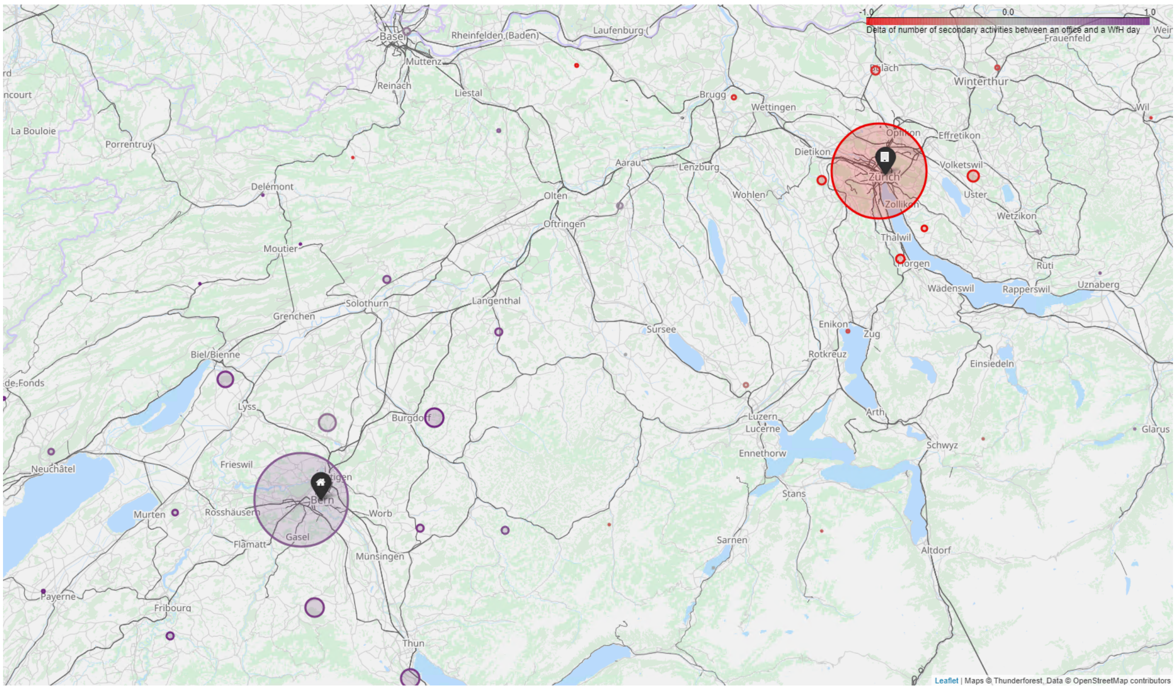

Agent-based simulation of mobility behaviour induced by working from home

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Abstract

An agent-based transport modelling framework is extended to predict the impact of working from home on future travel demand in Switzerland. This is done by selecting a proportion of employed persons to work from home and letting them reschedule their daily mobility choices. The rescheduling includes activity destinations, timings, and transport modes. The contribution of the presented work is threefold: We introduce (i) individual preferences towards working from home based on socio-demographic, household, as well as workplace attributes; (ii) realistic responses of the selected agents to changing commuting behaviour with a dynamic rescheduling of their daily activity patterns. Lastly, (iii) we demonstrate the sensitivity of the framework on both individual as well as aggregated statistics. The sensitivity analysis suggests that people tend to consume less time for travelling on working from home days, while the number of trips remains constant. Aggregated results of the model indicate that the passenger distance travelled by rail on workdays drops by 8.3% when working from home increases by 15%, assuming no other behavioural changes. Once the empirical basis is available, SBB plans to integrate other changes such as reinvestment of commuting time savings or relocation of households into the model.

Keywords

working from home, post-pandemic commuting, activity-based demand model, agent-based simulation

1 Introduction

Planning for future rail infrastructure, efficient service concepts, as well as rolling stock considering all possible changes (e.g., in population, policy, or technology) relies on quantitative forecasts of travel demand. The COVID-19 pandemic has caused a major disruption in mobility behaviour and poses a key challenge to predict travel demand (Jain *et al.*, 2022). Swiss Federal Railways (SBB) expect a substantial mid- to long-term impact (2025 onwards) particularly on commuter flows. The main driver of this change in commuter mobility is assumed to be working from home (WfH), which has become increasingly popular and accepted during the pandemic (Erath and Mesaric, 2021). This means that the pandemic is expected to be a long-term catalyst for a continuing trend towards more flexible working arrangements (Ravalet and Rérat, 2019).

To predict those kind of changes, SBB applies the modelling landscape *SIMBA* (Scherr *et al.*, 2018). SIMBA comprise a wide range of tools to support company-wide investment decisions (short-, mid-, and long-term). One tool to predict future travel demand in Switzerland is the agent-based transport model *SIMBA MOBi* (Scherr *et al.*, 2020a). The agent-based (or microscopic) model characteristics allow to treat mobility as individual decisions across many interwoven choice dimensions. Agent-based models like SIMBA MOBi afford a high-resolution representation of travel behaviour as they simulate each traveller as an autonomous decision-making unit and consider full consistency in time and space over a time period (e.g. a 24h-day) for each individual (Rasouli and Timmermans, 2014; Castiglione *et al.*, 2015).

In this paper, SIMBA MOBi is extended and applied to predict the impact of WfH on mobility behaviour with a particular focus on rail demand. The extension includes a behavioural model for WfH, which computes the relative likelihood of having the possibility to WfH based on individual preferences for each agent. Then, an overall probability for WfH is introduced to select a proportion of employed agents who are not intending to travel to the workplace on the simulated day. For the selected agents who are planning to WfH, the activity-based demand model *MOBi.plans* then reschedules their daily mobility choices. Finally, the updated mobility schedules are simulated using the agent-based transport simulation MATSim software (Horni *et al.*, 2016). The results allow to quantify the impact of WfH on decisions about the number of trips, secondary destinations as well as modes of transportation. Also, we can demonstrate the strength of the agent-based modelling approach by analysing model sensitivities on both individual as well as on aggregated levels. This helps SBB to have a picture of a future with much uncertainty as well as with rapidly changing trends and assumptions.

