Synthetic Population Generation:

From Hierarchical Snapshots to Panel Data

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Seminar at Université Gustave Eiffel
Paris

3rd March, 2026

EPFL

Outline

Motivation: Synthetic Data Generation

The quality of the input data determines the quality of the model outputs

Data collections: surveys, census, mobile phone tracking...

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- High cost of data collection
- Lack of representativity
- Data privacy constraints

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Solution: Synthetic data!

- Open source
- Bias correction
- Privacy preservation

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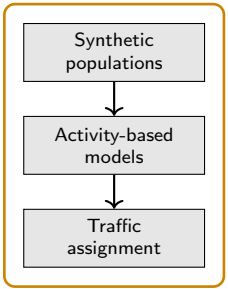
Limitations	**Solution: Synthetic data!**
High cost of data collection	Open source
Lack of representativity	Bias correction
Data privacy constraints	Privacy preservation

Synthetic population = tabular data describing socio-demographics of individuals and households

Motivation: Synthetic Population in Transportation

Literature: Synthetic populations (SynPop) provide the **input** needed for **Activity-Based Models** (ABMs) (Castiglione et al., 2014; La et al., 2025).

Travel demand modeling



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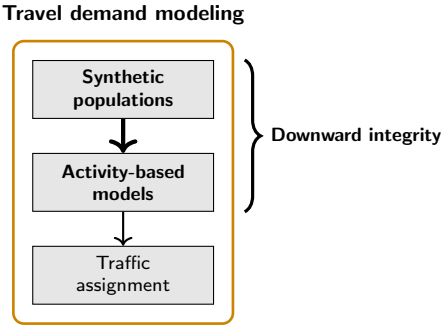

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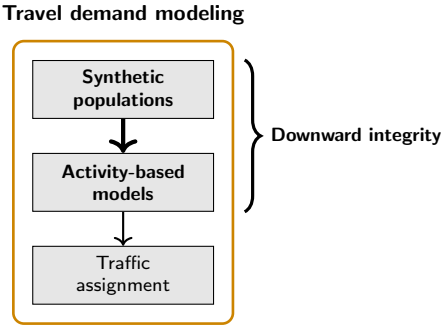

Practice: Most ABMs still **rely on real data** (Tajaddini et al., 2020) and **limitations** in SynPop methods **constrain** its **integration** into practical applications (Ramadan and Sisiopiku, 2019; La et al., 2025).

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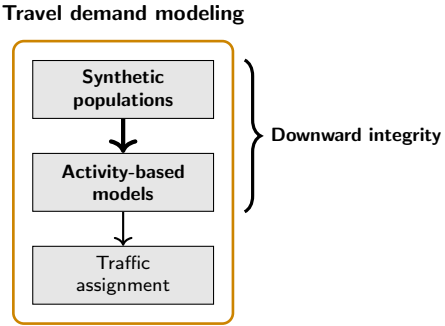

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Theoretical connection → But better integration of SynPop needed?

Motivation: Literature review on SynPop & ABMs

Research questions

- What is the interconnected development in both fields?
- Can advances in SynPop enhance adoption of ABMs?

Kukic, Marija, Rezvany, Negar, Bierlaire, Michel. *A Review of Activity-Based Disaggregate Travel Demand Models*. **Findings**, December 2024. **https://doi.org/10.32866/001c.125431**.

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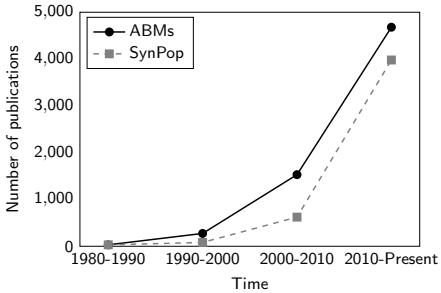

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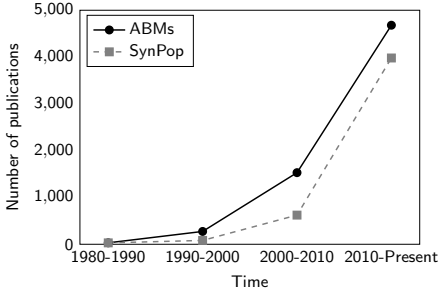

Key findings

- ABMs and SynPop methods: co-evolved and coupled.
- Most existing work: **individual-level** and **single-period**.

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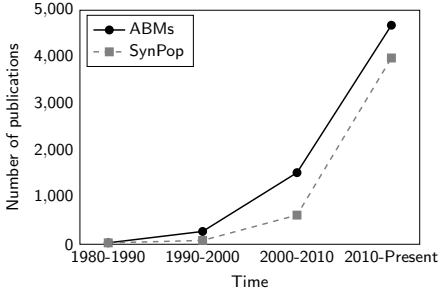

Key findings

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What are the implications of ignoring **multi-person** *and* **multi-period** *modeling contexts in SynPop?*

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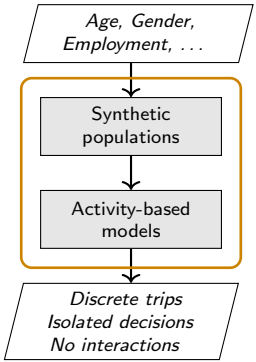
Motivation: Multi-person (Hierarchical) modeling

(1) Individual-level (single-level)



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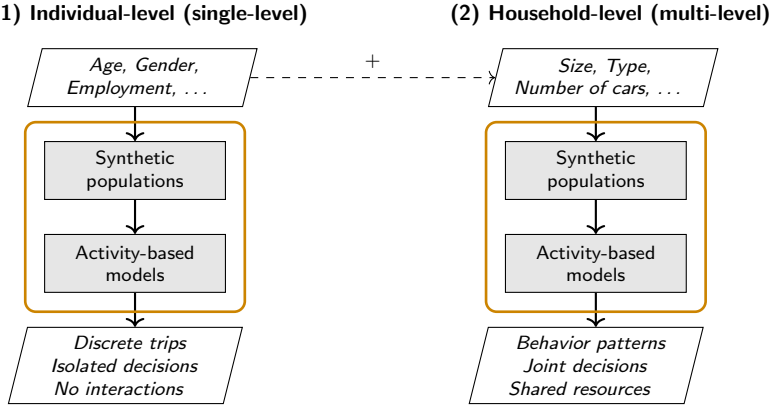

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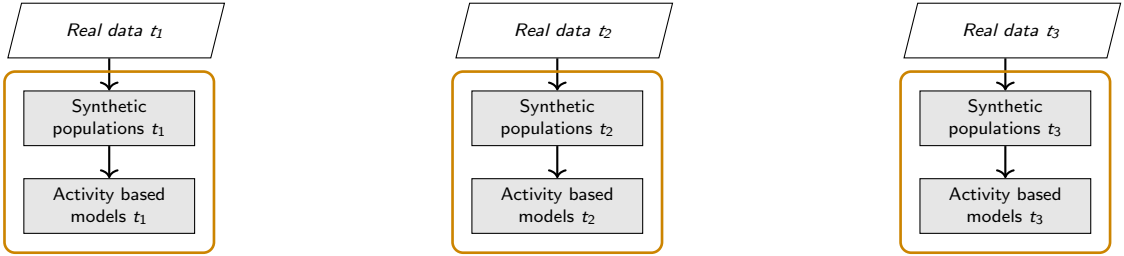

Synthetic static snapshots $\Rightarrow$ Regenerated from scratch!

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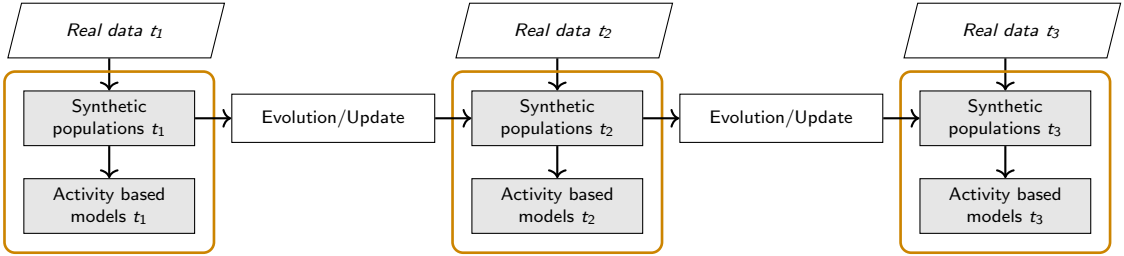

Real populations **evolve gradually** $\Rightarrow$ Can we also evolve a synthetic population?

