Using Bayesian online changepoint detection to reveal the impact of weather on individual-level cycling frequencies

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Abstract

The impact of weather on cycling demand was usually investigated from a collective perspective. However, the impact on individual-level cycling behavioral changes over time was overlooked in the literature. This study addresses this gap using Bayesian online changepoint detection (BOCD) for behavioral change identification and discrete choice models for weather effect estimation. The proposed method was applied to reveal the impact of weather on cycling frequencies measured by weekly cycling days. We used a GPS dataset from Zurich comprising 520 cyclists with observation periods from 31 to 47 weeks. Results show relatively stable cycling frequencies in our sample, with an average of 2.3 changepoints detected per individual. Snow and precipitation are found to be the most significant attributes for driving a decrease in long-term cycling frequencies, while the effect of temperature remains inconclusive.
Keywords: Weather impact, Cycling frequencies, Bayesian online changepoint detection.

1 Introduction

Stability and habitual effects in human travel behavior were well recognized in the literature regarding mode choice (Cherchi & Cirillo, 2014), car and public transit usage (La Paix et al., 2022). In contrast, the stability of bike usage was rarely investigated. This may be attributed to the lack of long-term observational data on individual-level bike use. Understanding the stability of individual bike use is important to assess the impact of external factors on long-term changes in bike use and explore the heterogeneous response to those external factors.

Evidence has shown that weather is an external factor significantly influencing cycling demand (Böcker et al., 2013). In stated preference studies, rain and snow were found consistently to negatively affect cycling demand, while the effect of temperature varies among cyclists (Motoaki & Daziano, 2015; Meng et al., 2016). Empirical studies using observational data (e.g., travel survey data, count data) present diverse impacts of weather conditions on cycling demand cross-sectionally, with no effects in Tyndall (2022), ambiguous effects in Hudde (2023), negative effects of low/high temperature, precipitation, high windspeed in Miranda-Moreno & Nosal (2011); de Kruijf et al. (2021). Most of the studies investigated the impacts of weather conditions on cycling demand from a collective perspective and showed heterogeneous effects across different built environments and cultural backgrounds. However, there is limited literature that reveals how the weather conditions influence the change of individual-level bike use. This may also contribute to exploring the sole impact of weather.

Efforts made in continuously passive data collection may facilitate this research as identification of any change of behavioral pattern requires long-term observations. There are usually many anomalies in longitudinal data describing an individual's regular bike use, which unobserved situational factors may largely cause. Zhao et al. (2018) developed a Bayesian online changepoint detection (BOCD) method to detect the change of long-term travel behavior patterns to avoid noise in the longitudinal data. This study aims to use the BOCD method to identify the time point of robust change in individual-level cycling frequencies using longitudinal GPS tracking data and explore the impact of weather conditions on cycling frequency changes.

2 Methodology

Detection of cycling frequency changes

In this study, the cycling frequency is measured as the number of cycling days in a week for illustration. For each individual, let x_t denote the number of weekly cycling days in a week $t = 1, 2, \dots, T$. As x_t represents the number of days of choosing to cycle in $U = 7$ independent days, x_t can be assumed to follow a binomial distribution. Its probability mass function is presented as:

$$P(x_t = b \mid \theta, U) = \binom{U}{b} \theta^b (1-\theta)^{U-b} \tag{1}$$

where b is the possible value of weekly cycling days ranging from 0 to 7. θ is the probability of choosing to cycle in a day for an individual. Let $x_{1:T}$ denote the vector of a sequence of observations of x_t from $t = 1$ to $t = T$.

