Modelling urban mode choice behavior during the COVID-19 pandemic in Switzerland using MDCEV models

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Author(s):
Meister, Adrian; Mondal, Aupal; Asmussen, Katherine E.; Bhat, Chandra R.; Axhausen, Kay W.

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Adrian Meister
Institute for Transport Planning and Systems, ETH Zürich
CH-8093 Zurich
ORCID: 0000-0002-3350-9044
adrian.meister@ivt.baug.ethz.ch

Aupal Mondal
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
Austin TX 78712, USA
aupal.mondal@utexas.edu

Katherine E. Asmussen
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
Austin TX 78712, USA
kasmussen29@utexas.edu

Chandra R. Bhat
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
Austin TX 78712, USA
bhat@mail.utexas.edu

Kay W. Axhausen
Institute for Transport Planning and Systems, ETH Zürich
CH-8093 Zurich
ORCID: 0000-0003-3331-1318
axhausen@ivt.baug.ethz.ch

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ABSTRACT

In this paper we describe and model the behavioral response of the COVID-19 pandemic in Switzerland. We use the MOBIS-COVID GPS-tracking dataset which includes a pre-pandemic reference base. We transform the trip-level data in weekly distance proportions per mode per week, and model the data using a multiple discrete-continuous extreme value (MDCEV) model. We derive four distinct segments from September 2019 until the end of 2020 and use these to uncover natural and forced behavioral adaptions. The descriptive and model estimation results confirm the trends partly observed around the globe, i.e. a large decrease in public transport usage, recovered car usage, and a cycling boom. We further provide behavioral insights as well as policy recommendations.

Keywords: MDCEV, discrete choice, mode choice, MOBIS, COVID-19, travel behavior
INTRODUCTION

Following the outbreak of the novel SARS-COV-2 virus in Europe in the beginning of 2020, the Swiss Federal Council classified the outbreak as an "extraordinary situation" on March 16th, and introduced measures to contain the outbreak of the virus (1). The daily activity- and travel patterns in Switzerland were consequently disrupted with effects still evident today. These unprecedented changes in mobility behavior pose new challenges to transport planners and policy makers, over and beyond the general challenges the transport sector faces regarding climate change and the urgent need to decarbonize transport.

Throughout 2020, Switzerland experienced two distinct waves of infections with corresponding implementation of containment measures. Two GPS tracking studies (2, 3) captured the behavioral response of the public over the two waves, which indicates a strong decline in public transport (PT) use, and a strong, at least temporarily, increase in cycling and active transport. The Swiss government, unlike neighboring countries such as France and Italy, at no point implemented restrictions regarding the actual right to move. The observed response can hence, to a certain degree, be considered a result of public awareness and a basic impulse for self-preservation, as opposed to a forced behavioral change. Apart from the high-level effects on travel behavior when considering the pandemic as a whole, further considerations related to the specific behavioral responses to the spatio-temporal distribution of containment measures and infection numbers are of interest. In this regard, a growing number of descriptive analysis studies have started to become available from numerous countries, but only little work has so far been undertaken regarding the actual modeling of observed response behavior using econometric models. This is partly due to the scarce data availability, especially those capturing the early stages of the pandemic.

In this paper, we use the MOBIS-COVID dataset to model the behavioral response regarding urban mode choice in Switzerland. The dataset is unique as it includes a panel with a pre-pandemic baseline. We apply a multiple discrete-continuous extreme value (MDCEV) model (4) that accounts for the panel structure of the data, and model the change in weekly proportions of distance traveled per mode. We further segment the timeline into different phases based on such variables as infection numbers, stringency of containment measures and total vehicle miles travelled (VMT). The resulting phases are used to discover travel behavioral changes in response to the epidemiological progress of the pandemic throughout 2020, particularly the heterogeneity in the behavioral response across individuals, so as to inform on-going and future policy-making in the context of a pandemic.

RELATED WORK

COVID-19 Timeline in Switzerland

The development of the COVID-19 pandemic over 2020 is described based on reports from (1) and visualized in Figure 1 based on the 7-day average of daily infections and deaths (5), as well as the stringency index from (6). The latter summarizes the implemented measures on a scale from zero to 100. As background, the first confirmed COVID-19 infection in Switzerland occurred on February 25th, 2020. The very first measures were implemented three days later by the Federal Council, after it declared a "special situation", giving it the legal authority to implement containment measures for all of Switzerland. The first death was reported on March 5th, 2021, and an "extraordinary" situation was declared on March 16th, 2021. While no general curfew was put in place, all non-essential businesses and public institutions had to close, leaving only grocery stores and doctors open for physical visits. The population was explicitly encouraged to stay at home, and
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it was recommended not to use PT. Borders to neighboring countries were closed with only few
exemptions. National transport, and international transport whenever possible, was kept running,
especially for freight. The frequency of some regional passenger transport services was reduced in
order to protect personnel and passengers.