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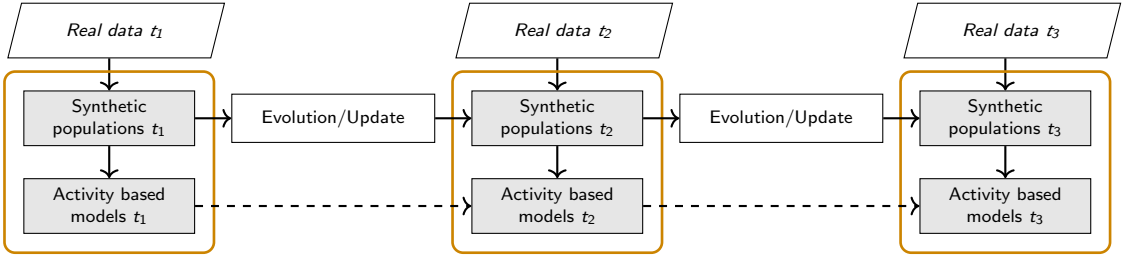

Most transport models recreate travel behavior from scratch each time the model runs (Ahmed and Moeckel, 2023).

Next-generation ABMs require **multi-year, evolving population inputs** (Haghighi and Miller, 2025).

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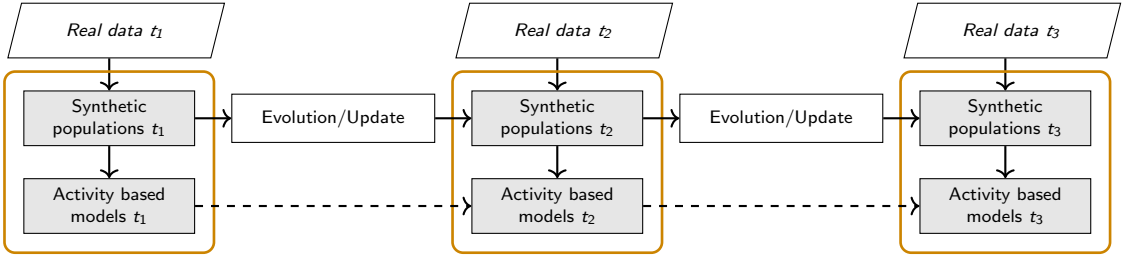

Can we **generate hierarchical** synthetic populations
that **evolve** at both the **aggregated** and **disaggregated** levels,
providing a foundation for next-generation models that can also adjust incrementally?

Research Overview: Gaps and Contributions

Generation of Synthetic Households

Question

How to generate **diverse**, **consistent**, **extendable** households?

Contribution

One-step Gibbs sampler

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Adaptive Synthetic Household Generation

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How to move from **regeneration** to **incremental** updates?

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Adaptive Gibbs-resampling

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Generating Synthetic Panel Data

Question

How to generate **synthetic panels** without real panels?

Contribution

Universal event–duration model

Research Overview: Gaps and Contributions

Generation of Synthetic Households	**Adaptive Synthetic Household Generation**	**Generating Synthetic Panel Data**
Kukic, Marija, Li, Xinling, Bierlaire, Michel. *One-step Gibbs Sampling for the Generation of Synthetic Households.* **Transportation Research Part C: Emerging Technologies**, 166:104770, September 2024. ISSN 0968-090X. **https://doi.org/10.1016/j.trc.2024.104770**.	Kukic, Marija, Bierlaire, Michel. *Adaptive Synthetic Generation using One-Step Gibbs Sampler.* **Transportation Research Interdisciplinary Perspectives**, 33:101597, September 2025. ISSN 2590-1982. **https://doi.org/10.1016/j.trip.2025.101597.**	Kukic, Marija, Bierlaire, Michel. *Simulation framework for generating synthetic panel data.* **Technical Report TRANSP-OR 251013**, Transport and Mobility Laboratory, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland, 2025.

From Hierarchical Snapshots to Panel Data!

Research Overview: From Hierarchical Snapshots to Panel Data

Generating Snapshot of Individuals

t = 2021

$[a_1, g_1, e_1, \dots]$

$[a_2, g_2, e_2, \dots]$

$[a_3, g_3, e_3, \dots]$

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Generating Hierarchical Snapshot

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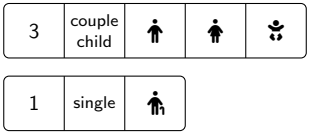

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Generating Hierarchical Snapshot

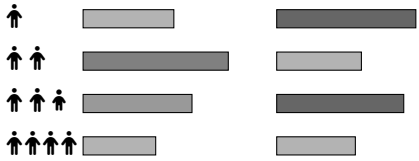
t = 2021

3	couple child			

1	single	

Evolution on Aggregated Level

t = 2021 t = 2025



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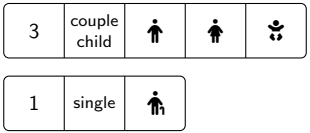
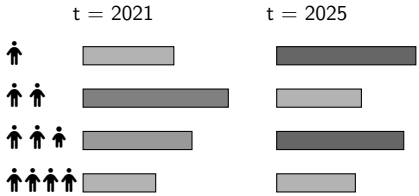
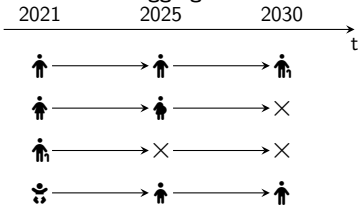


Evolution on Aggregated Level



Evolution on Disaggregated Level



Outline

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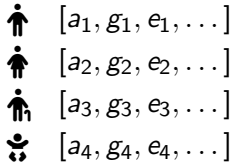
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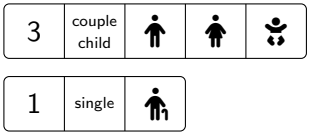
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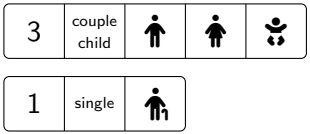

Literature (Yaméogo et al., 2021):

- Match marginals at both levels.
- Links within the same household.
- Relationships between households and individuals **most suitably?**

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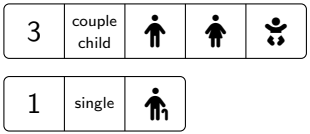

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- No constraints on input data.
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- Work with small samples.
- Stochastic → heterogeneous population.

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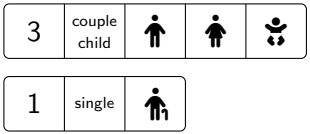

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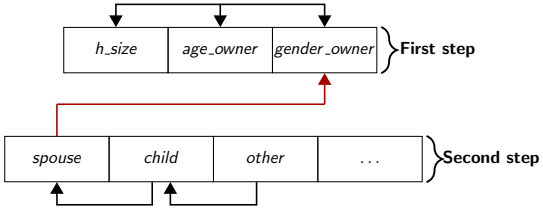
Despite beneficial properties → Rarely used?

Existing methods: Gaps



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  $\Rightarrow$ Limited diversity, illogical households.

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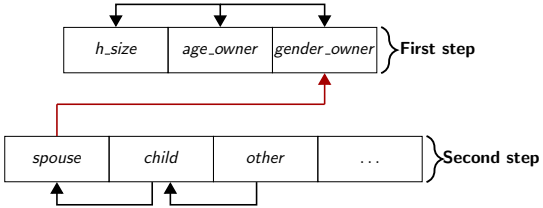

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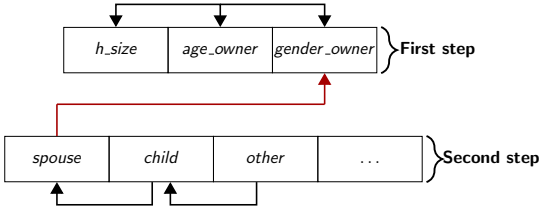

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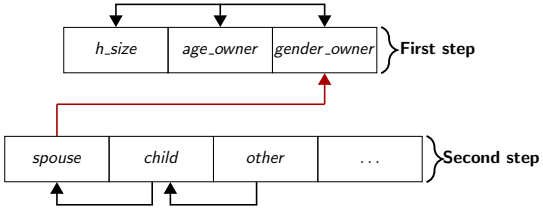

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Is there an alternative way that addresses these limitations?