Our goal is to detect the changepoints of the pattern of weekly cycling days in the time period T. k change points would divide time period T into $k+1$ segments. Each segment would have a different distribution of the parameter θ. The Bayesian online changepoint detection (BOCD) method detects changepoints by modeling the length of the segment at t, which is also called run length and denoted as c_t. c_t is an integer ranging from 0 to t and it can be presented as:

$$c_t = \begin{cases} 0, & \text{if a changepoint occurs in week } t, \\ c_{t-1} + 1, & \text{otherwise.} \end{cases} \tag{2}$$

Based on Bayes theorem, the posterior distribution of c_t can be calculated using the existing observations until time point t as:

$$\begin{aligned} P(c_t \mid x_{1:t}) &\propto P(c_t, x_t \mid x_{1:t-1}) \\ &= P(x_t \mid c_t, x_{1:t-1}) P(c_t \mid x_{1:t-1}) \\ &= P(x_t \mid c_t, x_{1:t-1}) \sum_{c_{t-1}} \Big(P(c_t \mid c_{t-1}) P(c_{t-1} \mid x_{1:t-1}) \Big) \end{aligned} \tag{3}$$

It shows that the probability of c_t given $x_{1:t-1}$ can be expressed recursively. As shown in Equation 2, the change of segment length c_t between two sequential segments only has two possible outcomes. One is to increase by one based on the segment length c_{t-1}; the other possibility is to drop to 0, which implies a changepoint occurs. The changepoint prior $P(c_t \mid c_{t-1})$ can be modeled based on a hazard function:

$$P(c_t \mid c_{t-1}) = \begin{cases} H(c_{t-1}+1), & \text{if } c_t = 0, \\ 1 - H(c_{t-1}+1), & \text{if } c_t = c_{t-1}+1, \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

where H is a hazard function representing the probability that an event is expected to occur. Assuming that the prior probability distribution of the segment length follows an exponential distribution with timescale λ, the hazard function is actually a constant $1/\lambda$. Then, the posterior probability of x_t conditional on existing observations and current segment length can be expressed as:

$$P(x_t \mid c_t, x_{1:t-1}) = \int_{\theta_{t-c_t:t}} P(x_t \mid \theta_{t-c_t:t}) P(\theta_{t-c_t:t} \mid c_t, x_{1:t-1}) \, d\theta_{t-c_t:t} \tag{5}$$

As x_t follows a binomial distribution, a member of the exponential family distribution, $P(x_t \mid c_t, x_{1:t-1})$ can be estimated based on the beta-binomial distribution as:

$$P(x_t \mid U, \alpha, \beta) = \frac{\Gamma(U+1)\Gamma(x_t+\alpha)\Gamma(U-x_t+\beta)\Gamma(\alpha+\beta)}{\Gamma(x_t+1)\Gamma(U-x_t+1)\Gamma(U+\alpha+\beta)\Gamma(\alpha)\Gamma(\beta)}. \tag{6}$$

where Γ is the Gamma distribution. α and β are hyperparameters of the beta distribution whose probability density function is calculated as:

$$P(\theta \mid \alpha, \beta) = \theta^{\alpha-1}(1-\theta)^{\beta-1} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}, \tag{7}$$

α and β at time t within each segment can be updated based on the run length c_t:

$$\alpha_t^{(c)} = \alpha_0 + \sum_{t' \in c_t} x_{t'}, \tag{8}$$

$$\beta_t^{(c)} = \beta_0 + \sum_{t' \in c_t} x_{t'}, \tag{9}$$

where α_0 and β_0 are predefined prior of the hyperparameters. The above algorithm will be applied to detect the changepoints for each individual.

Model evaluation

The last section shows that there are three predefined parameters of the BOCD method: constant hazard function $1/\lambda$, hyperparameters of the beta distribution α, and β. To select a proper constant hazard function and test the model's sensitivity to the prior hyperparameters, we need some criteria to evaluate the model performance. Assuming that in $x_{1:T}$, we detect k changepoints. The original dataset will then be divided into $k+1$ segments $(X_0, X_1, ..., X_K)$. The likelihood L of the model for each individual can be calculated as:

$$\begin{aligned} L = P(X \mid \Omega, \alpha, \beta) &= \prod_{k=0}^{K} P(X_k \mid \alpha, \beta) \\ &= \prod_{k=0}^{K} \int P(X_k \mid \theta_k) P(\theta_k \mid \alpha, \beta) d\theta_k \\ &= \prod_{k=0}^{K} \prod_{t=u_k}^{u_{k+1}-1} \int P(x_t \mid \theta_k) P(\theta_k \mid \alpha, \beta) d\theta_k \end{aligned} \tag{10}$$