The paper is structured as follows; First, a brief review of recent approaches to model WfH behaviour especially in combination of activity-based demand models is given. Next, we introduce the methodology, including the behavioural model to simulate decisions about WfH as well as the integration of those decision into the SIMBA MOBi modelling pipeline. This framework is then applied to Switzerland scenario of the year 2050. Finally, the impact of WfH on several individual and aggregated statistics is presented.

2 Background

The main motivation driving the transition from traditional aggregated models to microscopic or activity-based demand models has been stated to be the lack of behavioural realism in the traditional approach, which does not allow for forecasting new policies such as congesting pricing, teleworking and ride-sharing incentives (Rasouli and Timmermans, 2014). The implication is that activity-based models are well suited to predict teleworking behaviour. Early approaches to microscopic travel demand modelling were proposed in the 1990s (Axhausen and Gärling, 1992). For a more detailed overview of later advances in activity-based transport modelling, we direct the reader to reviews provided by Bowman (2009) and Castiglione *et al.* (2015).

The combination of WfH and transport planning appears in a number of articles in the literature. Already in the earlier days of the internet, Salomon (1986) investigates the interactions between telecommunication technologies and travelling. The work concludes that the net effect of the technology may be neutral. There are social and psychological reasons (e.g., the need for fact-to-face interactions or rebound effects such as more leisure trips) for doubting that teleworking will substitute travel. A bit later, Mokhtarian (1991) sees the need to clarify the term *telecommuting*. The work groups telecommuting into clusters based on the attributes commute reduction and remote management. In this article, we focus on home-based telecommuting for all kind of commuting distances. We refer to this type of telecommuting as *working from home* (in short: *WfH*).

Ravalet and Rérat (2019) analyse the WfH behaviour as reported in the Swiss mobility and transport microcensus MTMC (BfS and ARE, 2017). They found that the proportion of telecommuters was increasing from 2010 to 2015 in Switzerland. Also, they see dependencies between residential relocation and WfH as it may increase tolerance for long distance commuting. Overall, WfH may lead to an increase of distance travelled over a working week according to Ravalet and Rérat. A similar analysis has been done by Stiles and Smart (2021). They investigate the influence of flexible working arrangements in the United States from 2003 to 2017. Their findings show that WfH on a day only decreases daily travel duration and increases the likelihood of avoiding peak-hour travel.

Several models to quantify preferences towards WfH have been presented in the literature. Mannering and Mokhtarian (1995) estimate a multinomial logit model that differentiates between two levels of telecommuting frequency. The most important variables explaining the choice of frequency of WfH are the presence of small children in the household, the number of household members and the number of vehicles in the household. Mokhtarian and Salomon (1997) introduce a binary logit model of the preference towards WfH. The explanatory variables in their model include attitudinal (such as personal benefits, family, stress or workplace interactions) and factual information. They conclude that attitudinal measures play an important role on the choice of WfH.

Walls *et al.* (2007) estimate an ordered probit model to predict the frequency of WfH. They found that telecommuting tends to increase with age of the employee and degree of education. At the same time, quantitative effects of job characteristics were found to be at least as important as demographic factors. Singh *et al.* (2013) analyse the precise count of telecommuting days per month using an generalised ordered-response model. In their model, they see the importance of considering the possibility to WfH as well as spatial or built environment variables. In Switzerland, Danalet *et al.* (2021) propose a binary logit model to estimate preferences towards the possibility to WfH. They include variables such as the sector of the workplace, socio-demographic attributes as well the employment status. Also, they use the estimated parameters to make predictions about the proportion of persons who have the possibility to work from home in the years 2030, 2040 and 2050. Their results show that the proportion may increase from 28% in 2015 to around 38% in 2050. For another comprehensive review of existing models dealing with WfH, we refer to Asgari and Jin (2015).

The previously mentioned articles did not link their estimated choice models to actual travel behaviour such as average commuting distances, total daily distance travelled, or choices about transport modes. In contrast, Choo *et al.* (2005) quantify the impact of telecommuting on passenger vehicle-distance travelled. Their models show that WfH reduces vehicle-distance travelled. Later, Moeckel (2017) presents a conceptual framework to combine choice dimensions such as telecommute, household relocation as well as tendency to add non-work trips. The crucial part of the framework are travel time budgets for every household. E.g., spending less time commuting leads to more time for travelling to leisure activities. Shabanpour *et al.* (2018) apply a model for WfH within an activity-based model. The model suggests a significant decrease of vehicle-distance travelled when doubling the number of employed persons having a flexible working agreement.

The COVID-19 pandemic caused a major increase in WfH (Jain *et al.*, 2022; Erath and Mesaric, 2021). The lockdowns ordered to prevent the spread of the virus have forced many employees into flexible working arrangements. Jain *et al.* (2022) conducted a large survey to investigate the post-pandemic impact of WfH behaviour. According to their survey, the preference to WfH in the longer term will be crucially influenced by perceived behavioural factors such as job type, technology, but also subjective norms such as employer and family support. Attitudes will only have a weak impact on future intention to WfH, a finding which contrasts with previous research. They conclude that WfH can be expected to be 75% higher than before the pandemic. Erath and Mesaric (2021) conducted a survey during the COVID outbreak for two different institutions. The employees in the first company report a proportion of work from home of 10% before the pandemic, which is reported to increase to 30% after the pandemic. The responses of the second company show an increase of WfH from 6% to 35% after the pandemic given that the employees have free choice (no restrictions from the employer).

Overall, a number of models have been introduced to analyse and to quantify preferences towards WfH. There are only few attempts to predict the mobility behaviour that is induced by WfH reported in the literature. Also, the literature about the long-term influence of the COVID-19 pandemic on WfH is vague. Having this wide range of assumptions, outcomes as well as significant variables, the contribution of this work is the implementation and application of a flexible, agent-based framework that allows to predict a range of different WfH scenarios. A range of scenarios is crucial in an unclear future with much uncertainty and rapidly changing empirical basis. The agent-based approach contributes to realistic individual responses to changing commuting behaviour, since agents reschedule their daily activity patterns including activity destinations and timings. This allows to analyse the model sensitivity on both individual as well as aggregated levels.