![Figure 1: Development of infections, deaths and stringency of containing measures for 2020.](image)

The first containment measures were revoked on May 11th, 2021. Non-essential businesses
and public institutions were allowed to open-up again, even though with capacity constraints and
contact-tracing. Schools and universities were allowed to open as well. By end of May 2021, the
infection numbers declined to their lowest levels since the start of the first wave, with no reported
deaths in the first week of June. From early June, private and public gatherings with up to 300
participants were allowed again, and the gastronomy industry, including night-clubs, was allowed
to operate at almost full capacity. The borders to neighboring countries were opened on June
15th, 2021, and the "extraordinary" situation was revoked four days later. On July 6th, 2021, the
government ordered the mandatory usage of face masks in PT. In the following months Switzerland
experienced what could almost be considered a "normal summer" – hot and sunny.

With winter approaching, the epidemic situation started to deteriorate again after Septem-
ber. Public and private gatherings were restricted to 15 participants, the gastronomy sector again
faced stronger capacity restrictions and had to close from 11pm to 6am, and night-clubs had to
close completely. Mask-wearing became mandatory in all closed public places and in schools.
The second wave peaked throughout November, with approximately 120 daily death cases two
weeks later. This second wave was significantly more deadly than the first one. While the number
of infections dropped considerably beyond the peak in November, it started to rise again around
new-year, leading to what some considered to be a third infection wave. The number of deaths
remained fairly high throughout both the second and third infection wave, with a less cyclical pat-
tern, which some experts linked to the appearance of new COVID-19 variants which cause fewer
but more severe medical conditions.

Changes in Mobility and Mode Choice Behavior
This section focuses on urban transport changes induced by the COVID-19 pandemic. Even though
there is already a body of research that has analyzed the impact of pandemics (5) and unplanned
disruptions (e.g. terror attacks (6, 7)) on mobility behavior, these are not comparable to the global
scope and significance of the COVID-19 pandemic. The link between mobility and the spread
of viruses has been the subject of some previous research (8) in the context of COVID-19 (e.g.
US (9)). These recent studies are using a range of different sources of data, including GPS data,
cell-phone data, travel diaries, questionnaires, operational data from ITS, as well as data from
various static traffic flow sensors. The studies do uniformly indicate the rather depressed use of
public transit in western countries in response to COVID-19, though the impacts on other modes
of transportation such as private cars, walking, and cycling appear to highly dependent on city- and
local transport system characteristics, as well as the implemented containment measures. A few of
these studies are briefly discussed below.

Beck and Hensher (10) used an online survey distributed during the first week of April 2020
in Australia. Respondents reported a 50% reduction in trip frequencies, with the biggest reduction
associated with private car trips. PT shares fell significantly for bus and train. Active transport
modes (walking and cycling) saw an increase of 14%. Aloi et al. (11) used traffic flow counters and
cameras, as well as PT ITS data in Santander, Spain, to derive origin-destination matrices after the
first containment measures were implemented in mid-March 2020. Their results reveal a decrease
in overall trip frequency by around 75%, and also an increase in private motorized transport market
share by about 50% (most of this from walking and PT). The containment measures in Spain were
especially strict, including general curfews. Similarly, Bucsky (12) used traffic and user count data
as well as user data from local bike sharing systems and navigation apps in Budapest, Hungary.
The data revealed that trip frequencies decreased up to 60%, with, again, the private car shares
increasing the most, PT shares decreasing the most and almost unchanged shares for active modes.
de Haas et al. (13) gathered longitudinal data in Netherlands using an annual household panel.
The data indicated a drop of over 50% in trip frequencies and trip distances. The largest decrease
in modal shares was for PT and private cars, with a smaller decrease in the share of cycling too.
Walking increased significantly with almost double the share than of the 2019 reference period.