where Ω represents the model we used for changepoint detection. AIC and BIC values can then be calculated as follows:

$$\text{AIC} = 2M(k+1) - 2\ln(L) \tag{11}$$

$$\text{BIC} = \ln(T)M(k+1) - 2\ln(L) \tag{12}$$

where M is the number of the distribution parameter for each segment. T is the number of observed weeks of each individual. The model evaluation is based on the average value of AIC and BIC across all individuals. The lower the AIC and BIC values, the better the model's performance.

Impact of weather on cycling frequency changes

After obtaining the changepoints, the multinomial logit model (MNL) is used to explore the impact of weather conditions on the probability of the three possible choices regarding the change of cycling frequency (measured as number of weekly cycling days) pattern for each user week: choosing to increase, decrease or make no changes in the cycling frequency. The utility U of three alternatives (increase $= i$, decrease $= d$, no changes $= n$) where "no changes" is served as the base alternative is denoted as:

$$U_i = \alpha_i + X\beta_i + \epsilon \tag{13}$$

$$U_d = \alpha_d + X\beta_d + \epsilon \tag{14}$$

$$U_n = \epsilon \tag{15}$$

where α is the alternative specific constant term, X is the vector of weather condition attributes and other control attributes in each week, β is the vector of associated alternative specific parameters, $\epsilon \sim Gumbel(0, 1)$ is the random error term. Let $y \in \{i, d, n\}$ denote the chosen alternative, then the probability of choosing y can be expressed as:

$$P_y = \frac{exp(U_y)}{exp(U_i) + exp(U_d) + exp(U_n)} \tag{16}$$

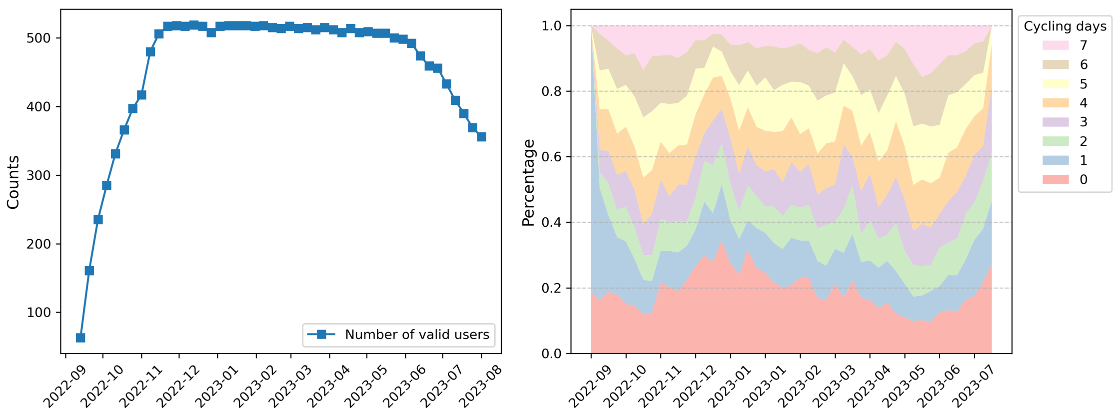
The MNL model is estimated in Biogeme (Bierlaire, 2023).

3 Case study

Longitudinal data description

For the case study, we used a Switerland-wide GPS tracking dataset from EBIS (E-Biking) project (Heinonen et al., 2024). Participants in EBIS project consist of cyclists and e-bikers. This project starts in September 2022, and four to eight weeks of GPS tracking is required to receive the incentive. It also includes a randomized control trial (RCT) to investigate the effect of transport pricing on the mode shift from car to e-bike. After the official experiment period, many participants keep tracking their trajectories, which gives this dataset the potential to investigate the behavior pattern change of cyclists within a long-term period. The post-study participation rate was found to be influenced mainly by the recruitment channel and the mobile operating system but not sociodemographic (Heinonen et al., 2024).