Methodology: One-step method

Population as a multidimensional random vector capturing all relevant attributes

N=1	Z_t	Z_c	$[X_{1a}, X_{1g}, X_{1m}, X_{1e}, X_{1l}]$	
N=2	Z_t	Z_c	$[X_{1a}, X_{1g}, X_{1m}, X_{1e}, X_{1l}]$	$[X_{2a}, X_{2g}, X_{2m}, X_{2e}, X_{2l}]$
⋮				
N=n	Z_k	$\cdots$	$[X_{1a}, X_{1g}, X_{1m}, X_{1e}, X_{1l}]$	$\cdots$ $[X_{na}, X_{ng}, X_{nm}, X_{ne}, X_{nl}]$

One-step method:

- Joint model for the household (sorted by age)
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How to handle these problems?
Simplification of full conditionals + Decomposition on household size!

Methodology: Modeling simplifications & Decomposition

$\pi(A, B, C, D)$

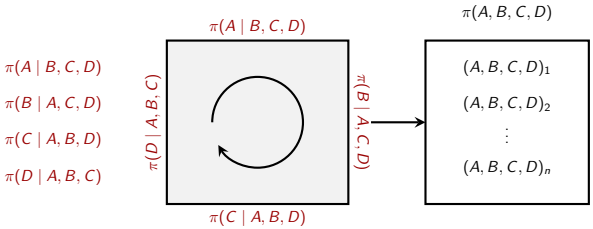
$(A, B, C, D)_1$

$(A, B, C, D)_2$

$\vdots$

$(A, B, C, D)_n$

Methodology: Modeling simplifications & Decomposition



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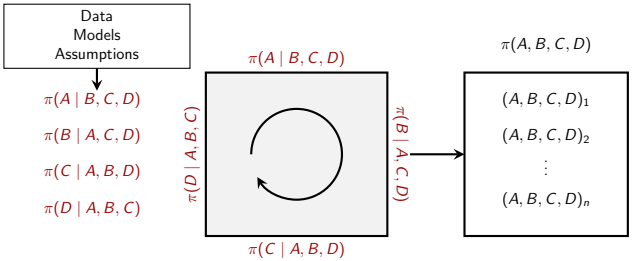
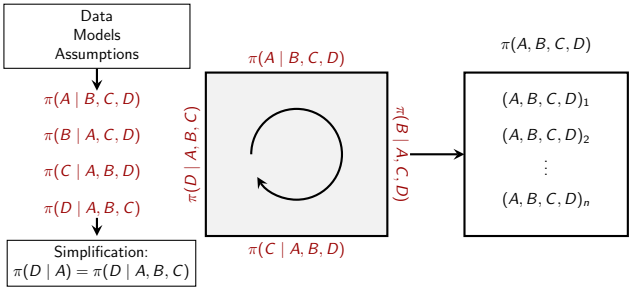


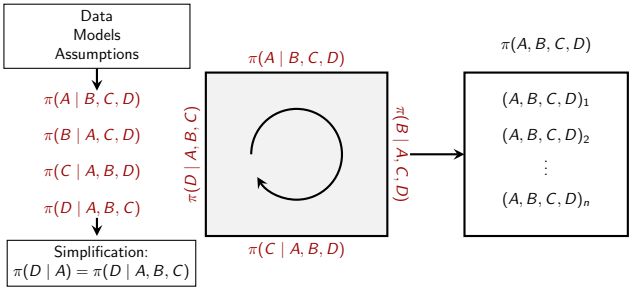
Methodology: Modeling simplifications & Decomposition



Modeling simplifications:

- Preserve relationships between households and members.
- Preserve relationships between individuals from the same household.
- Avoid illogical observations.

Methodology: Modeling simplifications & Decomposition



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- Preserve relationships between individuals from the same household.
- Avoid illogical observations.

Decomposition:

N = 1

1	single	

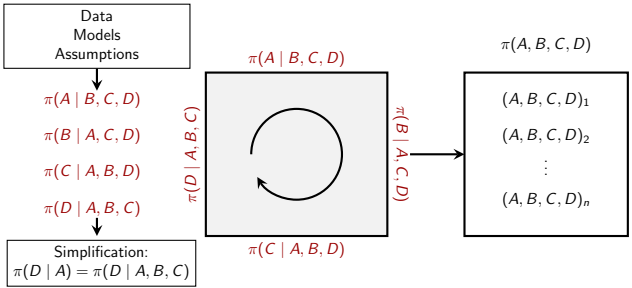
N = 2

2	single child		

N = 3

3	couple child			

Methodology: Modeling simplifications & Decomposition



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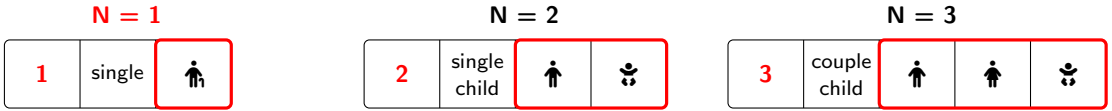

Results: Comparison with two-step method

Swiss Mobility and Transport microcensus (MTMC) data from 2015.
Marginal fit is not enough.
Consistency between the individual and household levels and realism of synthetic data.

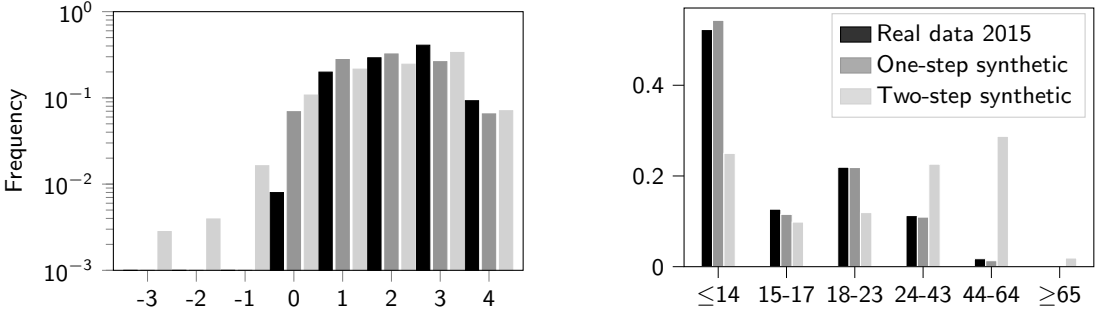

Figure: Distribution of age category gaps between a spouse and a child (left) and marginal distribution of age categories of children (right)

Summary

Idea

Adaptation of the Gibbs sampler for generating synthetic households by grouping all variables in the vector sorted in decreasing order of age.

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- Add household type for realism.
- Sampler per household size for efficiency.
- Conditional distributions for control.

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Adaptation of the Gibbs sampler for generating synthetic households by grouping all variables in the vector sorted in decreasing order of age.

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- Add household type for realism.
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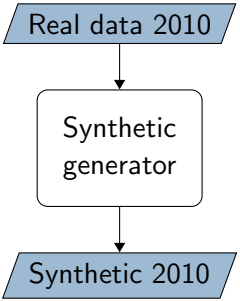
- Conditional distributions for control.

Can we use a one-step Gibbs sampler for updates?

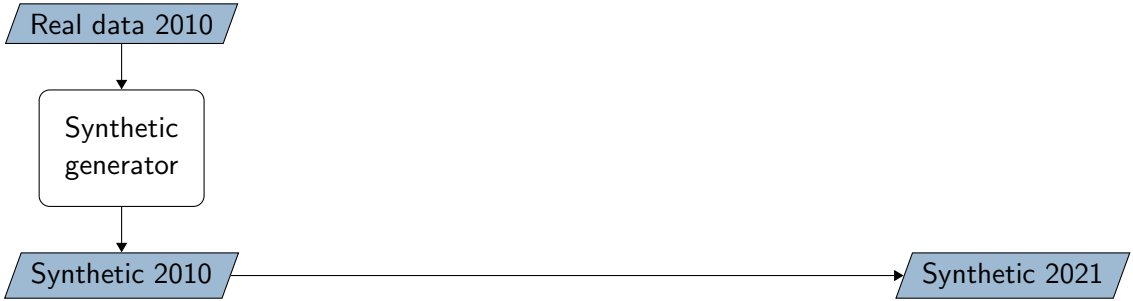
Outline

Existing methods



Step 1: Generation

Existing methods



Step 1: Generation **Step 2: Projection**

Existing methods

Existing methods: Gaps

Dynamic projection

Evolves population.

Heterogeneous sample.