All the above mentioned studies use descriptive analysis methods. While insightful, such
studies are not able to adequately capture the heterogeneity in behavioral response across different
demographic groups. Some of the studies that use analytic methods such as discrete choice models
are now discussed. Bhaduri et al. (14) used an online survey undertaken in April 2020 in India.
Respondents were asked about their mode choice frequencies before and during the early start of
the pandemic. The data was modelled using MDCEV methods and the results indicated a shift
toward modes that facilitate social distancing (primarily, private vehicles) and away from modes
(such as public transportation) that decrease the ability to socially distance. Interestingly, non-
motorized transport modes (walking and cycling) saw a decrease as well, which may be due to
the high level of crowding involved when choosing these modes in urban Indian areas. Almlöf
et al. (15) used smart card data to specifically look at changes in PT usage in Stockholm, Sweden. Using January 2020 as the reference period, the PT usage of smart card holders suggested a drop of about 75% during the first infection wave in spring 2020. The decrease in ridership was modeled using Logit models, with the highest drop in transit patronage being associated with individuals of higher socioeconomic status. Scorrano and Danielis (16) collected stated (SP) and revealed preferences (RP) before and during the pandemic between April and August 2020 in Italy. The data was modeled using a joint RP/SP integrated choice and latent variable (ICLV) framework, and included attitudinal factors such as environmental and COVID-19 related health concerns. Similar to observations in other western countries, a significant proportion of respondents avoided PT and switched to private cars and active modes. The analysis further revealed, as expected, that respondents who are highly health risk-averse are the ones who disproportionately avoid PT, while those with environmental concerns are the most disinclined to give up PT.

**METHOD**

**Data**

The MOBIS-COVID project (2) initially started as a mobility pricing experiment in Switzerland. In September 2019, about 5,400 people started an app-based GPS-tracking study in which each respondent was tracked for eight weeks. About 3,600 respondents stayed for the entire study period. In March 2020, 1600 of these former participants volunteered to reactivate their accounts in order to capture their data on travel responses to the pandemic and related containment measures. The project is still on-going and, in 2020, had an average of about 1000 active participants.

To limit the scope of this paper, the dataset used for the modelling only includes urban travel modes and local area travel. Plane, long-distance train, ferry, ski and cable-car were excluded. The specific urban modes include car, bus, train, bicycle, and walking. Some of these modes are composite modes that represent aggregations of more elementary modes. For example, car includes car-sharing and taxi, bicycle includes bike-sharing and electric bikes, and train includes local trains, trams and subways. The travel diary data from respondents is collected at a trip-level and then converted to weekly distance-based mode proportions that sum to one for each user and each week. It includes observations from September 2019 until November 2020 (week 47). From these observations, we selected only the weekly data of individuals who provided a full week of observations, resulting in a final dataset size of approx. 10,000 user weeks. The weeks come from a total of 514 different participants and are split about equally between 2019 and 2020. Each respondent has an average of 19 week-observations. Each calendar week in 2020 has approximately 180 observations from 180 different individuals. The data is additionally enriched with weather characteristics, including temperature and precipitation, as well as accessibility measures of respondents’ home locations, following Loder and Axhausen (17). Table 1 shows the distribution of socio-demographic attributes of the sample used in comparison to the MOBIS-COVID dataset as well as the mobility micro-census data cen (18). The extracted sample matches the socio-demographic distribution of the MOBIS-COVID dataset, which is skewed towards car-owning individuals due to the original target population of the MOBIS experiment. The sample is further slightly better educated, has slightly higher incomes, and is relatively more employed than the larger population. Further notable is the high share of car, bike and PT pass ownership.
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<table>
<thead>
<tr>
<th>Dataset</th>
<th>Subset</th>
<th>MOBIS-covid</th>
<th>Micro-census</th>
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<td>Age</td>
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<tr>
<td></td>
<td>18-25</td>
<td>12.0%</td>
<td>16.9%</td>
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<tr>
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<td>38.1%</td>
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<tr>
<td></td>
<td>45-65</td>
<td>52.7%</td>
<td>45.1%</td>
</tr>
<tr>
<td></td>
<td>over 65</td>
<td>2.2%</td>
<td>-</td>
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<tr>
<td>Gender</td>
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<td>49.4%</td>
</tr>
<tr>
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<td>50.6%</td>
</tr>
<tr>
<td>Income</td>
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<td>8.8%</td>
</tr>
<tr>
<td></td>
<td>Low (up to 4000 CHF)</td>
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<td>5.6%</td>
</tr>
<tr>
<td></td>
<td>Medium (4000-12000 CHF)</td>
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<tr>
<td></td>
<td>High (more than 12000 CHF)</td>
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<td>26.6%</td>
</tr>
<tr>
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<tr>
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<td>Secondary</td>
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<tr>
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<td>Higher</td>
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<td>33.4%</td>
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<td>53.9%</td>
</tr>
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<tr>
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<td>Unemployed, Retired, Other</td>
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<td>14.2%</td>
</tr>
<tr>
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<td>PT</td>
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<tr>
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<td>Bike</td>
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</tr>
<tr>
<td></td>
<td>e-Bike</td>
<td>16.1%</td>
<td>-</td>
</tr>
</tbody>
</table>

**TABLE 1:** Distribution of socio-demographic attributes from the modelling subset, the original MOBIS-COVID data, as well as the local census.