3 Modelling working from home behaviour

Our approach to predict the impact of increasing WfH on travel behaviour relies on four methodically different modelling steps. We need to (i) calculate the relative likelihood of employed persons for WfH based on individual preferences (Section 3.1), (ii) select a proportion of employees who WfH on the simulated day (Section 3.2), (iii) integrate the WfH behaviour into the activity-based modelling pipeline to update the daily schedules (Section 3.3), and (iv) feed the updated mobility schedules into an agent-based network simulation (Section 3.4).

3.1 Relative likelihood for working from home

In a first step, we calculate the relative likelihood of WfH for employed persons based on their individual preferences. To achieve this, the likelihood to have the possibility to WfH is derived from survey data available in Switzerland for each person. As previously done in Danalet *et al.* (2021), we introduce a binary logit model to quantify individual preferences when it comes to having the possibility to WfH.

The model builds on the utility specification as follows: When m is the number of variables to be estimated, the utility U_{ij} for individual employee i and alternative j is defined as

$$U_{ij} = \beta_{constant,j} + \sum_{k=1}^{m} \beta_{kj} \cdot k(i), \tag{1}$$

where $\beta_{constant,j}$ is a utility constant indicating an overall preference towards a certain alternative, β_{kj} is the estimated parameter for alternative j and variable k, and $k(i)$ is the value of variable k for individual i (e.g., the variable k may be *age* and the value for individual i may equal *25*).

By definition of the logistic regression model, the probability to choose alternative j for individual i can be computed as

$$p_{ij} = \frac{e^{U_{ij}}}{\sum_{a \in \mathcal{C}} e^{U_{ia}}}, \tag{2}$$

where $\mathcal{C}$ is defined as the choice set. In the binary form of the logit model, the choice set consists of two alternatives (in this case, $\mathcal{C} = \{yes, no\}$). The resulting individual probability indicates the relative likelihood that an agent has the possibility to WfH.

3.2 Scaling to absolute target

The second modelling step aims at scaling the absolute number of employees who are WfH on the simulated day to a global target. The target is a model assumption which will be derived from available empirical basis. We refer to this global target as the control total $\mathcal{E}(j)$ for each alternative j in the choice set.

To scale the results of the binary logit model (Section 3.1), a constant shadow constant will be added to the utility for each alternative. To derive the shadow constant, we use the expected value of the statistical probability distribution for each alternative j:

$$\sum_{i \in \mathcal{I}} p_{ij} = E(j), \tag{3}$$

where $\mathcal{I}$ is the set of all employed persons and E is the expected value of the probability distribution for alternative j. Together with Equation 2, Equation 3 can be written as

$$\sum_{i \in \mathcal{I}} \frac{e^{U_{ij}}}{\sum_{a \in \mathcal{C}} e^{U_{ia}}} = E(j). \tag{4}$$

If we want to achieve a given control total $\mathcal{E}(j)$ instead of $E(j)$, this equation can be extended by an additional utility term x_j

$$\sum_{i \in \mathcal{I}} \frac{e^{U_{ij}+x_j}}{\sum_{a \in \mathcal{C}} e^{U_{ia}+x_a}} = \mathcal{E}(j). \tag{5}$$

Having a control total $\mathcal{E}(j)$ for each alternative j, the number of variables x_j equals the number of equations and the solution is unique. This equation system can be solved by an openly available solver, e.g. the SciPy framework. Finally, the fitting process is completed by extracting the shadow constants x_j for all alternatives j and add them to the utility function to fit the model to the expected control totals

$$U_{ij} = x_j + \beta_{constant,j} + \sum_{k=1}^{m} \beta_{kj} \cdot k(i). \tag{6}$$

3.3 Integration into activity-based demand model

The behavioural model as described in Section 3.1 and 3.2 is used to simulate the decisions about WfH on the simulated day for each employed agent based on their preferences. The decisions have a direct impact on the daily mobility patterns of those individuals. To predict this impact, we integrate the choice model into the activity-based demand model *MOBi.plans*, which was introduced by Scherr *et al.* (2020b). MOBi.plans constructs a fully time-space consistent daily activity schedule for each agent as part of a synthetic population based on its socio-demographic attributes, the household location, and the transport supply. The methodology to generate a synthetic population is provided in Bodenmann *et al.* (2019) and goes beyond the scope of this paper.

MOBi.plans[1] applies the sequence of choice models as depicted in Figure 1. The information of the decisions made in the upper level choice models (i.e. long-term decisions) are fed into the following lower level choice models (i.e. daily mobility choices) to make the schedules as consistent as possible. The following long-term decisions are included:

- *Mobility tools*: Multinomial logit models for the ownership of mobility tools on individual (driving license and public transport subscription) and household level (number of cars) as proposed by Hillel *et al.* (2020). The models consider various socio-demographic attributes, household composition as well as network indicators such as parking cost and accessibility.
- *Long-term locations*: Nested mode and location choice model as described in Scherr *et al.* (2020b) for the decision about locations like workplace and school. The model considers mobility tools and a number of service indicators such as travel times, service frequency, waiting times or parking availability.