We first select stage records starting and ending in Zurich to reduce the uncontrolled disturbances for investigating the weather effects on cycling frequencies. To ensure the observation period of the users is long enough to detect robust behavioral change, we only selected users with active observation days longer than 210 days. As we are interested in the change in the number of weekly cycling days, we aggregated the data into week-level data based on the number of days with at least one cycling stage in a week. We also removed the records before the first complete calendar week and calendar weeks without any records for each user. Therefore, we ended up with 520 users and, in total, 21446 user weeks from September 2022 to August 2023 for further analysis. The number of observed weeks of users ranges from 31 to 47 (on average 41.2) weeks. The number of valid users in each week during othe bservation period is shown in Figure 1(a). Figure 1(b) shows the overall share of weekly cycling days during the observation period. There is an increasing share of higher weekly cycling days. This may be motivated by the official experiment of the first four to eight weeks. Participants reduced their weekly cycling days in the winter, especially during the Christmas break. After that, the weekly cycling days grew gradually, followed by a decreasing trend since late June. The following section will apply the BOCD method to detect the pattern change in individual-level weekly cycling days.



(a) Number of valid users (b) Share of weekly cycling days

Figure 1: Distributions of number of observed weeks per person

Changepoints detection

Among 520 users, the average number of detected changepoints is 2.3 (14% of users with zero changepoint, 25% of users with one changepoint, 19% of users with two changepoints, 18% of users with three changepoints, and 24% of users with four and more changepoints. Figure 2 shows the trajectory of every two adjacent changepoints for all users during the observation period. The red curve bridges two changepoints where the first changepoint is an increasing changepoint, and it represents the period with increasing cycling frequencies compared to the previous period. In contrast, the blue curve represents the period with decreasing cycling frequencies compared to the previous period. The size of the point along the timeline indicates the ratio of changepoints to the number of valid users for each week. Red points for the ratio of increasing changepoints and blue points for the decreasing changepoints. Although the trajectory pattern of changepoints seems quite diverse, we could still observe that many users started to increase their regular cycling frequencies during the official experiment period and then decrease their cycling frequencies during December and January. Cycling frequencies were relatively stable from January to April, and the observed changes were mixed across all users. Since April, both the ratio of increasing and decreasing changepoints have increased. The ratio of increasing changepoints peaks at the end of

May, while the ratio of decreasing changepoints peaks in mid-July.

In our BOCD algorithm, the constant hazard value λ is set to 25, and the initial parameters α_0 and β_0 of beta distribution are set to 1.0. The selection of constant hazard value is based on multiple model performance indicators. We tested our model with constant hazard values from 5 to 55 with an interval of 5. The average Log-likelihood, average AIC, and average BIC across all users were calculated as shown in Figure 3. We selected 25 because the average AIC and average BIC values are almost leveled after 25, and there is not much loss in average Log-likelihood compared to the best value. In our case, the intuition of the constant hazard value equals 25 is that a person's regular cycling frequency is expected to change after 25 weeks. We also tested the sensitivity of the initial distribution parameters as shown in Figure 4. The Discrepancy of the ratio of changepoints with different initial values of β only occurs at the beginning of two months. Changepoints detected within the group of lower value of β_0 are not captured anymore within the group of higher value of β_0, as the beta distribution with higher value of β indicates the distribution of the probability parameter in Bernoulli distribution is more skewed to 0. This may imply the disturbances or uncertainties in the model brought by the official experiment period.

