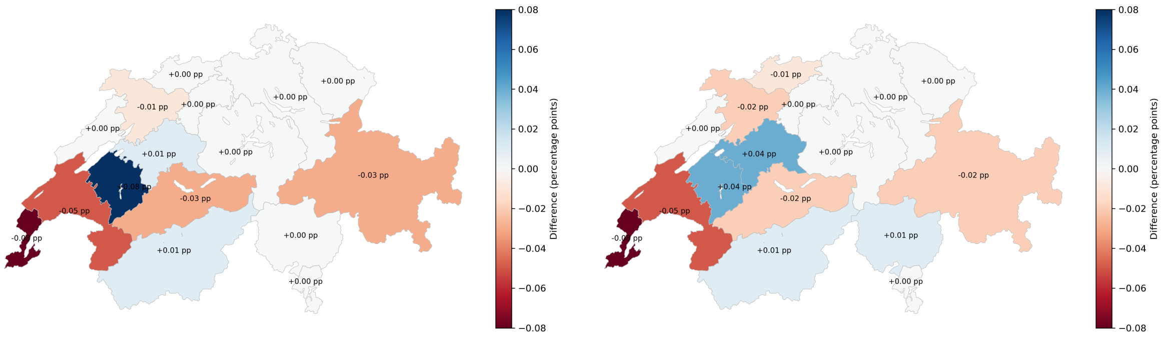


(d) WFH occurrence, by work location.

points (updated model minus baseline). The largest increase is observed in the Fribourg region (+0.08 pp by home location, Fig. 3(a)), with smaller increases also visible in Fribourg and the Bern regions when aggregated by work location (Fig. 3(b)). The negative changes observed in the Geneva region reflect a concurrent disruption in the tram system in Geneva, where replacement services incidentally reduced travel times, leading the model to predict a marginal decrease in WFH rates. This is a behaviourally coherent response consistent with the positive travel-time parameters in both model components.

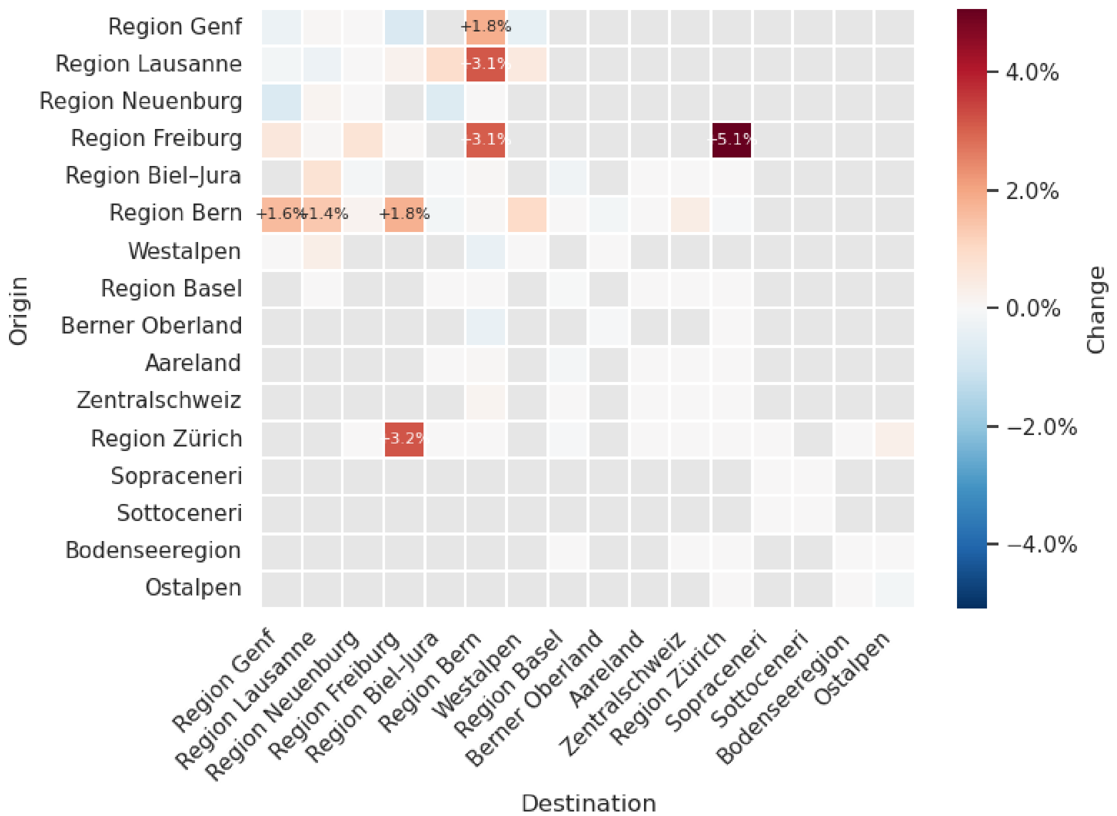
The OD matrix in Fig. 4 disaggregates these changes by commuter origin–destination pair. The largest responses are concentrated on corridors directly affected by the closure: WFH rates change most strongly for commuters between Fribourg and Bern, Fribourg and Zurich, and along the Geneva–Bern axis, with changes exceeding 3% in absolute value on the most affected flows. Regions with no direct exposure to the disrupted corridor show negligible responses, confirming that variations are resulting only from LoS changes.