Random resampling

Copying of data instead of evolving.

Lack of heterogeneity over time.

Existing methods: Gaps

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Evolves population.

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Increase of the error over time.

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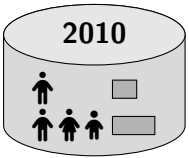
Can achieve a perfect fit of marginals.

Combine the strengths of both methods depending on the data availability!

Methodology: **Adaptive** Synthetic Generation using **Gibbs Resampling**



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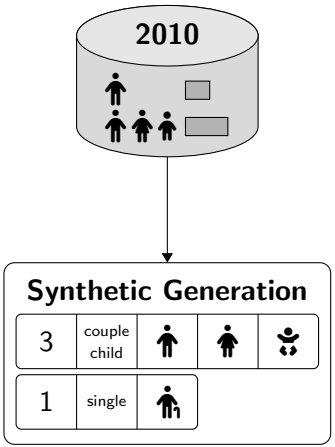

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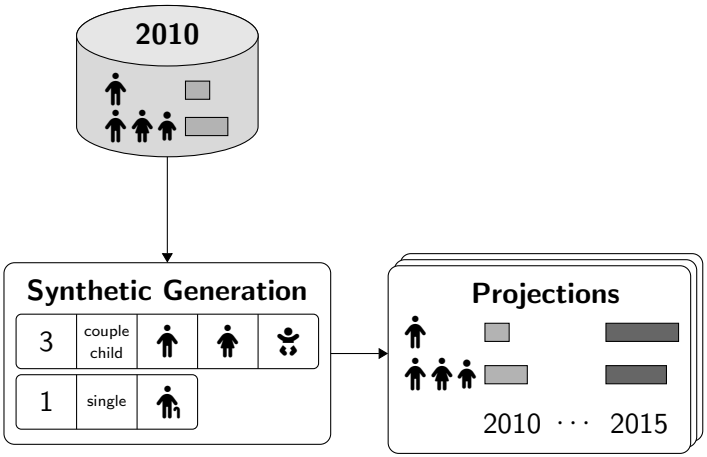

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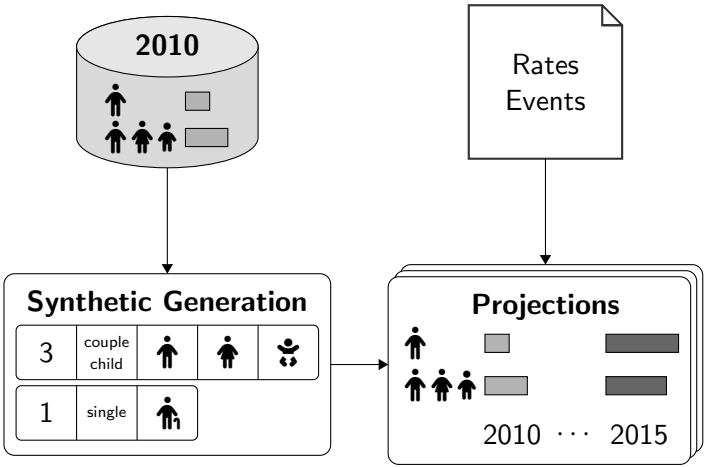

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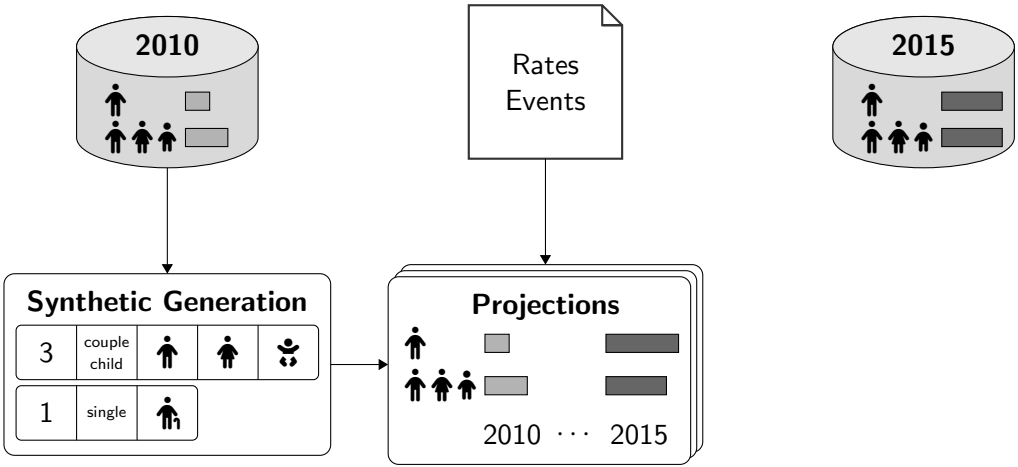

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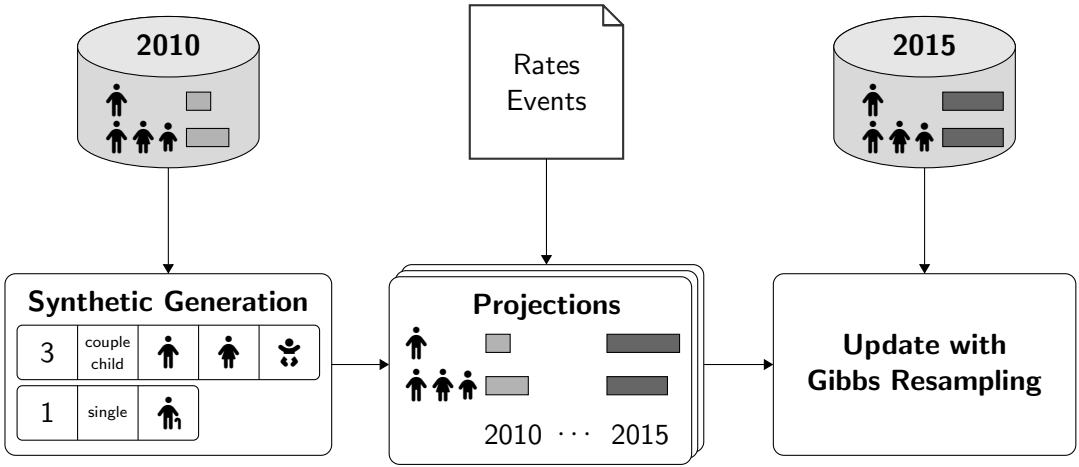


Methodology: Gibbs Resampling

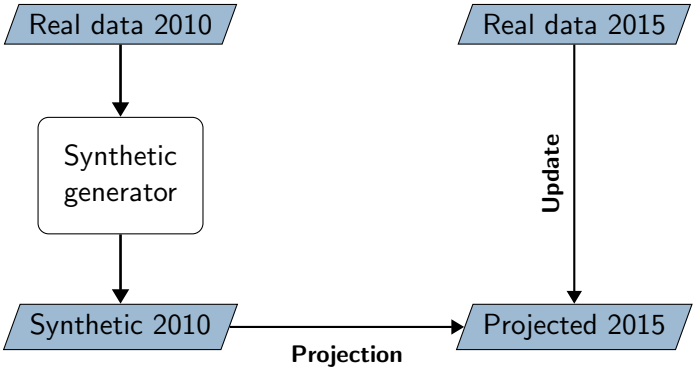
Objective
Align the projected synthetic population with the real marginal distributions observed at t.

Idea
Use the fact that the one-step Gibbs sampler takes the household size as input.

Method

1. **Determine** how much data is needed to match the real distribution.
2. **Generate** additional subsample calibrated on real data.
3. **Add** the new households to the projected synthetic population.
4. **Delete** households uniformly to restore the population size while keeping the adjusted distribution.