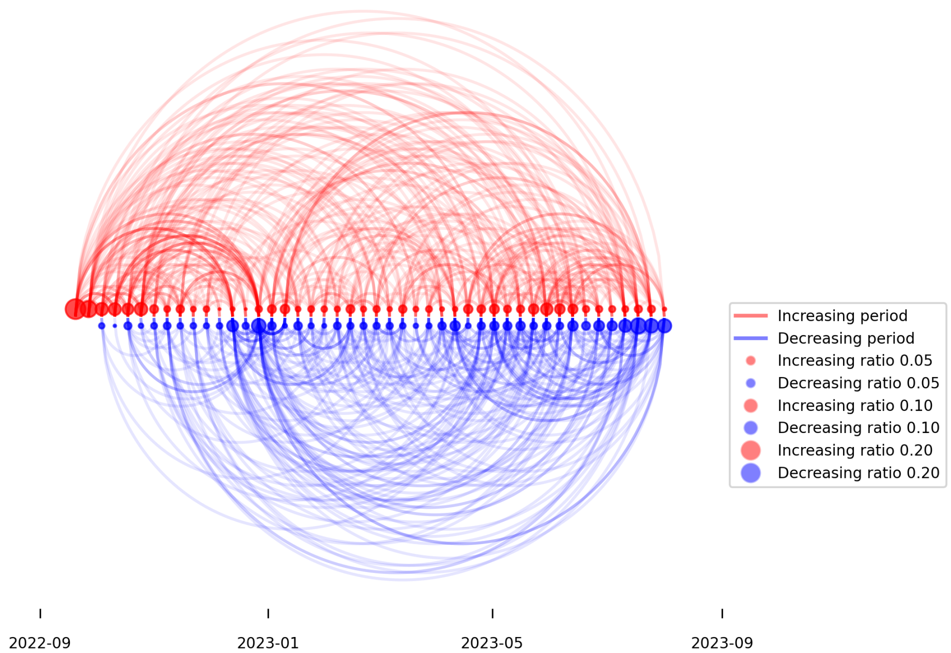


Figure 2: Trajectory of adjacent changepoints for users and ratio of changepoints

Weather effect

Weather data used in this study is from a public website (`https://www.visualcrossing.com/weather-history/Zurich,Switzerland`). We aggregate the value of daily weather attributes across the week into the weekly average. Table 1 summarizes the statistics of six main weather attributes we considered in our model.

Table 1: Summary statistics of weekly average value of weather attributes

Variable	Min	Q1	Q2	Q3	Max	Mean	Std
Temperature (°C)	-1.8	7.8	12.8	19.1	24.3	12.7	7.1
Precipitation (mm)	0.0	0.6	2.0	3.9	12.9	2.7	2.7
Snow (mm)	0.0	0.0	0.0	0.0	0.7	0.0	0.1
Windspeed (km/h)	6.8	12.1	13.9	16.5	28.3	14.8	4.1
Humidity (%)	42.3	64.3	72.9	77.7	92.1	71.3	11.2
Cloudcover (%)	3.0	40.6	53.6	71.0	89.6	53.9	19.5

The advantage of using the BOCD method for behavior change detection is to eliminate the impact of behavior anomalies and to identify robust pattern change. However, the effect of the official experiment period and long holidays also seems to be captured from the changepoint detection results. To control the impact of these two major external factors on all users, we introduce two binary control variables in our model. The first variable, 'holiday,' is set to 1 for three weeks during Christmas and New Year break and two weeks during Easter. The second variable, 'experiment,' is set to 1 for the official experiment period of each user (first 4 to 8 weeks, depending on the user group). For average weekly weather attributes, we considered the current week's value and the difference between the current week and the previous week. Weather attributes with correlation coefficients greater than 0.5 are excluded in our model to avoid multicollinearity. Two models, one with constant and control variables only and the other with additional weather attributes are estimated as shown in Table 2. As the share of having an increasing changepoint (3.81%) and a decreasing changepoint (3.88%) across observations is low, the utility of having a changepoint is mainly contributed by the negative constant term. This indicates that the regular cycling frequency is stable in our sample. Two control variables are significant, with the negative effect of the holiday period and the positive effect of the official experiment period on the utility of having an increasing changepoint, and their effects on the utility of having an increasing changepoint being adverse. Increasing snow has a significant negative effect on increasing changepoints and a positive effect on decreasing changepoints. Higher precipitation only impacts decreasing changepoints positively. The temperature has a positive effect on both types of changepoints, which may imply heterogeneous preferences for the temperature consistent with Miranda-Moreno & Nosal (2011) and de Kruijf et al. (2021). Unintuitively, a larger windspeed would reduce the probability of decreasing changepoints. Increasing temperature and humidity compared to the previous week would increase the probability of decreasing changepoints.