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1 **Descriptive Results**
2 Figure 2 shows the percentage change in mode usage based on distance as well as trip frequency.
3 The segments correspond to the time lines shown in Figure 1. Segment 1 is the reference pre-
4 lockdown period from September 2019 until week 12 (first week of March) in 2020. Segment 2
5 represents the first wave until restrictions were relaxed, with cases reaching their lowest levels in
6 week 25 (in June 2020). Segment 3 is the summer period with low cases and low levels of restric-
7 tions, and proceeds until week 43 (in October 2020). The last segment 4 represents the second (and
8 third depending on interpretation) wave with the highest numbers of cases and stringency reaching
9 the same levels as in the first wave. The beginning of the "lockdown" on March 16th in the first
10 infection wave is clearly visible in the top graph of Figure 2, with a drop of around 60% in VMT
11 and relative drops for all modes except cycling. The same pattern is observable in the change of
12 trip frequencies (bottom graph), with only cycling showing an strong increase. In both graphs,
13 it can be observed that the VMT/frequencies start dropping slightly before the lockdown started,
14 which indicates that the population was well informed and naturally adapted.
FIGURE 2: Changes in traveled distance (top) and trip frequencies (bottom) by mode, including derived timeline segmentation.
In the summer of 2020 (segment 3 in Figure 2), and with the easing of the restrictions, the car VMTs and trip frequencies recovered to reference levels, while PT bus and train) remained well under pre-pandemic levels at around -50%. PT recovered only slowly and reached -35% levels by the start of autumn. The implementation of the mandatory facial covering in PT did not lead to any observable effect. Walking also remained under the reference levels fluctuating around -20%. Cycling usage jumped reached by 150% in terms of VMT compared to reference levels. This is partly explained by the above-average sunny summer, but nevertheless significantly too high to be explained just by seasonal effects. A deeper analysis in (2) regarding the change in temporal distribution, number, and distance of cycling trips indicated that a large share of these additional trips had a leisure purpose. In segment 4, i.e. the second wave, VMT by private vehicles did not drop significantly, while PT and cycling did. The decrease in cycling usage may be partly explained by the winter season settling in. The low decrease in car VMT certainly partly depends on the sample characteristics. The fact that the VMT only slightly decreased and recovered through-out the second wave shows that the Swiss population and politics adapted to "go back to normal" as much as possible, while dealing with the ongoing pandemic. As described in Section 2, Switzerland had rather loose measures during the summer (segment 3) with a majority of the restaurants, business and even night clubs open.

Modelling Framework
MDCEV models were first proposed in 2005 by Bhat (4) and extended by numerous works to introduce or relax certain key model assumptions. As opposed to traditional discrete choice models, they allow to model the simultaneous choice of multiple goods (discrete dimension) and the corresponding continuous quantities of consumption (continuous dimension). This problem framing is by design well suited to represent real-world and relevant choices in many fields including time-use, marketing, and transport research. For example, in the latter field, MDCEV models have been applied to the choice of household vehicle holdings and usage (19), MaaS services and usage (20), general time-use (21), travel-based time use (22), as well as modelling of social networks (23). MDCEV models are derived from RUM theory and use non-linear additive utility functions that consider the goods as imperfect substitutes. Satiation parameters in the utility functions introduce diminishing marginal returns for each alternative’s consumption. The framework assumes the existence of a budget constraint that has to be allocated among different alternatives. The budget itself may take the form of total hours in a day, VMT, or a monetary budget. The framework can further assume the existence of an outside good, defined as a good that has a positive consumption by all respondents. The specification of such constraint affects whether corner solutions in the utility space are considered. Similar to conventional discrete choice models, the various error terms can be subjected to different assumptions. Relaxing the assumption of IID error across alternative using a mixing error structure results in the mixed MDCEV (MMDCEV).