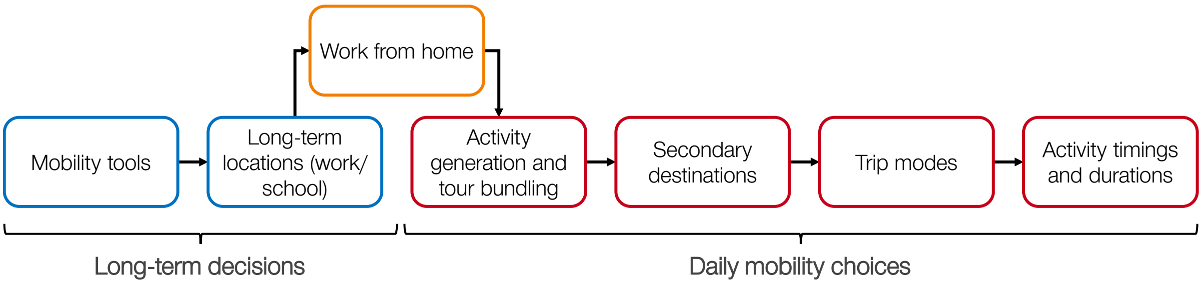
Daily mobility choices include:

- *Activity generation*: Multinomial logit models for the number and type of activities as well as how they are bundled into tours. All models depend on all long-term choices and various socio-demographic attributes.
- *Secondary destinations*: Nested mode and location choice model (see long-term locations) with a rubberbanding methodology. The model considers long-term decisions, activity type, socio-demographic attributes as well as service indicators.
- *Trip modes*: Tour-based mode choice model.
- *Activity timing and durations*: Data-driven decisions about activity start times and

[1]software is published under `https://github.com/SchweizerischeBundesbahnen/abm-in-visum`

durations. The decisions depend on activity type, number of activities as well as socio-demographic attributes.

Figure 1: The decision sequence in the activity-based demand model MOBi.plans.



In this work, we extend MOBi.plans by the additional binary logit model including the scaling procedure for the decision about WfH (see Figure 1). We insert the modelling step after the decision about the long-term locations and before all following daily mobility choices. This means that WfH is partly a long-term decision (does an employee have the possibility to WfH as part of its lifestyle?) and party a daily choice (does an agent actually WfH on the simulated day?). Methodically, we reset the workplace to the home location for all agents who decide to WfH on the simulated day. Doing so, the agents do not lose any time to move from the home to the work activity. This allows the daily mobility choices to react accordingly, e.g. performing more or longer activities or adjusting secondary destinations (e.g., it is unlikely that a person WfH eats lunch at the workplace).

3.4 Agent-based network simulation

The resulting mobility schedules from Section 3.3 are simulated using the agent-based simulation software MATSim (Horni *et al.*, 2016). The network simulation in MATSim is a spatially fully disaggregate and multimodal assignment, where each single car and public transport vehicle is simulated throughout the network and where they are interacting with each other. Depending on the network conditions, agents can iteratively adapt route, mode of trips and duration of activities. This so-called co-evolutionary algorithm converges to an equilibrium, where the mean plan utility across all agents stabilises. The use of MATSim in SIMBA MOBi is described in more detail in Scherr *et al.* (2020a).

4 Calibration of behavioural preferences

This section demonstrates the application of the behavioural model for WfH as introduced in Section 3.1. First, the data sets which were used for calibration and for validation are described (Section 4.1). Second, the behavioural preferences towards WfH are quantified in Section 4.2 and validated in Section 4.3.

4.1 Data

The preferences towards WfH are estimated using the survey data available in the Swiss mobility and transport microcensus MTMC (BfS and ARE, 2017). The computer-assisted telephone survey (CATI) takes place every 5 years, the most recent available data is from 2015. It contains a representative sample of 57'090 respondents from all over Switzerland. The persons report about a large number of socio-demographic attributes, household and workplace characteristics as well as mobility behaviour on one specific day.

About a third of all respondents were interviewed about their options regarding WfH. They answered three questions, (i) WfH possibility (" do you have the possibility to carry out parts of your work at home? "), (ii) WfH percentage (" What percentage of your professional activity do you WfH? "), and (iii) WfH reason (" What is the main for reason for WfH? "). In this work, we focus on the responses to Question (i). The answer comprises three options; yes, partly, and no. We group yes and partly into one option, which makes to model binary (yes/no). First, a data cleaning procedure is applied to exclude all interviews with incomplete or invalid responses. After this, 7'631 observations remain in the data set. In the MTMC of 2015, 30.7% of those observations report that they have the possibility to WfH.

To validate the model results, we simulate the decisions for all employed persons in a synthetic population of Switzerland for the year 2017. The synthetic population[2] was developed by Bodenmann *et al.* (2019) and is used for the transport models of the Swiss government and the Swiss Federal Railways. It contains all 8.6 Mio. Swiss residents as of 2017 including household location and compositions as well as detailed individual attributes such as age, education status, job rank, or nationality. Additionally, it includes a full geo-referenced dataset of all businesses in Switzerland with the number of the jobs and the sector of each individual business.

[2]Parts of the synthetic population are openly available, see SBB and ARE (2021)

4.2 Estimation of preferences for working from home

Having the empirical data from the MTMC (Section 4.1), we can estimate a binary logit model using Biogeme (Bierlaire, 2020) to quantify the preferences towards having the possibility to WfH. We tested individual, household, workplace and spatial variables. The resulting parameter values for all significant variables are depicted in Table 1.

Individual variables include the age as a piecewise variable and the binary variables of being a student or in a management position. As shown in Walls *et al.* (2007), the likelihood of WfH tends to increase with age. Both students and managers have a significantly higher likelihood for the possibility to WfH compared to the others as already stated in Danalet *et al.* (2021). In terms of household compositions, single parents are less likely to have the possibility, whilst the number of children present in the household linearly increases the likelihood. This was also observed in Mannering and Mokhtarian (1995). Mobility tools have a significant influence on the choice. The higher the ratio between the number of cars that are available in the household and adults with a permit in the same household, the higher the probability to WfH (Mannering and Mokhtarian, 1995). The same applies for public transport subscriptions (general and half fare abonnements). Accessibility (number of jobs and inhabitants within a certain range) is included as a categorical variable. Persons living in locations with higher accessibility tend to have higher preference towards the possibility to WfH.

The model contains a detailed representation of the workplace including the commuting distance, the spatial category (rural) as well as the sector of the workplace. Employees with long commuting distances (60km and more) have a higher likelihood to have the possibility to WfH. The implication of this result might be that people only commute long distances if they can at least partly WfH. The sector of the workplace is highly relevant as concluded before in Walls *et al.* (2007). Employees in gastronomy and retail have the lowest likelihood to have the possibility to WfH. On the other hand, finance and service are sectors with higher likelihood compared to others. Also, persons working in the agricultural sector often report to have the possibility to carry out parts of their work at home (Danalet *et al.*, 2021). However, they may not mean the home-based telecommuting with their answer since there is no commute reduction (Mokhtarian, 1991).

