Insights from E-bike adoption in Denmark: A 10-year synthetic pseudo-panel analysis

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1 Introduction

Micromobility is reshaping travel patterns in cities around the world, influencing how individuals access activities and interact with the built environment. E-bikes have emerged as a particularly significant mode, alongside e-scooters. They offer opportunities to reduce emissions, improve accessibility, and promote more sustainable travel behaviour, while simultaneously challenging established transport modes such as private cars, public transport, and conventional bicycles. Understanding the adoption and usage of e-bikes is therefore crucial for developing effective transport strategies and policies.

E-bike diffusion is shaped by a combination of socio-demographic, spatial, and infrastructural factors, making it a complex and heterogeneous process. International evidence demonstrates that adoption patterns vary substantially across regions and population groups. In contexts with strong cycling traditions, such as the Netherlands, e-bikes have become a mainstream mobility option, influencing overall cycling levels and travel distances [Kroesen, 2017, Sun et al., 2023, de Haas et al., 2020]. Meanwhile, studies from North America and Asia highlight different dynamics in which e-bikes often substitute for car or public transport trips, reflecting contrasting baseline mobility cultures [Fishman and Cherry, 2016, Cherry et al., 2009, Weinert et al., 2007]. Longitudinal research further points to potential changes in daily mileage following adoption, though the persistence and long-term behavioural impacts remain uncertain [Fyhri et al., 2017].

In the Danish context, existing research indicates that e-bike trips tend to be longer than conventional bicycle trips and that adoption mechanisms differ across age groups and travel purposes [Haustein and Møller, 2016, Argyros et al., 2026]. However, it is still unclear if they can counteract the declining cycling trends observed among certain cohorts [Rich et al., 2023]. These trends position Denmark as an important case for analysing e-bike adoption and its interaction with existing transport behaviours.

Our study provides significant insights by improving the understanding of who adopts e-bikes, under what conditions, and how these behaviours vary across socio-demographic and geographic segments over a 10-year period, by filtering out socioeconomic variations across the survey period. The finding can assist policymakers in better anticipating future mobility patterns and designing targeted interventions that support national climate, health, and accessibility objectives.

2 Methodology

This study applies a *Synthetic Pseudo-Panel* (SPP) approach to analyse e-bike adoption using repeated cross-sectional data [Borysov and Rich, 2021, Deaton, 1985]. The method combines generative modelling with reallocation analyses to reconstruct coherent behavioural trajectories without requiring true longitudinal observations. It can support policy design by isolating behavioural trends from population changes, allowing a clearer identification of groups and areas with high e-bike potential.

2.1 Synthetic pseudo-panels

Traditional pseudo-panels rely on cohort aggregation, which can introduce noise and obscure heterogeneity [Verbeek, 1996]. In contrast, SPPs approximate the conditional distribution of travel preferences V,

$$P(V \mid S, X, t),$$

where S denotes socio-demographic variables, X contextual factors (e.g. accessibility), and t the time period. By keeping S fixed and varying (X, t), we simulate how the same population would respond under different system states (i.e. time and accessibility conditions).

To estimate the conditional distribution, we employ a *Conditional Variational Autoencoder* (CVAE) [Kingma and Welling, 2013, Borysov and Rich, 2021]. The encoder produces an approximate posterior,

$$q_\phi(z \mid v, s, x, t),$$

mapping observed preferences v to latent variables z, while the decoder reconstructs synthetic outcomes:

$$\tilde{v} \sim p_\theta(v \mid z, s, x, t).$$

The model is trained by minimising the ELBO, combining reconstruction accuracy with a KL-divergence regularisation term, using the β-VAE formulation [Higgins et al., 2017].

Given that travel data exhibit structural zeros (i.e. zero trips imply zero distance) to preserve logical consistency, trip counts are modelled categorically. In contrast, positive distances are generated from Gamma distributions, ensuring realistic combinations of trips and distances in the generated behavioural trajectories. This two-part structure is conceptually similar to Heckman-style selection models [Heckman, 1976] and prevents infeasible trip–length combinations.

2.2 Generating preference trajectories

Once trained, the CVAE is used to generate synthetic trajectories for each individual across all survey years, meaning the analysis reflects behavioural changes under a stable population composition rather than demographic shifts. For each mode $m \in \mathcal{M}$, the decoder outputs:

$$\left(\tilde{q_m}, \tilde{\ell_m}\right) \subseteq \tilde{v}_m,$$

where q_m parameterizes the categorical distribution over trips, and ℓ_m parameterizes a Gamma distribution for positive lengths.

For each time period t, we draw multiple samples conditional on fixed socio-demographic attributes, yielding annual aggregates such as: mode-specific trips (Q^t_m), mileage (D^t_m), average trip lengths (L^t_m), modal shares (C^t_m), mileage shares (Ψ^t_m). This procedure reflects aggregated behavioural change due solely to temporal and contextual factors.