Methodology: **Adaptive** Synthetic Generation using **Gibbs Resampling**



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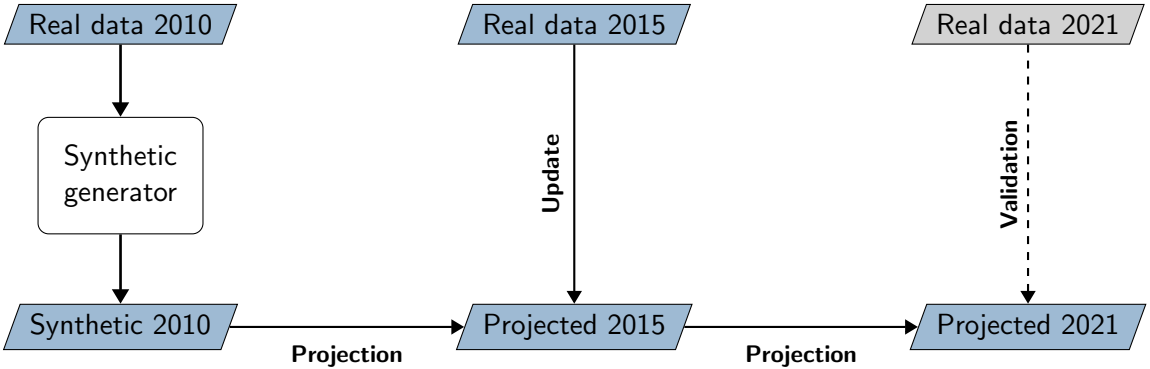

Results: Adaptive Synthetic Generation versus other methods

Data: MTMC 2010, 2015, 2021.
Experiment: Regenerate for 2010, 2015, 2021.
Result: more efficient and suitable for cases with limited or biased real data.

	Computational Efficiency
Independent regeneration	✗
Dynamic projection	∼
Random resampling	✓
Adaptive approach	✓

Table: Symbols: ✓ (High), ∼ (Moderate), ✗ (Low), - (not applicable)

Results: Adaptive Synthetic Generation versus other methods

Data: MTMC 2010, 2015, 2021.
Experiment: Projection from 2010 to 2021.
Result: incremental updates reduce accumulated errors over time.

	Computational Efficiency	Marginal Fit
Independent regeneration	✗	✓
Dynamic projection	∼	✗
Random resampling	✓	✓
Adaptive approach	✓	✓

Table: Symbols: ✓ (High), ∼ (Moderate), ✗ (Low), - (not applicable)

Results: Adaptive Synthetic Generation versus other methods

Data: MTMC 2010, 2015, 2021.
Experiment: Projection from 2010 to 2021.
Result: adding new subsample preserves heterogeneity.

	Computational Efficiency	Marginal Fit	Population Heterogeneity
Independent regeneration	✗	✓	✓
Dynamic projection	∼	✗	∼
Random resampling	✓	✓	✗
Adaptive approach	✓	✓	✓

Table: Symbols: ✓ (High), ∼ (Moderate), ✗ (Low), - (not applicable)

Results: Adaptive Synthetic Generation versus other methods

Data: MTMC 2010, 2015, 2021.
Experiment: Projection from 2010 to 2021.

	Computational Efficiency	Marginal Fit	Population Heterogeneity	Robustness to Unforeseen Events
Independent regeneration	✗	✓	✓	-
Dynamic projection	∼	✗	∼	✗
Random resampling	✓	✓	✗	∼
Adaptive approach	✓	✓	✓	✓

Table: Symbols: ✓ (High), ∼ (Moderate), ✗ (Low), - (not applicable)

Summary

Idea

Simulation framework that uses one-step Gibbs sampling for the **adaptive** generation and **updating** of synthetic households by incorporating new disaggregated data without regenerating.

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Simulation framework that uses one-step Gibbs sampling for the **adaptive** generation and **updating** of synthetic households by incorporating new disaggregated data without regenerating.

Contribution

- Gibbs resampling: improves errors in long-term, more robust, enriching sample.
- Access to up-to-date synthetic samples.
- Making use of available real data.

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Simulation framework that uses one-step Gibbs sampling for the **adaptive** generation and **updating** of synthetic households by incorporating new disaggregated data without regenerating.

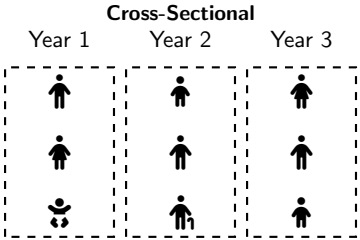
Contribution

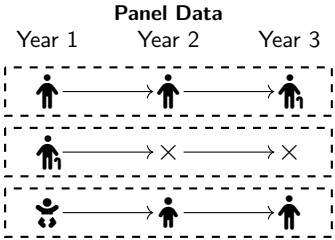
- Gibbs resampling: improves errors in long-term, more robust, enriching sample.
- Access to up-to-date synthetic samples.
- Making use of available real data.

Can we model the evolution at the disaggregated level?

Outline

Motivation: Different data types





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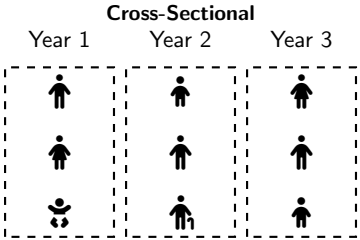
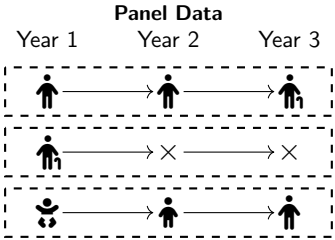




Why is there overemphasis on the cross-sectional data, although panel data are needed?

Motivation: Different data types

	Cross-sectional	**Panel**
Strengths	Low cost Easy to collect Accessible Large samples	Tracks behavior dynamics Captures hidden differences Enables causal insights
Limitations	No temporal aspect Misleading conclusions Assumption: *Variation = Dynamics*	Expensive to collect Attrition Panel fatigue Panel conditioning

Gaps, Research question, Contribution

Problem

Real panel inaccessible

$\Rightarrow$ Over-reliance on cross-sectional

$\Rightarrow$ Hinders other models!

Gaps, Research question, Contribution

Problem	Solution
Real panel inaccessible ⇒ Over-reliance on cross-sectional ⇒ Hinders other models!	Generate synthetic panel data ⇒ No practical problems ⇒ Accessible!

Gaps, Research question, Contribution

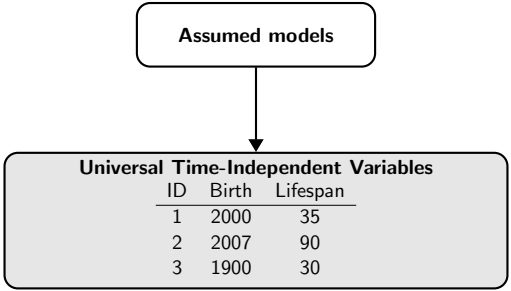
Problem	Solution	Question
Real panel inaccessible ⇒ Over-reliance on cross-sectional ⇒ Hinders other models!	Generate synthetic panel data ⇒ No practical problems ⇒ Accessible!	How to generate synthetic panel data when no real panel data is available?

Gaps, Research question, Contribution

Problem	Solution	Question
Real panel inaccessible ⇒ Over-reliance on cross-sectional ⇒ Hinders other models!	Generate synthetic panel data ⇒ No practical problems ⇒ Accessible!	How to generate synthetic panel data when no real panel data is available?

Generate a universal **time-independent dataset** of individual **life sequences**, created either **without data** or by **integrating cross-sectional** data, enabling **synthetic panels** for any year.

Methodology: Overview of the framework



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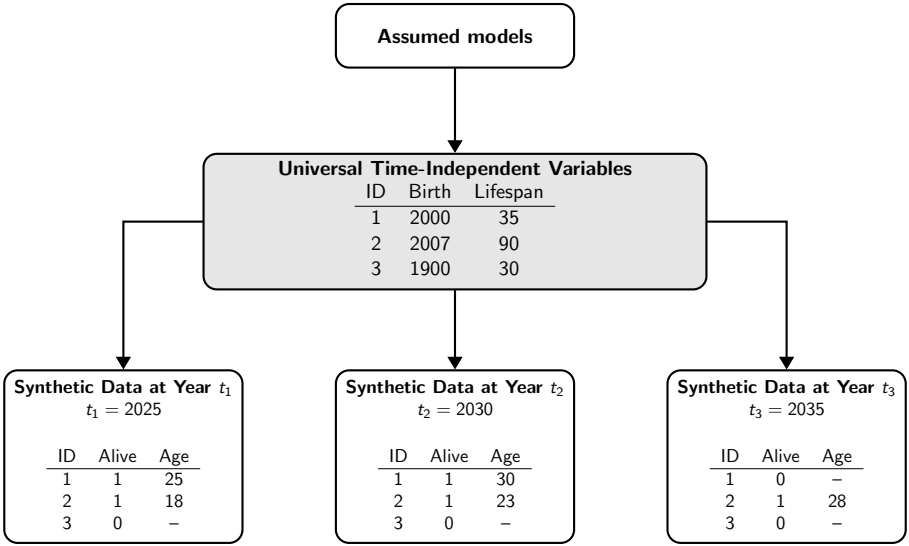