In this paper, a panel version of the mixed multiple discrete-continuous extreme value (MMDCEV) model is formulated to analyze the proportion of weekly traveled distance among the five considered urban modes, as we are interested in the shifts between modes during the different stage as opposed to the absolute change in the traveled distance. The data at hand represents a case with no outside good. The model formulation accommodates heterogeneity (i.e., differences in behavior) across individuals due to both observed and unobserved individual attributes. In the following presentation of the panel MMDCEV model structure, the index \( q(q = 1, 2, \ldots, Q) \) is used to denote individuals, \( t(t = 1, 2, \ldots, Tq) \) for weekly choice occasion, and \( k(k = 1, 2, \ldots, K) \)
for travel modes. Let \( x_{qt} = \{x_{q1}, x_{q2}, \ldots, x_{qK}\} \) be the vector of travel distance proportions in week t for the five travel modes. Using these notational preliminaries, the structure of the weekly mode proportion model for panel (or repeated choice) data is discussed below. Consider the following additive utility functional form:

\[
U_{q,t}(x_{qt}) = \sum_{k=2}^{K} \gamma_k \psi_{qtk} \ln \left( \frac{x_{qtk}}{\gamma_k} + 1 \right)
\]  

(1)

In the above utility function, \( U_{q,t}(x_{qt}) \) refers to the utility accrued to the individual due to travel proportion vector \( x_{q,t} \) for week t. The term \( \psi_{qtk} \) refers to the baseline preference of the five alternative modes and control the discrete choice participation decision in these alternatives \( (k = 1, 2, 3, \ldots, K) \) for individual q at choice occasion t. The term \( \gamma_k \) \((\gamma_k > 0)\) is a translation parameter that serves to allow corner solutions (zero consumption) for the alternatives. Further, in combination with the logarithmic functional form, it also serves to allow differential satiation effects across these alternatives, with values of \( \gamma_k \) closer to zero implying higher satiation (or lower time investment) for a given level of baseline preference \((19)\). To complete the model specification, the baseline parameter for the five alternatives are given by

\[
\psi_{qtk} = \exp(\theta_k + \beta z_{qk} + \mu_q s_k + \epsilon_{qtk})
\]  

(2)

The first term \( \theta_k \) represents the “average” (across individuals) effect of unobserved variables on the baseline utility associated with alternative k. The second component \( \beta z_{qk} \) captures heterogeneity across individuals due to observed individual specific attributes. In this component, \( \beta \) is a vector of coefficients, and \( z_{qk} \) is a vector of observed attributes specific to individual q and introduced in an alternative-specific fashion. The third component \( \mu_q s_k \) represents individual q’s differential preference for the alternative k compared to the “average” preference for the alternative k across all her/his peer individuals. In this component, \( s_k \) is a column vector of dimension K with each row representing an alternative (the row corresponding to alternative k takes a value of 1 and all other rows take a value of 0), and the vector \( \mu_q \) (of dimension K) is specified to be a K-dimensional realization from a multivariate normally distributed random vector \( \mu \), each of whose elements have a variance of \( \sigma_k^2 \). The elements of \( \mu \) are assumed to be independent of each other, and the realization vector for any individual is independent of the realization vector of other individuals. The result is a variance of \( \sigma_k^2 \) across individuals (with no resulting covariance effects) in the utility of alternative k. Thus, the third component captures heterogeneity across individuals due to unobserved individual attributes that are not correlated across alternatives (i.e., unobserved pure variance inter-individual heterogeneity). The fourth term \( \epsilon_{qtk} \) is an idiosyncratic choice-occasion specific term for individual q and alternative k, assumed to be identically and independently standard type I extreme-value distributed across individuals, alternatives (travel modes), and choice occasions. The variance of this standardized error term captures unobserved intra-individual heterogeneity (i.e., variation across choice occasions of individual q) in the baseline preference for alternative k.

The reader will note here that the vector \( \mu_q \), which is a realization of the \( \mu \) vector for individual q, takes the same value for all observations (or choice occasions) of a given individual. This generates correlations across the choice occasions of a given individual and accommodates
the panel effect. Thus, individuals who may be predisposed to use car due to unobserved personality traits will show this predisposition across all her/his choice occasions. For given values of $\mu_q$, the probability of the observed time investments (or, in view of the analyst, the optimal time investments) $x_{qt}^*$ of individual q at choice occasion t is given by Bhat and Sen (19):