Finally, we analyse preference reallocation between modes. The primary mode for individual i in time period t is:

$$m^*_i(t) = \arg\max_m \mathbb{E}[\tilde{q}^t_{im} \tilde{\ell}^t_{im}].$$

Then, transition matrices are constructed across states to capture shifts between modes, including induced demand from individuals who were previously non-travellers. This reveals which modes gain or lose preference towards another during the e-bike diffusion period.

3 Results and Discussion

This section presents the outcomes of the SPP analysis and discusses their implications for understanding e-bike adoption dynamics in Denmark. Using the Danish National Travel Survey (TU) [Anderson and Christiansen, 2024], we reconstructed synthetic cohorts based on stable socio-demographic attributes and examined how their propensity to adopt e-bikes evolves over time.

The TU continuously monitors travel behaviour in Denmark using a representative sample of one-person, one-day interviews collected year-round. For this study, we use data from 2015 onward, when e-bike usage was first recorded. We include respondents aged 10–84 and group travel modes into walking, biking, e-biking, car (driver), car (passenger), and public transport. After excluding international trips and cases with missing information, the final dataset contains 96,238 observations from 2015–2025, with annual sample sizes ranging from 8,273 to 11,076.

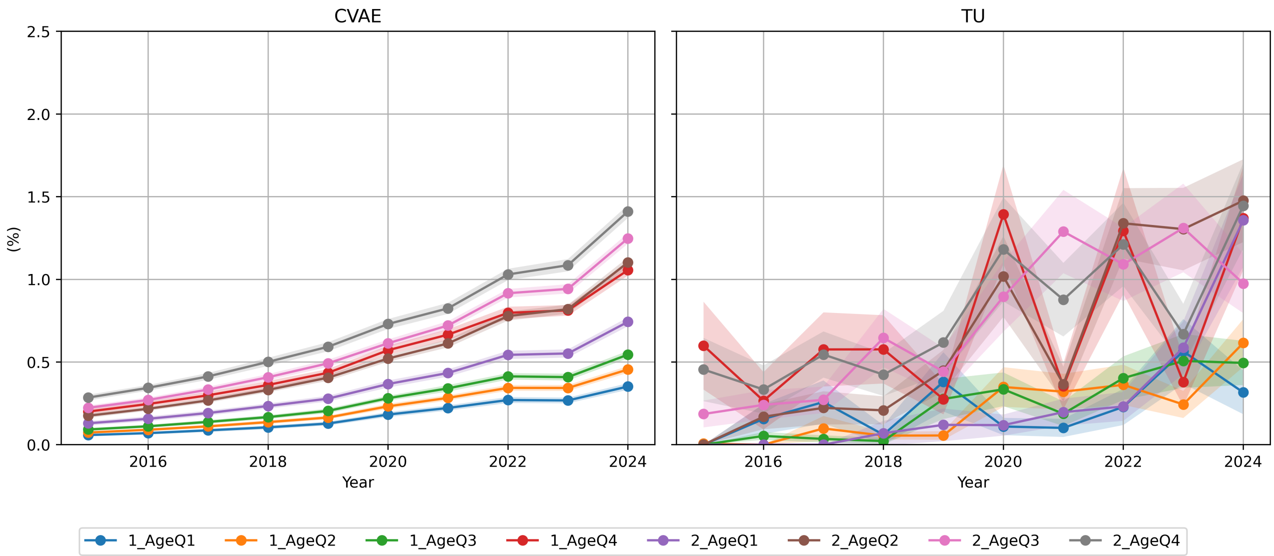

Figure 1: E-bike mileage share based on gender ((1): male and (2): female) and age quartiles (Q1–Q4). The first plot represents estimates from the CVAE model, while the second represents the TU. Shaded areas indicate st. deviation, derived from 100 samples for CVAE and 100 weighted bootstraps for TU.

E-bike adoption has increased steadily since 2015, with trip share rising from 0.4% to 2.1% and mileage share from 0.1% to 0.8% (Figure 1). Adoption differs markedly across demographic groups: elderly females show the highest levels (3.3%), while young males remain the lowest adopters, and the synthetic panel provides a clearer depiction of these cohort trends by reducing sampling noise in the TU. Spatial variation is similarly strong, with urban and suburban areas exhibiting earlier and more substantial uptake, often exceeding 2% mileage share, and peripheral zones around Aarhus and Copenhagen showing the highest adoption levels.

Table 1 further highlights systematic differences in the uptake development across socioeconomic and travel-related segments. The oldest quartile (Q4) increases its e-bike mileage share by 0.99% compared with 0.45% for the youngest (Q1), reflecting the higher utility of electric assistance among older adults. Lower-income groups show relatively larger increases, suggesting that e-bikes help overcome affordability constraints. Households without car access experience the largest rise in e-bike mileage share (from 0.55% to 2.30%), more than double that of single-car households (1.10%). Furthermore, zones with different accessibilities mirror the broader spatial patterns, with high-accessibility areas showing the strongest growth. Lastly, trips for other trip purposes see slightly larger gains (0.94%) than work or education trips (0.71%), indicating that e-bikes support a wide range of activities beyond commuting.