Table 1: Parameter values for the possibility to work from home. All parameters are significant at 2.5 % level.

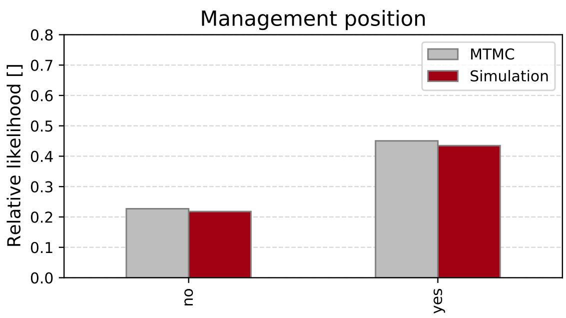
Variable	Value (*Std. err.*)
Alternative-specific constants	
ASC no possibility to work from home	-
ASC possibility to work from home	-5.28 (*0.29*)
Individual	
Age 18–35 (piecewise)	0.07 (*0.01*)
Student	0.69 (*0.20*)
Management position	1.00 (*0.06*)
Household	
Single parent	-0.40 (*0.17*)
Number of children	0.13 (*0.03*)
Mobility tools	
Car availability in household	0.16 (*0.06*)
SBB abonnement	0.62 (*0.06*)
Home location	
Accessibility <200'000 (ref)	-
Accessibility 200'000–900'000	0.23 (*0.06*)
Accessibility >900'000	0.40 (*0.11*)
Workplace	
Commuting distance 0–60km (piecewise)	0.004 (*0.00*)
Commuting distance 60–90km (piecewise)	0.041 (*0.01*)
Rural workplace	0.24 (*0.10*)
Sector gastronomy and retail (ref)	-
Sector agriculture	1.40 (*0.18*)
Sector production	0.40 (*0.12*)
Sector wholesale	0.57 (*0.14*)
Sector finance and services	1.22 (*0.11*)

Summary statistics	
Number of parameters	17
Sample size	7'631
Initial log-likelihood	-5'289.41
Final log-likelihood	-4'148.19
$\bar{\rho}^2$	0.213
Estimation time (sec)	5.75

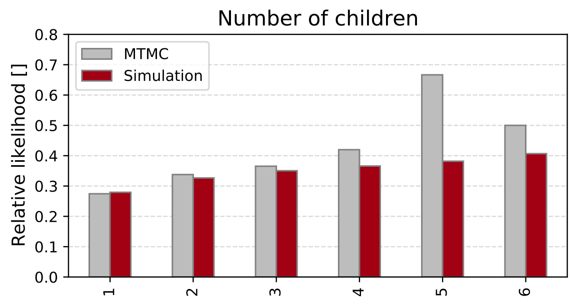
4.3 Validation of the choice model

For the validation of the presented choice model, the parameter values are applied to a synthetic population of Switzerland (Section 4.1). The simulated decisions are then compared to the observations in the Swiss MTMC. Figure 2 demonstrates the results for selected variables. In general, the simulation on the synthetic population reproduces the trends as observed in the MTMC well.

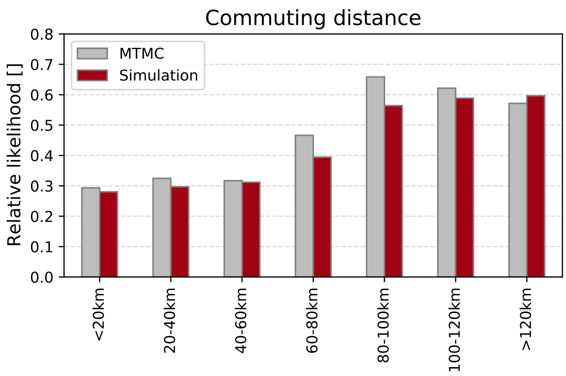
Figure 2: Validation of the likelihood of having the possibility to work from home as simulated in a synthetic population compared to the Swiss MTMC.



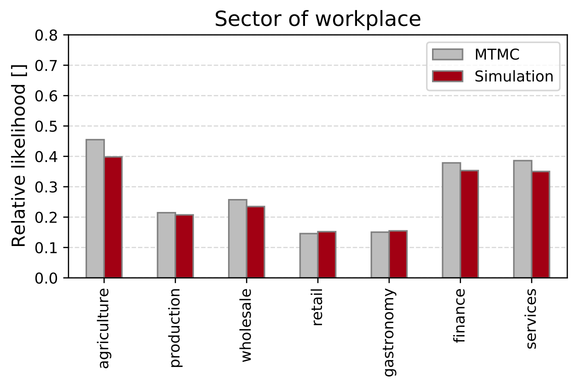
(a) Management position



(b) Number of children in the household



(c) Commuting distance



(d) Sector of workplace

Employees with a management role have a higher likelihood to have the WfH possibility, which is well captured in the simulation (Figure 2(a)). The likelihood depending on the number of children present in the household (Figure 2(b)) is slightly underestimated in the simulation. On the other hand, the commuter distance has a significant influence on the possibility to WfH (Figure 2(c)). Over 80km, the likelihood is twice as high compared to the commuting distances below 60km. Lastly, the working sector plays an important role in the model and the effects are well represented in the simulation (Figure 2(d)). Retail and gastronomy are the sectors with the lowest probabilities to WfH. Besides the special case of the agricultural sector (Section 4.2), the financial and service sector tend to have more possibilities to WfH.

5 Simulation of induced mobility behaviour

The impact of WfH on mobility behaviour is derived from an integration of the quantified preferences (Section 4.2) into the SIMBA MOBi modelling pipeline. First, a sensitivity analysis is conducted to demonstrate the differences in mobility behaviour between a WfH day and an office day for two different individuals (Section 5.1). Then, the scenarios including the different levels of overall WfH proportions are introduced (Section 5.2). Finally, the aggregated statistics (e.g., commuting distances, modal splits, or rail demand) of the agent-based simulation are presented (Section 5.3).