Table 2: Model estimation results

		Control variables			Control & weather variables		
Alternative	Variable	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value
Increasing changepoint	Constant	**-3.725**	0.052	0.000	**-3.899**	0.197	0.000
	Control variables						
	Holiday period (binary)	**-0.596**	0.174	0.001	**-0.497**	0.197	0.012
	Experiment period (binary)	**1.117**	0.091	0.000	**1.122**	0.093	0.000
	Average						
	Temperature (°C)				**0.037**	0.008	0.000
	Precipitation (mm)				0.001	0.023	0.950
	Snow (mm)				**-2.158**	0.575	0.000
	Windspeed (km/h)				-0.012	0.013	0.330
	Difference compared to previous week						
	Temperature (°C)				0.004	0.017	0.805
	Humidity (%)				-0.014	0.008	0.093
	Cloudcover (%)				0.000	0.003	0.992
Decreasing changepoint	Constant	**-3.504**	0.047	0.000	**-4.415**	0.226	0.000
	Control variables						
	Holiday period (binary)	**0.358**	0.112	0.001	**0.872**	0.131	0.000
	Experiment period (binary)	**-1.328**	0.224	0.000	**-1.360**	0.229	0.000
	Average						
	Temperature (°C)				**0.077**	0.009	0.000
	Precipitation (mm)				**0.116**	0.020	0.000
	Snow (mm)				**1.928**	0.397	0.000
	Windspeed (km/h)				**-0.028**	0.011	0.011
	Difference compared to previous week						
	Temperature (°C)				**-0.111**	0.019	0.000
	Humidity (%)				**-0.027**	0.008	0.001
	Cloudcover (%)				0.002	0.004	0.638
Number of observations		21446			21446		
Log-likelihood		-5240			-5121		
Adjusted		0.777			0.782		
BIC		10541			10441		

Note: estimates highlighted in bold have a p-value no greater than 0.05.

To reveal the impact of different weekly average weather attributes on the probabilities of having changepoints more straightforwardly, we calculated the predictive probability for each type of changepoint under several weather conditions as shown in Table 3. The medium value of each weather attribute was used in the base scenario, and we tested scenarios where one of the attributes was changed to its minimum or maximum value. In the base scenario, the probability of increasing and decreasing changepoints are 3.06% and 2.61%, respectively. Overall, the change in weather conditions has a larger impact on the probability of increasing change points. For increasing changepoints, its probability is the lowest during 'extreme' snowy and rainy weather and highest during high temperatures, and other attributes have marginal effects within the range of their observed values. For decreasing changepoints, its probability is the highest, with four times the base scenario during 'extreme' snowy weather, followed by 'extreme' rainy weather and high temperatures. Its probability is the lowest during the 'extreme' cold weather.

Table 3: Predictive probability under different weather conditions

Temperature (°C)	Precipitation (mm)	Snow (mm)	Windspeed (km/h)	Temperature difference(°C)	Probability of increase (%)	Probability of decrease (%)
12.8	2.0	0.0	13.9	0.0	3.06	2.61
-1.8	2.0	0.0	13.9	0.0	1.84	0.87
24.3	2.0	0.0	13.9	0.0	4.43	6.00
12.8	**0.0**	0.0	13.9	0.0	3.08	2.09
12.8	**12.9**	0.0	13.9	0.0	2.87	8.69
12.8	2.0	**0.7**	13.9	0.0	0.60	10.06
12.8	2.0	0.0	**6.8**	0.0	3.04	3.16
12.8	2.0	0.0	**28.3**	0.0	3.09	1.76
12.8	2.0	0.0	13.9	**-5.0**	3.00	4.46
12.8	2.0	0.0	13.9	**6.3**	3.10	1.31

Note: values in bold are different from the medium value of the attributes in the base scenario.