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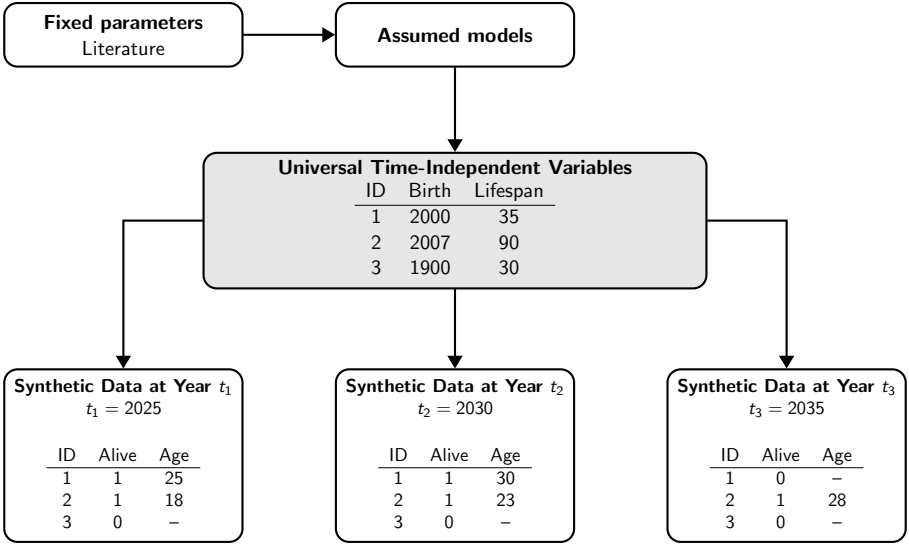

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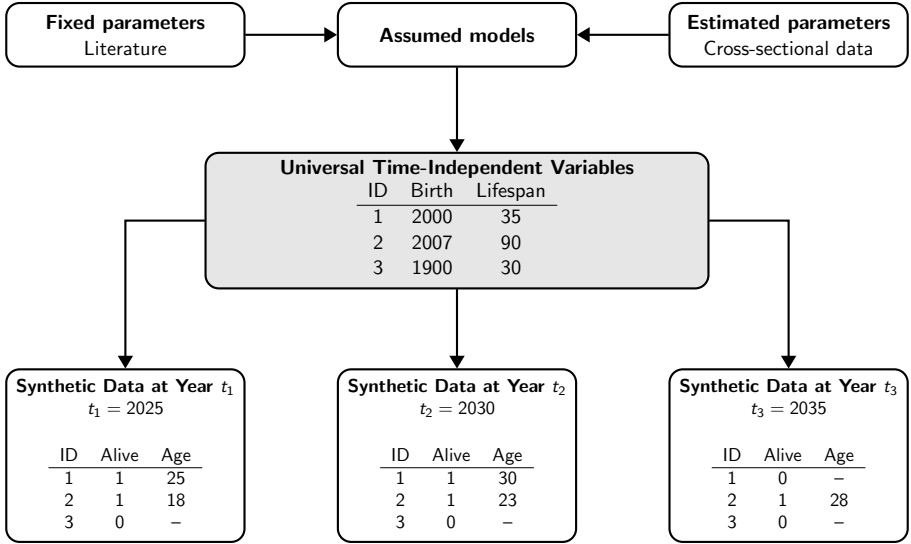

Methodology: Design of universal variables

Time-independent variables

Birth year Lifespan	License year Validity	Education phases	Employment phases	Initial home phase	Home phases	Work phases

Methodology: Design of universal variables

Time-independent variables

Birth year Lifespan	License year Validity	Education phases	Employment phases	Initial home phase	Home phases	Work phases

Event-duration tuples

(e_1, d_1) (e_2, d_2) $\{(e_3, d_3), (e_4, d_4)\}$ $\{(e_m, d_m, \text{inc}_m)\}_m$ $(e_{M+5}, d_{M+5}, c_0^h)$ $\{(e_n, d_n, c_n^h)\}_n$ $\{(e_q, d_q, c_q^w)\}_q$

Methodology: Design of universal variables

Time-independent variables

Birth year Lifespan	License year Validity	Education phases	Employment phases	Initial home phase	Home phases	Work phases

Event-duration tuples

(e_1, d_1)	(e_2, d_2)	$\{(e_3, d_3), (e_4, d_4)\}$	$\{(e_m, d_m, \text{inc}_m)\}_m$	$(e_{M+5}, d_{M+5}, c_0^h)$	$\{(e_n, d_n, c_n^h)\}_n$	$\{(e_q, d_q, c_q^w)\}_q$

Assumed models

Uniform$(y_{\min}, y_{\max})$ Weibull (k, λ)	Mixture (π, μ, σ)	TruncNorm (μ_d^S, σ_d^S) Exp (μ_g^T) Weibull (k_T, λ_T)	Exp (μ_g) Exp $(\lambda(a_m))$ Exp (μ_b)	Population distribution	Income-boost model	Neighbour model (p_h, p_w)

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Birth year Lifespan	License year Validity	Education phases	Employment phases	Initial home phase	Home phases	Work phases

Event-duration tuples

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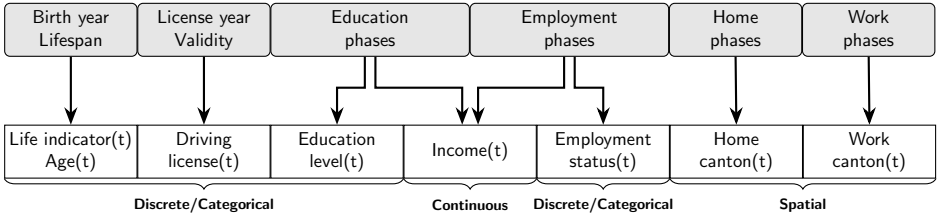
Generated sequence

(1995, 30)	(2015, 10)	$\{(2010, 4), (2014, 4)\}$	(2018, 7, 3000)	(1995, 23, VD)	(2018, 7, ZH)	(2018, 7, ZH)

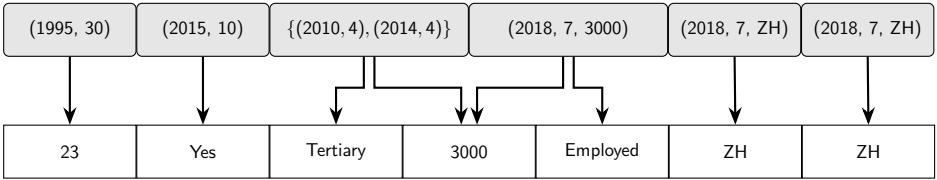
Within lifetime **Realistic** **Consistency**

Methodology: Specification of time-dependent variables



Deterministic mapping rules

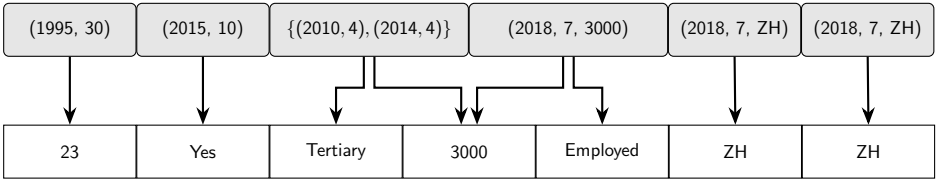
Methodology: Specification of time-dependent variables



$t = 2018$

- Derivation faster than regeneration.
- Control of consistency.
- Changes are automatically reflected.

Methodology: Specification of time-dependent variables



$t = 2018$

- Derivation faster than regeneration.
- Control of consistency.
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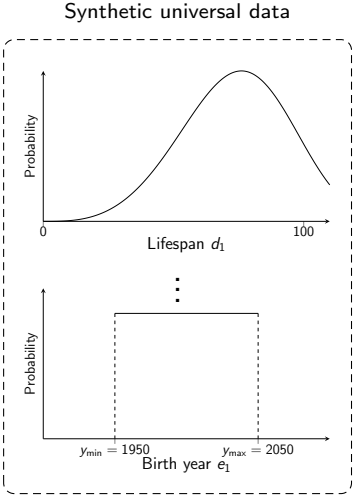
We control the **panel effect** → But how do we know that the **aggregated properties** are satisfied?