Figure 3: Change in WFH rate (percentage points, updated model minus baseline) by major labour market region, induced by the Fribourg–Bern line closure. Blue indicates an increase in WFH; red indicates a decrease.



(a) By home location. (b) By work location.

Figure 4: Change in WFH share by origin–destination region pair, induced by the Fribourg–Bern line closure. Cells are shown only for region pairs with at least 100 workers in the reference scenario; labels are shown only where the absolute change exceeds 1%.



5 Conclusions & further work

This paper presents a two-stage sequential model of WFH behaviour, comprising a binary possibility component and an ordinal intensity component, estimated on the 2021 Swiss MTMC and integrated into SBB's nationwide activity-based model, SIMBA MOBi. We identify three contributions: (i) the sequential binary-ordinal structure captures both whether an individual can WFH and how frequently they do so, exploiting questions in the MTMC wave that record both dimensions; (ii) replacing distance with travel-time-based level-of-service attributes and so enabling both model components to be sensitive to the transport network; and (iii) integration into SIMBA MOBi and validation against a real-world counterfactial example demonstrates that the updated model produces geographically targeted increases in WFH rates on affected commuter corridors, consistent with observed passenger and traffic counts.

Two limitations warrant acknowledgement. The travel-time parameters in both model components are subject to residential sorting endogeneity, and the estimates are best interpreted as reduced-form associations rather than causal effects. In addition, the sequential estimation approach does not account for correlation in unobserved factors across the two stages; a joint model would be preferable in principle, though the stability of parameter estimates across specifications provides some reassurance.

The immediate priority for further research is to validate the simulation output of the new work-from-home model against observed count data from replacement buses and highway traffic during the train line interruption. In parallel, we plan to investigate hybrid machine learning choice models, in particular RUMBoost and ParamBoost (Salvadé and Hillel, 2025, 2026), for both model components, with the aim of relaxing linearity assumptions in the utility functions and enabling data-driven specification of non-linear effects.

With the next wave of the MTMC, conducted in 2025, it will be possible to identify the specific day(s) of the week on which respondents work from home. These new data, collected without mobility restrictions related to the COVID-19 pandemic, will be available in 2027. Recent analysis of 2024 data show that the share of work-from-home days ranges between 13% and 18% depending on the weekday. However, the impact of part-time employment on the effective number of days worked on-site over the course of a week appears to be greater than the impact of working from home (Guillaume-Gentil *et al.*, 2025).

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