4 Conclusions and future work

This study explored the impact of weather conditions on the change in individual-level regular cycling frequencies (measured as weekly cycling days) by 1) identifying the robust changepoints of cycling frequencies using the Bayesian online changepoint detection (BOCD) method and 2) statistically estimating the effect of different weather attributes on the probability of having an increasing or decreasing changepoint using multinomial logit (MNL) models.

We tested our methods on a Swiss GPS tracking dataset targeting bike or e-bike owners. A sub-dataset for records in Zurich consisting of 520 users and 21446 user weeks was used for our case study. Cycling frequencies were found to be relatively stable in our sample. The robustness of the algorithm was proved by testing different initial distribution parameters. On average, 2.3 changepints were detected during 31 to 47 weeks. Estimation results of MNL models show significant impacts of weather conditions on changepoint probabilities after controlling the influence of long-term holidays and experiment periods. The probability of decreasing changepoints is more affected than increasing changepoints by weather conditions. Snow and precipitation have the most significant positive effect on decreasing regular cycling frequencies and the most significant negative effect on increasing regular cycling frequencies. The temperature has a similar impact on both types of changepoints, with the cycling frequency changes more likely to occur in higher temperatures and less likely in lower temperatures. Cyclists also have a lower probability of decreasing their cycling frequencies when the temperature is increasing than the previous week. Windspeed has an unexpected negative effect on decreasing changepoints, which may be related to the difference between windspeed measurement and the perception of cyclists due to the hilly topography of Zurich.

There also exist several limitations. The proposed framework was only tested in a single city, and the sample is biased toward the male, highly educated, and high-income urban populations (Heinonen et al., 2024). The observation period was less than one year. Although major external factors that may cause long-term behavioral change were controlled in the model, factors such as home location change were not considered. For future work, it would be interesting to extend the MNL model to 1) consider the nonlinear-in-parameter effect or threshold effect of the continuous weather attributes, 2) explore the time lag effect of the weather change, and 3) capture the heterogeneity of weather impacts on people with different sociodemographics and travel and time use habits.

Appendix

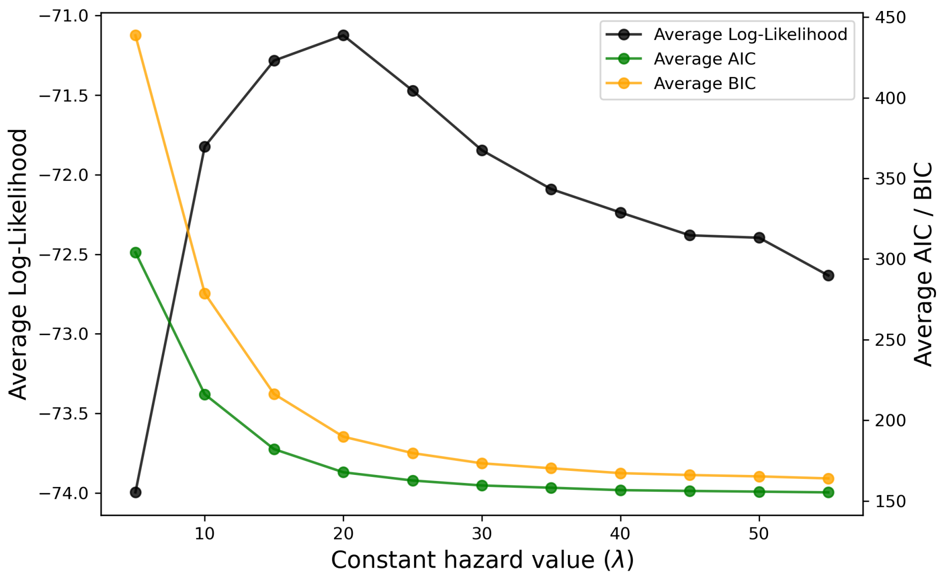


Figure 3: Model evaluation for different prior hazard constant (λ)