Table 1: E-bike adoption in (% shares of total mileage) across different cohorts.

	2015 (SD)		2024 (SD)		Increase		2015 (SD)		2024 (SD)		Increase
Gender											
Male	0.10	(0.00)	0.57	(0.01)	0.47	Female	0.20	(0.01)	1.13	(0.02)	0.93
Age											
Q1	0.09	(0.01)	0.54	(0.02)	0.45	Q3	0.15	(0.01)	0.87	(0.02)	0.72
Q2	0.12	(0.01)	0.75	(0.02)	0.63	Q4	0.24	(0.01)	1.23	(0.03)	0.99
Income Family											
Q1	0.22	(0.01)	1.06	(0.02)	0.85	Q3	0.12	(0.01)	0.71	(0.01)	0.59
Q2	0.15	(0.01)	0.84	(0.02)	0.69	Q4	0.13	(0.01)	0.80	(0.02)	0.67
Home Car ownership											
0	0.55	(0.03)	2.30	(0.06)	1.75	2	0.05	(0.00)	0.38	(0.01)	0.32
1	0.18	(0.01)	1.10	(0.02)	0.92	3+	0.04	(0.01)	0.25	(0.02)	0.21
Accessibility (car)											
Q1	0.11	(0.01)	0.65	(0.01)	0.52	Q3	0.13	(0.01)	0.66	(0.01)	0.55
Q2	0.12	(0.01)	0.72	(0.02)	0.61	Q4	0.26	(0.02)	1.49	(0.02)	1.23
Purpose											
Work/Edu.	0.11	(0.01)	0.71	(0.02)	0.60	Other	0.17	(0.01)	0.94	(0.01)	0.77

Beyond the overall adoption trends, the reallocation of underlying primary mode preferences shows that bicycles remain the largest proportional source of new e-bike users. In 2024, approximately 19% of e-bike adopters previously relied on cycling, and although similarly large groups shifted from car drivers (24%) and from car passengers (15%), the transition is more pronounced for cyclists when measured relative to their smaller baseline population in 2015. In other words, only about 0.5% of all 2015 car drivers became primary e-bike users, whereas roughly 2% of cyclists made the same shift.

Smaller but still meaningful contributions originate from public transport and walking, accounting for around 8% and 12% of new e-bike users, respectively. These figures show that e-bikes are becoming more and more popular among people with a variety of travel habits, not just those who are inclined to cycle. A further share of adopters had no trips in 2015, pointing to a modest level of induced demand as e-bikes become embedded in everyday mobility.

Taken together, these patterns show that e-bikes extend the reach of existing cyclists while also drawing in a non-negligible group of former car users. This distribution of new users highlights where e-bike uptake can most effectively support Denmark's national mobility and climate objectives, particularly in suburban and high-accessibility areas where shifts from car use can yield substantial benefits.

While our results provides a clearer view of behavioural developments by filtering out socio-demographic noise (e.g. increasing car ownership and ageing population), the approach also has limitations. The method learns from available cross-sectional data and therefore cannot fully capture long-term behavioural persistence or structural changes outside the range of observed conditions. Forecasts beyond the historical period should thus be interpreted with caution.

Additionally, the reallocation patterns reflect shifts in predicted preference distributions rather than verified behavioural transitions, and further validation with longitudinal data would strengthen the interpretation of substitution effects. Future work could integrate policy scenarios, explore the role of infrastructure, and combine the SPP with theory-driven diffusion models to predict longer-term adoption. This would support more detailed evaluations of how different measures may accelerate e-bike use across Danish regions and population groups.

4 Conclusion

This study applied an SPP approach to the TU to analyse how e-bike adoption has evolved across demographic and spatial segments in Denmark. By reconstructing consistent behavioural trajectories from repeated cross-sectional data, the SPP framework provides a clearer picture of underlying mobility trends than raw survey samples, which are affected by sampling noise and sociodemographic shifts.

E-bike adoption has increased steadily since 2015, with pronounced differences across gender, age, and residential context. Elderly females show the highest uptake, while young males remain the lowest adopters, and urban and suburban areas exhibit earlier and stronger growth than rural regions. These patterns highlight the growing role of e-bikes in medium-distance mobility and their substitution potential for trips that are less suited to conventional bicycles.

The results illustrate the value of synthetic panels for mobility research, enabling the detection of stable long-term patterns and cohort-specific dynamics that are not directly observable in cross-sectional data. While the analysis remains descriptive, the findings offer a robust empirical basis for understanding the diffusion of e-bikes in Denmark and provide a foundation for future work exploring policy impacts, infrastructure effects, and behavioural transitions.

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