For given values of $\mu_q$, the probability of the observed time investments (or, in view of the analyst, the optimal time investments) $x_{qt}^*$ of individual q at choice occasion t is given by Bhat and Sen (19):

$$P(x_{qt}^* | (\mu_q) = \prod_{i=1}^{M} c_{qti} \left[ \frac{1}{\sum_{i=1}^{M} c_{qti}} \right] \left( \frac{\prod_{i=1}^{M} e^{\gamma_{qk}}}{\sum_{k=1}^{K} e^{\gamma_{qk}}} \right)^{M-1}!$$ (3)

where, $M =$ the number of alternatives chosen by individual q at choice occasion t,

$$c_{qti} = \left( \frac{1}{X_{qti}^* + \gamma_i} \right), \text{ for } i = 1, 2, 3, \ldots, M, \text{ and}$$ (4)

$$V_{qtk} = \theta_k + \beta z_{qk} + \mu_q s_k - \ln \left( \frac{x_{qtk}}{\gamma_k} + 1 \right), \text{ for } k = 1, 2, 3, \ldots, K$$ (5)

The parameters to be estimated in the panel MMDCEV model include the $\theta_k$ and $\gamma_k$ scalars for each alternative k, the $\beta$ vector, and the $\sigma_k^2$ variance elements characterizing the variance matrix of $\mu$. Let $\theta$ be a vector of the $\theta_k$ elements; $\gamma$ be a vector of the $\gamma_k$ elements, $\sigma$ be a vector of parameters characterizing the variance-covariance matrix of $\mu$; the maximum likelihood inference approach is used to estimate the parameters of the MMDCEV model. To develop the likelihood function for parameter estimation, the probability of each sample individual’s set of observed time investments is needed. Conditional on $\mu_k$, the likelihood function for individual q’s observed set of time investments is:

$$L_q(\theta, \psi, \beta)(\mu_q) = \prod_{t=1}^{T_q} [P(x_{qt}^*, \theta, \psi, \beta) | \mu_q]$$ (6)

The unconditional likelihood function for individual q’s observed set of choices is:

$$L_q(\theta, \psi, \beta, \omega) = \int_{\mu} [L_q(\theta, \psi, \beta)(\mu_q)] dF(\mu | \omega)$$ (7)

The log-likelihood function is:

$$L(\theta, \psi, \beta, \omega) = \sum_q ln[L_q(\theta, \psi, \beta, \omega)]$$ (8)

where $F$ is the multivariate cumulative normal distribution. The reader will note that the dimensionality of the integration in the above expression depends on the number of elements in $\mu$. Simulation techniques are applied to approximate the multidimensional integral in Equation 6, and the resulting simulated log-likelihood function is maximized using a scrambled Halton sequence method.
RESULTS

The estimation results are shown in Table 2. Starting from a base model without any interaction effects we successively increased the complexity and filtered out insignificant variables. We further evaluated different start- and end calendar weeks for the four considered time segments. The model has 377 parameters, and so the following discussion focuses only on the most significant effects. The car alternative is the base category, so the parameters for the other modes for segment 1 need to be viewed as relative baseline utilities between a specific non-car mode and the car mode. For the other segments (segments 2, 3, and 4), the parameters may be viewed as the relative shifts in the baseline preference for each non-car mode from segment 1 relative to the shift in the car mode from segment 1. The baseline utility parameters control the participation rate of the certain alternative i.e. how often a mode is chosen, while the satiation parameters describe how much i.e. how far/over which total distance a respective mode is used if chosen. The baseline utility interaction effects include socio-demographic, weather and accessibility measures. Interaction effects on the satiation parameters were not considered in order to keep the model estimation and interpretation manageable.

General Findings

The alternative specific constants (ASCs) of all modes except walking are below the car reference in segment 1 (the reference segment). This is explained by the sample composition, with around 90% car-owners and the consequently high share of car-VMT in the data. The ASC for cycling shows the highest negative constant in the baseline utility in the reference segment. It must however be noted that the reference period includes cold and rainy Swiss winter. Walking is strongly positive in the baseline utility for the reference segment, though this is also capturing short inter-modal trip transfer changes (rather than actual whole trips to an activity location).

The heavy negative effects on PT seen in other studies and in the data on hand are also reflected in the obtained model parameters. Bus and train have relatively largest negative ASCs relative to the private car for all the segments. The frequency and distance levels shown in Figure 2 also underline this, with a slow recovery in the train mode, and even that only to about 40% of reference levels. Bus usage shows a similar pattern regarding the parameters; however, the ASCs for bus appear to become positive in the second and third segments, suggesting a faster recovery of patronage for the bus mode. Looking at cycling, the large effect seen in Figure 2, is reflected in the largest positive effects on baseline utility, especially through summer i.e. segment 3 with very low infection rates and the lowest stringency levels. The last segments shows a small negative effect which is partly caused through the epidemiological development, as the weather is controlled for through interaction effects (more below). Walking has a small negative effect during the first wave which turns positive but still small from the summer on. Figure 2 shows that walking is the most "stable" i.e. constant compared to all other modes regarding frequency and distance.