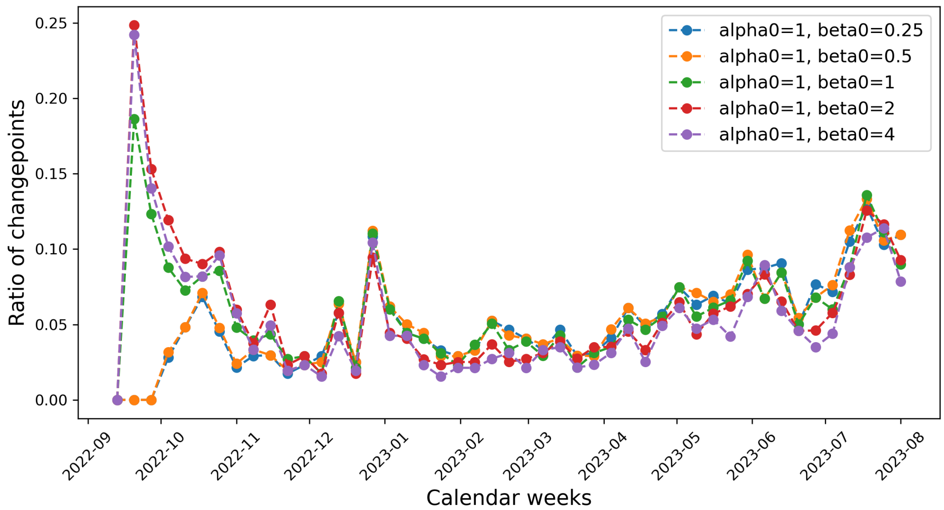


Figure 4: Ratio of changepoints with different initial hyperparameters

References

Bierlaire, M. (2023). A short introduction to biogeme. *Transport and Mobility Laboratory, ENAC, EPFL.*

Böcker, L., Dijst, M., & Prillwitz, J. (2013). Impact of everyday weather on individual daily travel behaviours in perspective: a literature review. *Transport reviews*, *33*(1), 71–91.

Cherchi, E., & Cirillo, C. (2014). Understanding variability, habit and the effect of long period activity plan in modal choices: a day to day, week to week analysis on panel data. *Transportation*, *41*, 1245–1262.

de Kruijf, J., van der Waerden, P., Feng, T., Böcker, L., van Lierop, D., Ettema, D., & Dijst, M. (2021). Integrated weather effects on e-cycling in daily commuting: A longitudinal evaluation of weather effects on e-cycling in the netherlands. *Transportation research part A: policy and practice*, *148*, 305–315.

Heinonen, S., de Freitas, L. M., Meister, A., Schwab, L., Roth, J., Hintermann, B., … Axhausen, K. (2024). The e-biking in switzerland (ebis) study: methods and dataset. *Transportation*, 1–24.

Hudde, A. (2023). It's the mobility culture, stupid! winter conditions strongly reduce bicycle usage in german cities, but not in dutch ones. *Journal of Transport Geography*, *106*, 103503.

La Paix, L., Oakil, A. T., Hofman, F., & Geurs, K. (2022). The influence of panel effects and inertia on travel cost elasticities for car use and public transport. *Transportation*, *49*(3), 989–1016.

Meng, M., Zhang, J., Wong, Y. D., & Au, P. H. (2016). Effect of weather conditions and weather forecast on cycling travel behavior in singapore. *International journal of sustainable transportation*, *10*(9), 773–780.

Miranda-Moreno, L. F., & Nosal, T. (2011). Weather or not to cycle: Temporal trends and impact of weather on cycling in an urban environment. *Transportation research record*, *2247*(1), 42–52.

Motoaki, Y., & Daziano, R. A. (2015). A hybrid-choice latent-class model for the analysis of the effects of weather on cycling demand. *Transportation Research Part A: Policy and Practice*, *75*, 217–230.

Tyndall, J. (2022). Cycling mode choice amongst us commuters: The role of climate and topography. *Urban Studies*, *59*(1), 97–119.

Zhao, Z., Koutsopoulos, H. N., & Zhao, J. (2018). Detecting pattern changes in individual travel behavior: A bayesian approach. *Transportation research part B: methodological*, *112*, 73–88.