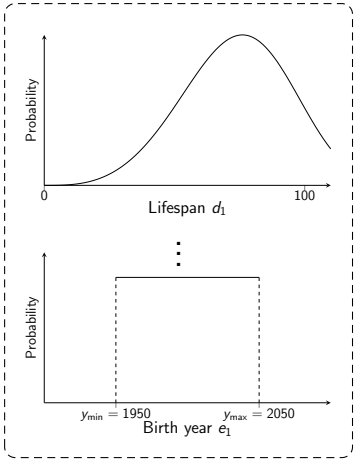
Methodology: Cross-sectional data integration



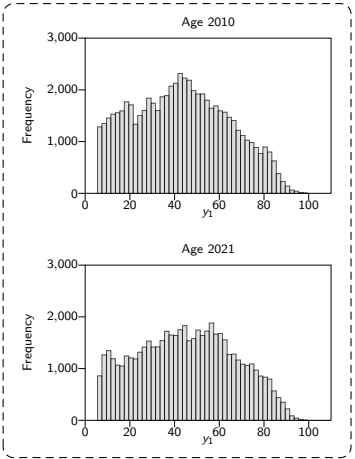
How do we know if the generated sequence produces **realistic data** at moment t?

Methodology: Cross-sectional data integration

Synthetic universal data

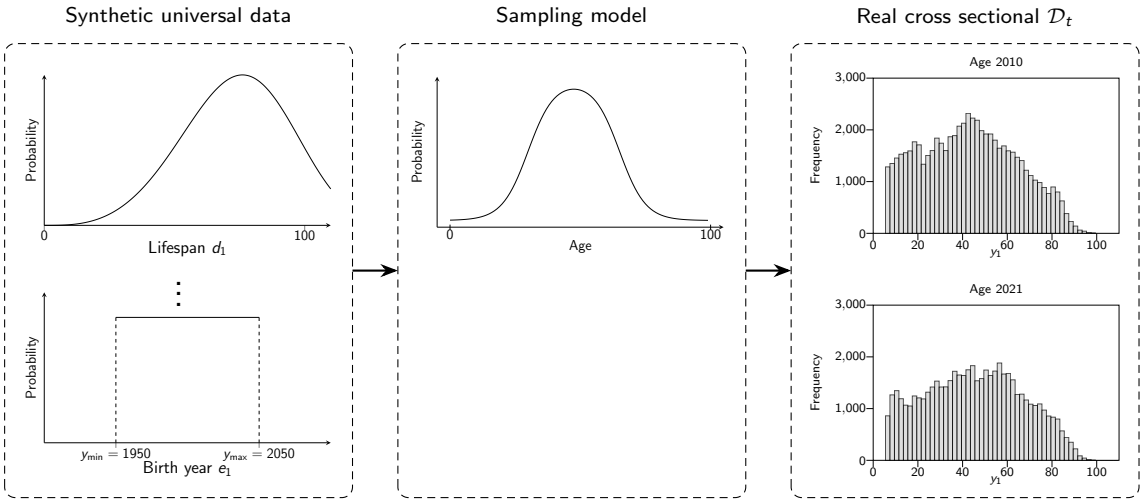


Real cross sectional $\mathcal{D}_t$



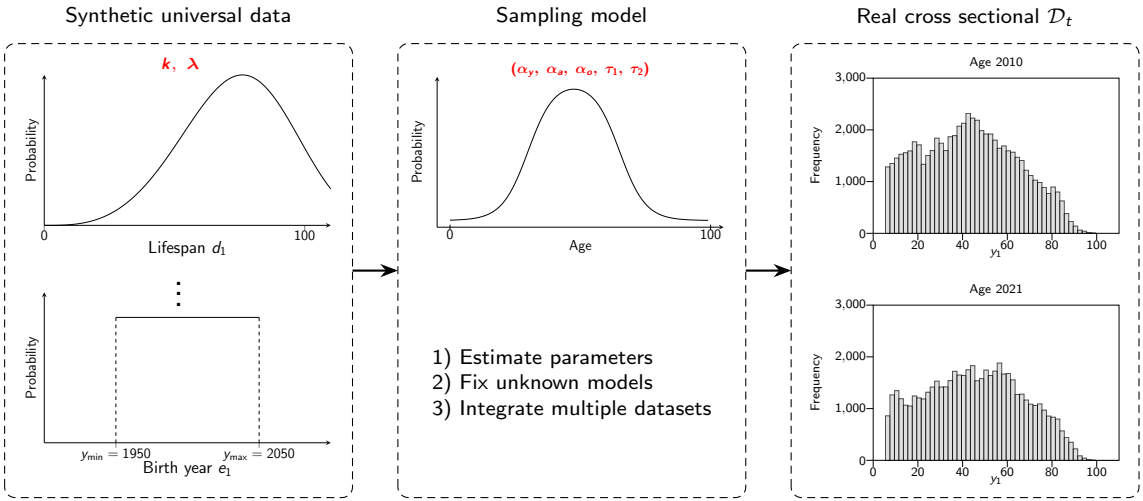
Can we use the information from **observed data** to improve **unobserved variables**?

Methodology: Cross-sectional data integration



Cross-sectional datasets **are outcomes of a sampling mechanism** applied to the universal population at moment t.

Methodology: Cross-sectional data integration



MLE to **estimate parameters** of universal-variable distributions using available cross-sectional datasets.

Cross-sectional Data Integration: MLE

$$\mathrm{L}(\theta) = \prod_{t \in \mathcal{T}} \prod_{i \in \mathcal{D}_t} \mathrm{P}(s_{i,t} = 1,\, z_{i,t} \mid \theta)$$

$s_{i,t} = 1$ sampled individuals

$z_{i,t}$ observed variables at time t (e.g., age, driving license status, ...)

θ parameters (e.g., $k, \lambda, \alpha_y, \alpha_a, \alpha_o, \tau_1, \tau_2$, ...)

Cross-sectional Data Integration: MLE

$$\mathrm{L}(\theta) = \prod_{t \in \mathcal{T}} \prod_{i \in \mathcal{D}_t} \mathrm{P}(s_{i,t} = 1,\, z_{i,t} \mid \theta)$$

$$\mathrm{L}(\theta) = \prod_{t \in \mathcal{T}} \prod_{i \in \mathcal{D}_t} \sum_{\mathbf{u}_\theta} \mathrm{P}(s_{i,t} = 1,\, z_{i,t},\, \mathbf{u}_\theta \mid \theta)$$

$s_{i,t} = 1$ sampled individuals

$z_{i,t}$ observed variables at time t (e.g., age, driving license status, ...)

θ parameters (e.g., $k, \lambda, \alpha_y, \alpha_a, \alpha_o, \tau_1, \tau_2$, ...)

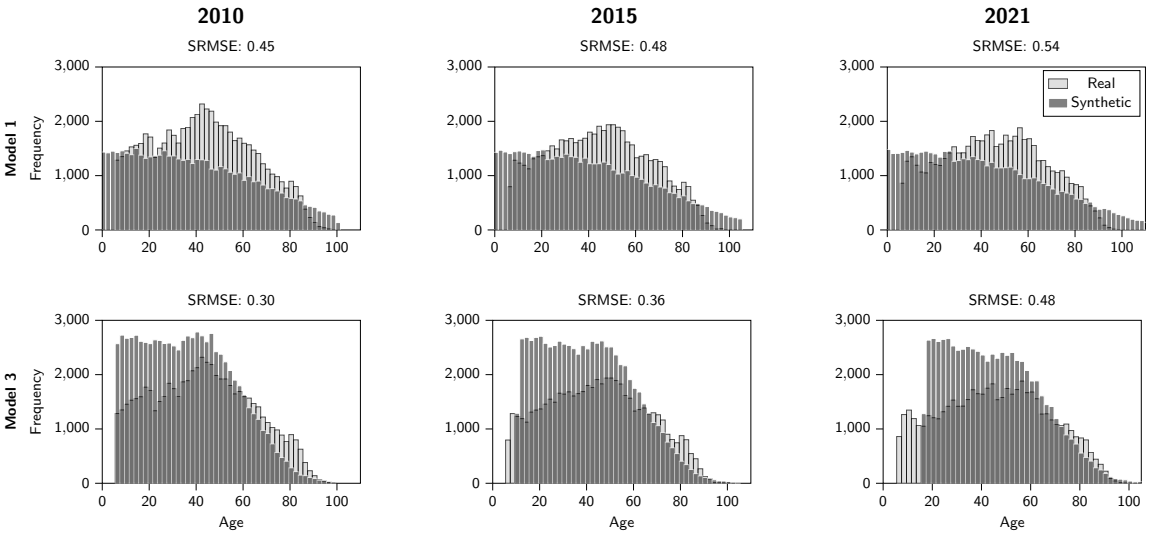
$\mathbf{u}_\theta$ universal variables (e.g., birth year, lifespan, age of getting driving license, ...)