5.1 Sensitivity analysis on individual level

The simulation of WfH behaviour relies on an activity-based demand model that is responsive to changes in individual commuting behaviour. To analyse the sensitivity of our demand model MOBi.plans, we simulate a distribution of daily schedules for two different individuals for both an office day and a WfH day. Distribution means a simulation of schedules using a number of different random seeds for the same agent. In our case, the result includes 100'000 different schedules for an intended office day and 100'000 schedules for a WfH day for one specific agent. Both distributions are analysed to investigate the influence of planning a WfH day on key mobility statistics.

In the presented sensitivity analysis, we generate the distributions for two different agents. They have the following characteristics:

1. *Public transport-oriented person:* Household location in the city of Bern, workplace in Zurich, age is 50 years, has a car available, has a full public transport subscription (GA[3]), 100% employment rate, and kids are present in the household.
2. *Car-oriented person:* Household location in Muensingen, workplace in Zollikofen, age is 59 years, has a car available, has no public transport subscription, 95%

[3]around 4000$ per year to use all public transport means in Switzerland

employment rate, and no kids are present in the household.

The *pt-oriented person* is a typical inter-city traveller in Switzerland. Having full public transport subscription allows to commute between the city of Bern and Zurich in a bit more than 1 hour. The *car-oriented person* has a more rural home and workplace. Both Muensingen and Zollikofen are smaller cities (10'000 inhabitants) around Bern. Public transport is available, but taking the car is the fastest option (20 minutes to commute).

Table 2 presents several key behavioural statistics for the two agents for an office day versus a WfH day. Note that even if the agents are planning an office day, they are allowed to not perform a work activity on the simulated day (e.g. because of being sick or on leave). The pt-oriented person has at least one work activity in three quarters of all schedules. The likelihood to have at least one (short) work activity is slightly higher when WfH. On an office day, the person is more likely to bundle the activities in less out-of-home tours, meaning that the person returns home less often during the day. The average number of trips remains fairly constant. The total time spent at home (WfH not included) is higher on a WfH day. This can be explained by the time spent to commute, which is substantially higher on an office day (average of 4 hours travelling on an office day versus 1.4 hours on a WfH day). However, it is interesting that the additional time spent at home on a WfH day does not equal the time saved due to less commuting. This means that the person also extends the performing time of out-of-home activities. The car-oriented person has a slightly lower probability to perform at least one work activity (95% employment rate). Compared to the pt-oriented person, the average number of out-of-home tours is higher, but the average number of trips is lower. Wfh increases the average number of trips by 4% for the car-oriented person. On the other hand, the impact of WfH on the time spent at home and the total daily travel times is less significant compared to the pt-oriented person.

Table 2: Statistics from a simulation of 100'000 daily schedules for an office day versus a WfH day of two individuals.

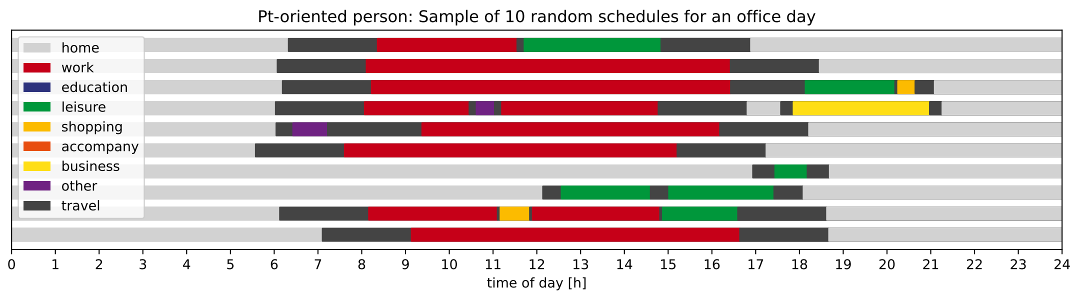
	Pt-oriented person		**Car-oriented person**	
	office	wfh	office	wfh
Min. one work activity [%]	76.4	78.6	71.3	74.1
Avg. number of tours [ ]	1.47	1.56	1.54	1.63
Avg. number of trips [ ]	4.24	4.26	3.96	4.12
Avg. time at home[1] [h]	13.46	14.72	15.37	15.45
Avg. time travelling [h]	4.03	1.39	1.53	1.11

[1]: working from home not included

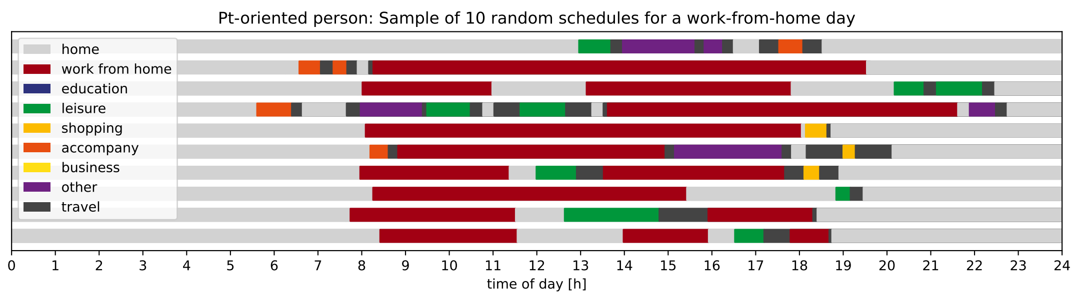
A more individual insight into the daily schedules is given in Figures 3 and 4. From the 100'000 simulated schedules, they show the activity behaviour over a full day for 10 randomly selected schedules. In general, it is clearly visible that there is a high variety in schedule structures. This comes from the wide spectrum of choice dimensions (e.g., activity frequency, locations, timings, durations).