The satiation parameters are also mostly intuitive and correspond to the findings from the descriptive analysis. Car has the largest positive satiation effect due to the overall share, but also, as only mode, shows a negative effect through the first wave and positive effects for the summer and second/third wave. Bike shows a strong increase in usage throughout all segments with the highest effect during the first wave. The PT modes have constant, slightly decreasing satiation parameters over the whole study period. The random effects parameters $\sigma_k$ indicate that there is little unobserved heterogeneity for car and walking. For bus and train there is a small significant effect, which triples for cycling.
### TABLE 2: Model estimation results, key parameters.

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TABLE 2: Model estimation results, key parameters.

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σk

|          | 0.098     | 0.463**  | 0.571**   | 1.558**    | 0.116      |

*** 99% significance, ** 95% significance, * 90% significance

1 Public Modes
2 The public transportation modes clearly show the fall off in ridership from the reference levels.
3 However, PT pass ownership and accessibility have a strong positive effect on usage and a clear
4 negative effect on car usage, across all the segments. The educational effects indicate that partici-
5 pants with higher education tend to use PT less (both modes) in the first wave and slowly recover,
6 i.e. positive parameters, until the end of 2020. A further notable effect includes bike and e-bike
7 ownership, which show a negative effect for trains, and a clear negative e-bike effect for bus usage.
8 This might suggest that especially e-bikes are used an alternative for public transport modes. The
9 weather-related parameters do not indicate clear and intuitive effects, though a weak negative ef-
10 fect of cold temperatures and high precipitation environments appear to exist for PT usage during
11 the winter period.

12 Active Modes
13 Considering walking over all segments, a clear and expected effect of weather indicators can be
14 seen, especially for precipitation (similar to PT with amplified effect sizes in the winter periods).
15 The PT and car ownership parameters indicate expected effects as in PT being positive and car
16 negative. Especially car ownership has clear negative effect according to the difference in urban,
17 sub-urban and rural home locations characteristics from the sample. Compared to PT, education
related parameters do not show any clear and intuitive pattern. Furthermore, there is generally
no clear distinct patterns between the different segments which is analogous to the "rather stable"
behavior of walking compared to other modes as shown in the descriptive analysis and the baseline
utility parameters. Walking can be considered the least affected mode with respective to infection
numbers and stringency of measures.

The effects on biking are of specific interest because of the large increased usage, often
referred to as cycling-boom and observable around the globe, as well as its role for sustainable
urban transport. As previously mentioned and shown, cycling saw a large relative increase in
frequencies and distance traveled during the first wave and the summer, before naturally decreasing
with incoming winter. This is a good indicator that the cycling behavior seems unaffected by policy
stringency and epidemiological development. The baseline utility parameters support this findings.
The group of respondents which were bike user since the start of the first wave and all 2020, can
be characterised as slightly more male and less educated. These differences in relation to the
pre-pandemic bike users might be cause by new users that started cycling due to the pandemic.
The effect of live-changing events as triggers for behavioral change has been shown in previous
research (24, 25). The random effect parameters also suggest that the bike users are composed of
different population segments with a rather large heterogeneity. The accessibility parameters show
intuitive and reasonable effects, similar to PT and walking, as do the ownership indicators. Effects
sizes tend to be always slightly larger for e-bike ownership. The weather, especially precipitation
also shows the excepted effects. The consistency of all these parameters throughout the different
segments and modes speak for the general validity of the model.

CONCLUSION

Summary

Similar to patterns observed in most other countries, PT saw the largest decrease in traveled dis-
tance and trip frequencies, with an almost 100% reduction respectively during lockdown. Numbers
slowly recovered but up to the end of 2020 were still at around -50%, also due to the second wave
and increased measure stringency. Car usage decreased up to around 40% but returned to pre-
pandemic levels after the first wave, and from there on stayed stable. An arguably foreseeable
behavioral adaption in the population is the increased private car use, to avoid public transport
and potential infection risks. This effect has specifically also been observed in other countries,
typically after the first infection wave, e.g. (11, 10). Walking experienced the smallest drop in trip
frequencies relative to pre-pandemic 2020, and the distance distribution is approx. stable during
the rest of the year. It can be considered the least affected by the pandemic, however the high share
of urban home locations in the sample has to be considered. The patterns are similar to the results
in the Netherlands (13), which have similar European city characteristics like Switzerland. Bike
and e-bike usage saw a surge during the first wave and the summer. This effect was observed in
most other countries around the world. Interestingly not in the just mentioned Netherlands, where
the corresponding study shows a decrease in cycling activity. It must however be considered that
the Netherlands has some of the highest shares of utilitarian cycling trips, which are more affected
by measures like e.g. home-office regulations. In our data, the traveled distance increased up to
150% and frequencies increasing up to 40%. The average trip length of cycling trip also increased
analogous to the higher share of leisure trips. With the incoming second wave the usage numbers
dropped, whereas most of the variation is expected to be due seasonal winter.