Results: Data-free vs. Data-Integrated approach

Estimation of parameters - Model 1 (data-free) and Model 2 – 4 (data-integrated).
MTMC cross-sectional data 2010, 2015, 2021.

Parameter	Meaning	Model 1	Model 2	Model 3	Model 4
k	Shape (lifespan)	3.00	2.84	3.44	3.37
λ	Scale (lifespan)	85.00	69.28	77.36	74.41
α_y	Weight of young group	–	0.02	0.16	0.06
α_a	Weight of adult group	–	0.95	0.79	0.84
α_o	Weight of old group	–	0.04	0.05	0.10
τ_1	Young–adult threshold	–	33.98	38.06	37.73
τ_2	Adult–old threshold	–	84.89	82.50	87.76
π	Probability of never obtaining a license	0.15	0.17	0.19	0.21
μ	Log-location (license age)	3.02	2.89	2.87	2.90
σ	Log-scale (license age)	0.15	0.13	0.11	0.11

Results: Data-Free vs. Data-Integrated approach



Results: Data-Free vs. Data-Integrated approach

Model	Unseen data		
	2010	2015	2021
Model 1	**0.45**	**0.48**	**0.54**
Model 2	(0.38)	**0.43**	**0.50**
Model 3	(0.30)	(0.36)	**0.48**
Model 4	(0.29)	(0.36)	(0.47)

- Model 1: data-free $\rightarrow$ Worst fit

Results: Data-Free vs. Data-Integrated approach

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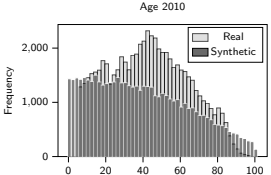
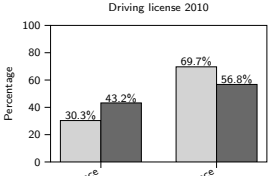
- Model 1: data-free → Worst fit
- Model 3 & Model 4:
  more integrated data → Better fit.
- Fit decreases over time
  (i.e., SRMSE increases).

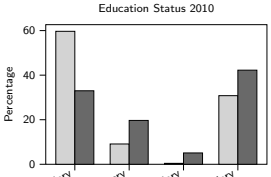
Results: Data-free vs. Data-Integrated approach

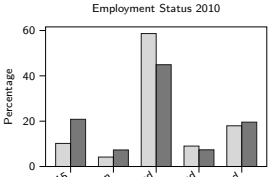
Aggregated validation: generate universal variables, derive year-specific datasets (e.g., 2010), and compare resulting marginals with observed data.

Data-free (Model 1)

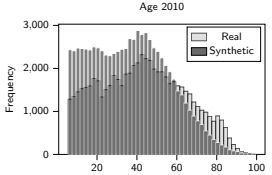


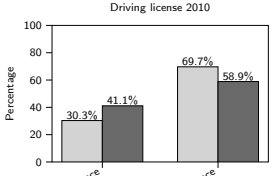


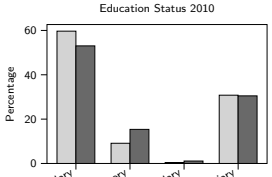


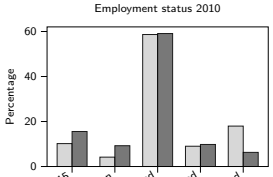


Data-integrated (Model 3)



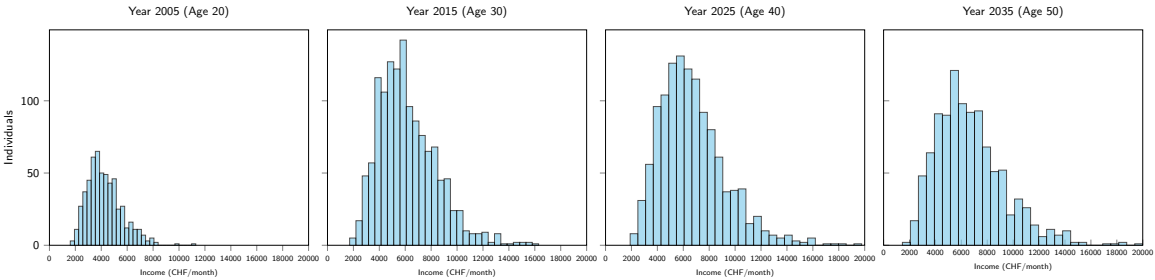






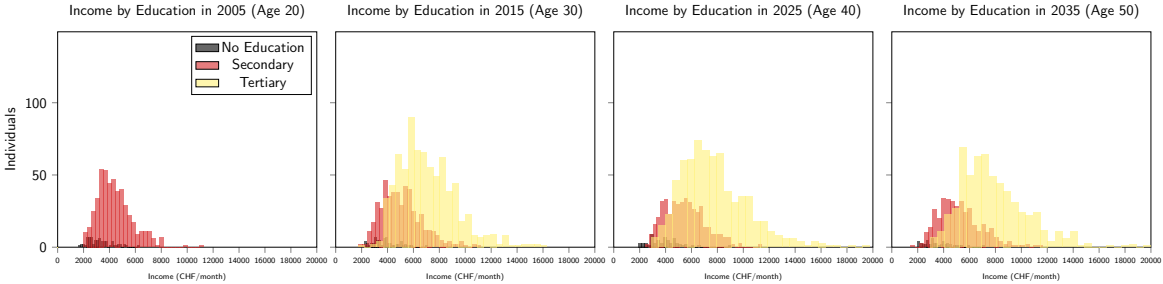
Results: Panel effect

Generate a universal dataset and select people born in 1985.
For these people, derive data for 2005, 2015, 2025, 2035.



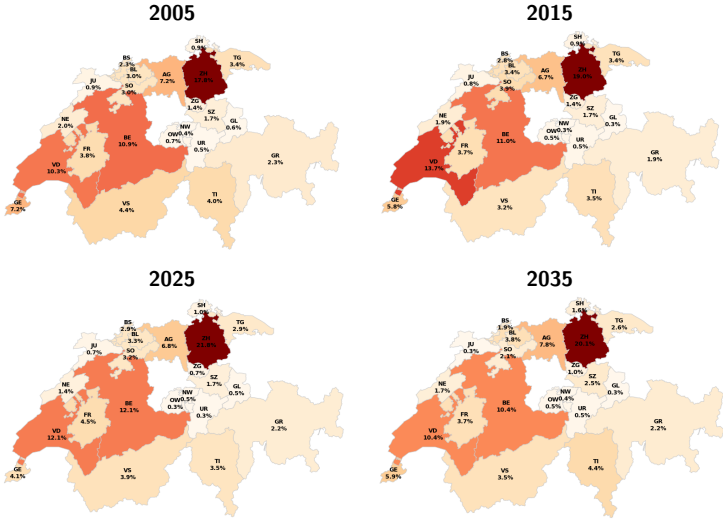
Income increases and the spread widens over time.
Longer tails mean more extreme incomes and greater income differences.

Results: Panel effect



Income levels strongly correlate with education level.

Results: Panel effect



Summary

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Universal life-course event–duration model for generating synthetic panel data.

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Universal life-course event–duration model for generating synthetic panel data.

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- Data-free and data-integrated generation.
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Limitations

- Simple models.
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Future directions

Expand on tracking synthetic households.

Bayesian updating using defined models as priors.

User-defined panels for hypothetical testing.

Outline

Conclusion: Main Findings

Motivation

- Synthetic populations: **single-level** and **static**.
- No temporal **continuity** or **adaptability** to new data.

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- No temporal **continuity** or **adaptability** to new data.

Contributions

- Hierarchical generation.
- Adaptive updates.
- Synthetic panel data.

Vision

- Synthetic populations as **evolving** systems.
- **Adaptive**: **model-based** reasoning with **data-driven** calibration.

Conclusion: Future work

- Improving validation of synthetic data (e.g., rare households).
- Extension to other hierarchical structures.
- Formal more general life-trajectory framework with explicit structural constraints.
- Open-source software for generating synthetic panels under user-defined constraints.

Thank you! Questions?

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