Figure 3(a) shows the pt-oriented person on office days. 8 schedules contain a work (red) activity, which comes with a long travel episode (dark grey). Commuting and working consumes a high proportion of the day, the time left for performing secondary activties (e.g., leisure or shopping) is relatively short. On a WfH day (Figure 3(b)), the person is more flexible in scheduling work timings and secondary activities. For example, there is more time to perform accompany (orange) activities (e.g., bring the kids to school). The behavioural differences of the car-oriented person between an office day (Figure 4(a)) and a WfH day (Figure 3(b)) are considerable smaller compared to the pt-oriented person with its long-distance commutes. On WfH days, there are more home activities between working (e.g., eating lunch at home), whilst this only appears once on office days.

Figure 3: Public transport-oriented person: selection of 10 random daily schedules.

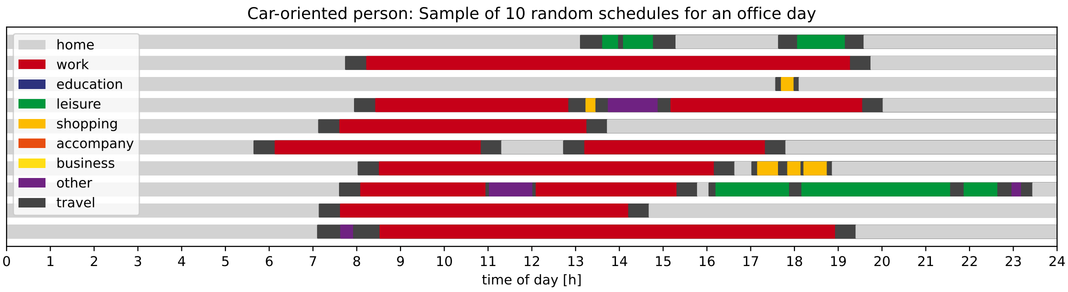


(a) Office day

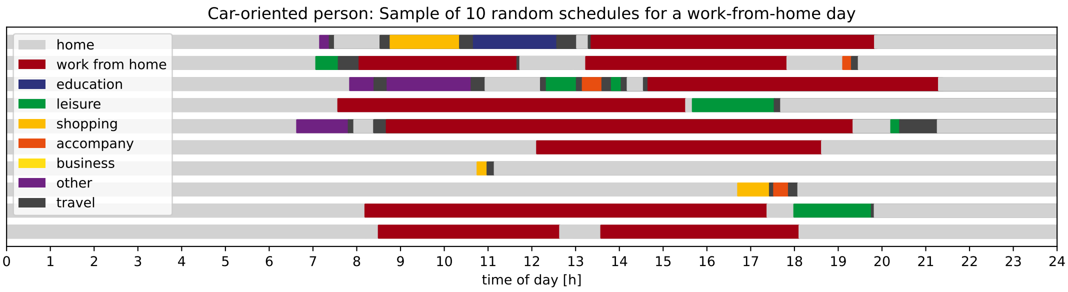


(b) WfH day

Figure 4: Car-oriented person: selection of 10 random daily schedules.



(a) Office day



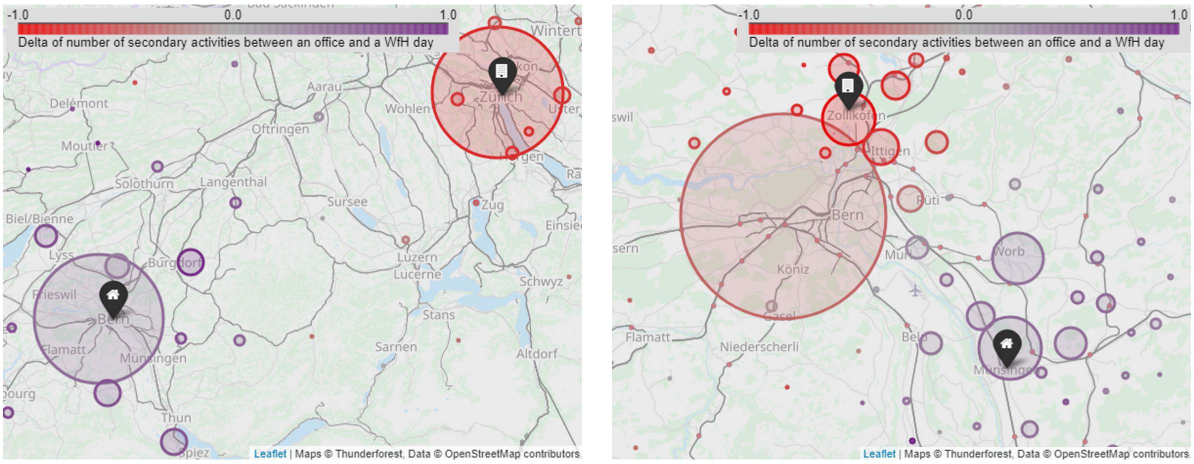
(b) WfH day

Figure 5 demonstrates the behavioural differences between WfH and commuting to the office on a map. The circle sizes indicate the absolute difference of number of secondary activities (all activities besides work and home) between an office day and a WfH day. The colours show the relative deltas, the lighter the smaller the relative delta. Red means less secondary activities on a WfH day compared to an office day. In contrast, violet means more secondary activities on a WfH day. The pt-oriented person (Figure 5(a)) performs many secondary activities around the workplace in Zurich on an office day. On a WfH day, the activity space is much more locally distributed around Bern. Similar behaviour is shown by the car-oriented person (Figure 5(b)). The secondary activities around the workplace are only scheduled on an office day. The radius of movement on a WfH day is smaller and much more concentrated on the home location.

5.2 Scenario range

In this study, we use the SIMBA MOBi scenario of Switzerland for the year 2050 as a case study. Based on latest estimations of the Swiss Federal Office for Statistics (BfS,

Figure 5: Differences in secondary activity space between office and WfH days.



(a) Pt-oriented person

(b) Car-oriented person

2020), the scenario contains 10.46 million permanent residents, which means 22% more than in the year 2017. Additionally, there are commuters and tourists travelling to and from locations abroad. As the society in 2050 will be older in average than today (the number of residents older than 64 years increases by 73% from 2017 to 2050) and the percentage of employed persons remains fairly constant, mobility patterns shift somewhat away from today's commuter-dominated patterns.