The insights gained from the MDCEV model confirm many of the patterns observed in the
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descriptive analysis. The model parameters indicate a good model fit with intuitive effects which mostly align with a-priori expectations. The parameters to a certain degree also reflect the skewed sample composition of the final modelling subset. The baseline utility and satiation parameters show, e.g. positive effects of cycling during the first wave and the summer, or constant negative effects for both public modes in all segments. From the socio-demographic attributes, the mobility tool ownership and accessibility measures had strong and intuitive effects in all segments and all modes. The weather-related parameters also show reasonable and constant effects. The consistent behavior of these effects over all segments are a further indicator for a good model fit and accurate representation of the data. The socio-demographic interactions effects allow for deeper behavioral insights, and e.g. indicates a change in user group composition for PT and cycling. For the former, the results e.g. indicate a shift towards better educated, higher income and higher age individuals, whereas for the latter a shift towards slightly elderly and less educated men can be inferred.

Considering both the descriptive and model insights reveal distinct differences in how the population adapted its behavior to the first infection wave, as opposed to the much deadlier second wave. During the first wave, the implemented measures were the strictest with a short but complete lockdown of about 6 weeks. Even-though the lockdown imposed a forced behavior adaption, the travel activities already started decreasing slightly before which indicates a more natural behavioral adaptation. The cycling boom during the first wave also speaks for a natural adaptation, as the stringency of measures was on yet highest ever implemented levels. During the second wave, the model results show a dependency of the decrease in usage of not only weather, suggesting a relation to the increased stringency. It is however unclear whether the model was able to fully disentangle the seasonal weather and the epidemiological time segments from each other. The development of car usage speaks for a natural adaptation after the first wave, and shows little dependency from the implemented measures during the second wave.

Policy Perspective

Regarding PT, policy makers are faced with the on-going pandemic which shows a more dynamical pattern due to new virus variants in 2021. The PT usage is hence expected to continue to recover only slowly, potentially also due to new measures, as well as possibly also permanently remain under pre-pandemic levels. In the short-term policy makers and PT operators should focus on operational aspects in order to operate in a safe manner at the greatest possible capacity. In the long-term, the need for PT will increase due to its small climatic footprint.

For cycling, more concrete recommendations can be offered. Even though our data indicates the surge to be partly explained by additional leisure trips, it is still expected that new bike users started to cycle and that the pandemic will have a long-term effect on demand. This comes on top of a previous increasing trend in bike and e-bike usage. General consent exists in Switzerland that the surge in cycling was often meet with insufficient cycling infrastructure. Building new cycling infrastructure is comparably cheap and fast, and temporary cycling infrastructure, like implemented in many cities around the globe, can easily be made permanent in times with high political and behavioral flexibility. Furthermore, the model revealed a strong relationship between (e-)bike ownership and usage. This would suggest to implement specific buying programs, such as tax-breaks or grants. Especially e-bikes are significantly more expensive than regular bikes. The model results also confirm that income is a predictor for increased bike usage. E-bikes however also offer the greatest potential as substitution for car and PT trips, and are hence of specific interest in the long-term sustainability context. Similar to PT, private bikes and e-bikes offer some of the
greatest lifetime CO2 reduction potentials per km, but have the disadvantage of being exposed to
weather. The recommendation for more cycling infrastructure can hence be extended when think-
ing long-term, as in having sophisticated, climate resilient and ideally weather protected cycling
networks with large capacities.
REFERENCES

15. Erik Almlöf, Isak Rubensson, Matej Cebeauer, and Erik Jenelius. Who is still travelling by public transport during covid-19? Socioeconomic factors explaining travel behaviour in
stockholm based on smart card data. *Socioeconomic Factors Explaining Travel Behaviour in Stockholm Based on Smart Card Data (September 8, 2020)*, 2020.