In the *base case*, WfH will only be present in today's form, with a linear extrapolation of the existing behaviour. This means that the WfH as introduced in Section 3.1 is not applied in the base case. In the *WfH case*, an increase of 15% in flexible working arrangements is assumed. The total increase of 15% is divided into a 11.25% increase in actual WfH and a 3.75% in flexible work timings. This scaling assumption has been derived after conducting an extensive internal survey amongst stakeholders during Summer and Fall 2021.

5.3 Aggregated results of agent-based simulation

The results are derived from a simulation of the full SIMBA MOBi modelling pipeline for both the base case and the WfH case. The modelling pipeline includes a full activity-based demand model (see Figure 1) as well as a fully disaggregated network simulation using the MATSim software (Horni *et al.*, 2016). Comparing the results of both cases, we can analyse key mobility statistics like average commuter distances, modal shifts, or changes rail demand.

Table 3 depicts several aggregated statistics for Swiss residents (commuters from abroad and tourists not included). First, the scaling utility term (x_{WfH}, see Equation 6) is determined to select 11.25% additional employed residents (in total 584'337 persons) to WfH on the simulated day based on individual preferences. x_{WfH} resulted in -1.22 for the WfH case. In the base case, the WfH model is not applied and no additional employed residents are selected.

Table 3: Statistics of base case versus WfH case for Swiss residents in the year 2050.

	Base case	**WfH case**	*Delta*
Preferences			
Scaling utility term [ ]	-	-1.22	
Trip behaviour			
Avg. trips per capita [ ]	3.58	3.52	*-1.6%*
Avg. work trips per capita [ ]	0.71	0.64	*-10.3%*
Total trips [10^6]	35.31	34.73	*-1.6%*
Avg. distance per trip [km]	8.24	7.99	*-3.0%*
Avg. work trip distance [km]	12.35	11.66	*-5.6%*
Total distance travelled [10^6 km]	290.98	277.58	*-4.6%*
Modal split - trips			
Individual motorised [%]	38.6	38.8	*+0.2%*
Non-motorised [%]	42.0	42.1	*+0.1%*
Public transport [%]	19.4	19.1	*-0.3%*
Thereof rail[1] [%]	7.2	6.9	*-0.3%*
Modal split - distance			
Individual motorised [%]	55.0	55.8	*+0.8%*
Non-motorised [%]	8.5	8.7	*+0.2%*
Public transport [%]	36.5	35.5	*-1.0%*
Thereof rail[1] [%]	27.0	26.0	*-1.0%*

[1]: includes trips with at least one rail leg

The trip behaviour presented in Table 3 shows several interesting differences between the WfH case and the base case. The average number of trips per capita does change only marginally (-1.6%), even though the average number of trips to the workplace drops by 10.3% from 0.71 to 0.64. This finding in line with the results of the sensitivity analysis (Section 5.1), which shows a fairly constant number of trips between office days and WfH days. The average trip distance in 2050 decreases by 3% and the average commuting distance decreases by 5.6% from 12.35km in the base case to 11.66km in the WfH case. As a result, the total distance travelled (-4.6%) decreases over-proportionally compared to the number of trips (-1.6%).

The modal split experiences a shift from public transport to individual (both motorised and non-motorised) transport. Motorised individual transport modes include car as a driver or passenger as well as automated vehicles. Non-motorised transport modes include walking and cycling. The share of trips with public transport decreases by 0.3%, and the share of rail trips proportionally decreases by 0.3% as well. In contrast, both motorised and non-motorised transport gain in modal shares. The effects have the same sign for modal shares in distance travelled. The share of distance travelled of trips including at least one rail leg drops from 27% to 26%.

The decrease in rail trips is also observed on a map in Figure 6. It shows the impact of the introduced WfH case on rail demand in Switzerland. The impact shows a clear heterogeneity across the country. Typical commuter lines (e.g., between Genève and Lausanne or Zurich and Bern) lose more passengers compared to more touristic connections (e.g., the north-south line through the Gotthard tunnel).

Figure 6: Relative delta of rail demand (long-distance trains only) between Wfh and base case in Switzerland.

6 Conclusion and outlook

In this work, we demonstrate the integration of WfH predictions into our agent-based model SIMBA MOBi. Based on individual preferences, we select a proportion of employed agents to WfH on the simulated day. The preferences consider various individual, household, spatial attributes as well as commuting distance and the sector of the workplace. The selected agents then reschedule their mobility behaviour and adapt their secondary activities destinations and timings.

The approach allows to quantify the impact of WfH on aggregated statistics such as modal split or rail demand. In this work, we introduce a WfH case with 15% additional flexible working arrangements in the year 2050 and compare it to a baseline scenario in 2050. When increasing WfH by 15% without introducing other behavioural changes, the average commuting distance goes down by 5.6%. The model results suggest that the modal share of distance travelled by public transport on workdays decreases from 36.5% (baseline scenario) to 35.5% (WfH case). This shift in modal share leads to an 8.3% decrease in the total passenger distance travelled by rail. The model does not consider compensatory effects such as reinvestment of commuting time savings or relocation of households as reported in Ravalet and Rérat (2019). SBB plans to investigate the impact of those additional behavioural changes in future work.

The results give valuable insights into a future with great uncertainty and rapidly changing assumptions. This helps SBB to develop strategic directions, for example adjusting the commuter-oriented rail service and product line (e.g., subscriptions). Also, new incentives for people may be found to enjoy trains more often for leisure-oriented activities (e.g., more capacity on weekends). Furthermore, SBB has a broader view about future commuter behaviour and is rethinking the extension of the term working from home to the next level of *work anywhere*. Work anywhere does not limit teleworking to home-based teleworking and allows for more flexibility in the choice of the workplace. As a result, work anywhere may stimulate the combination of working and leisure activities concentrated around recreational areas. Gathering more empirical evidence about this type of telecommuting is part of future work as well.

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