

# Adjusting Survival Estimates for Treatment Switching: New Guidance and the Role of Real-World Evidence

**ISPOR Europe 2024, Workshop 312, 20<sup>th</sup> November 2024**

# Speakers

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# **ISPOR Workshop. Overview of crossover adjustment methods**

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20<sup>th</sup> November 2024

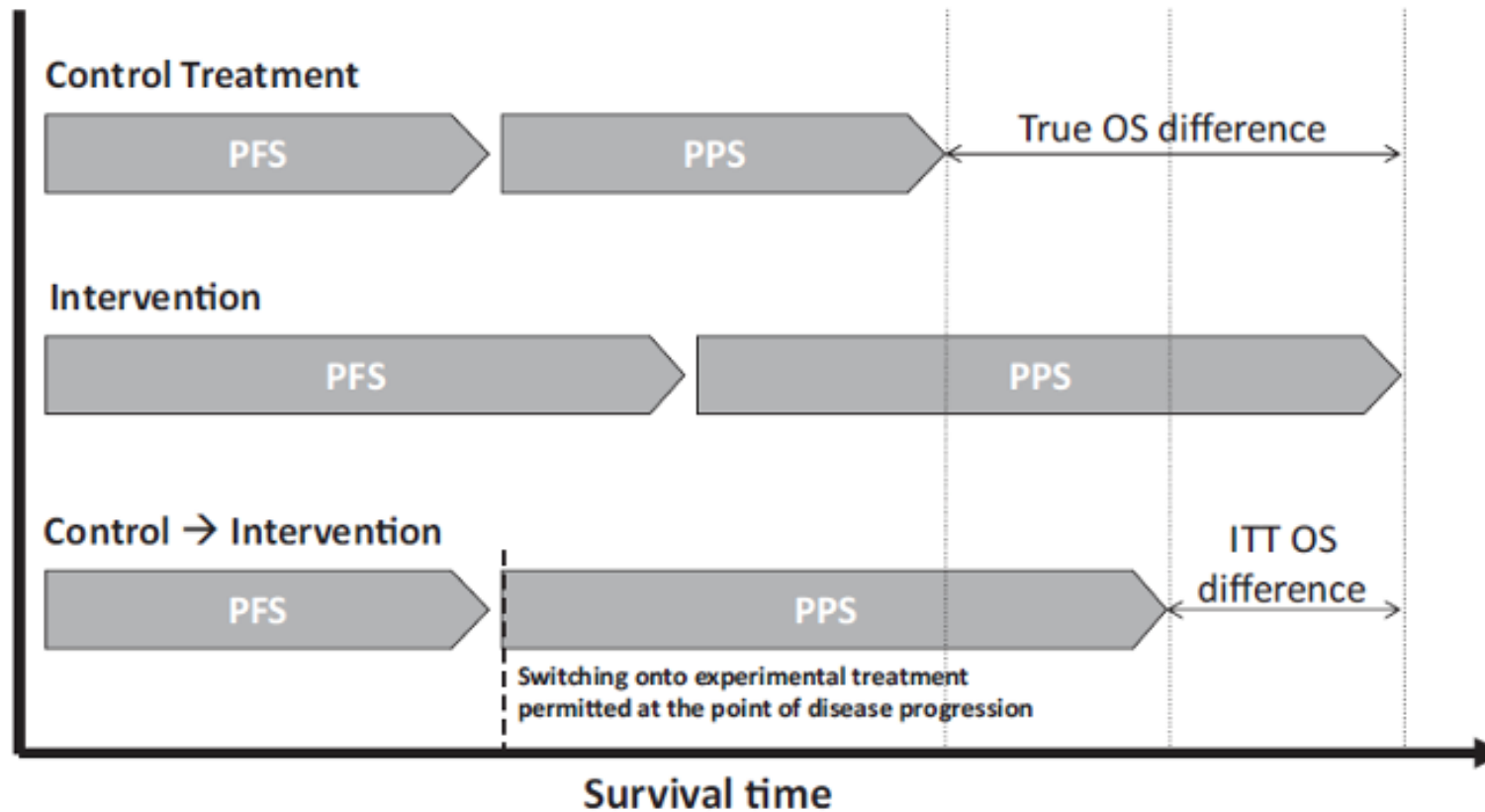


# Disclosures

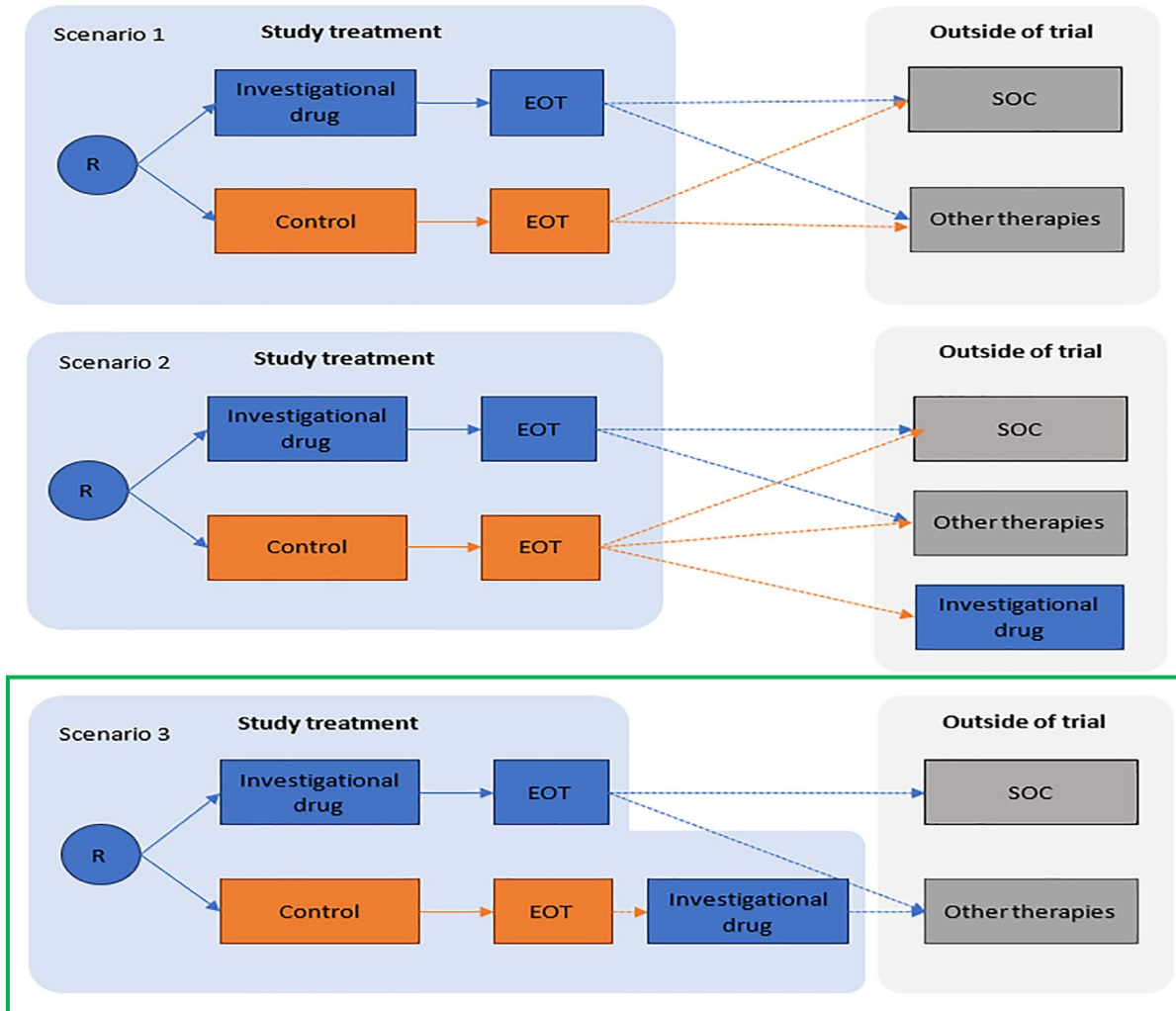
No conflicts of interest relevant to the content of this workshop.

# Why is crossover adjustment needed?

- Crossover or “treatment switching” causes a contamination of randomized groups
- Intention to treatment (ITT) analysis unlikely to be suitable

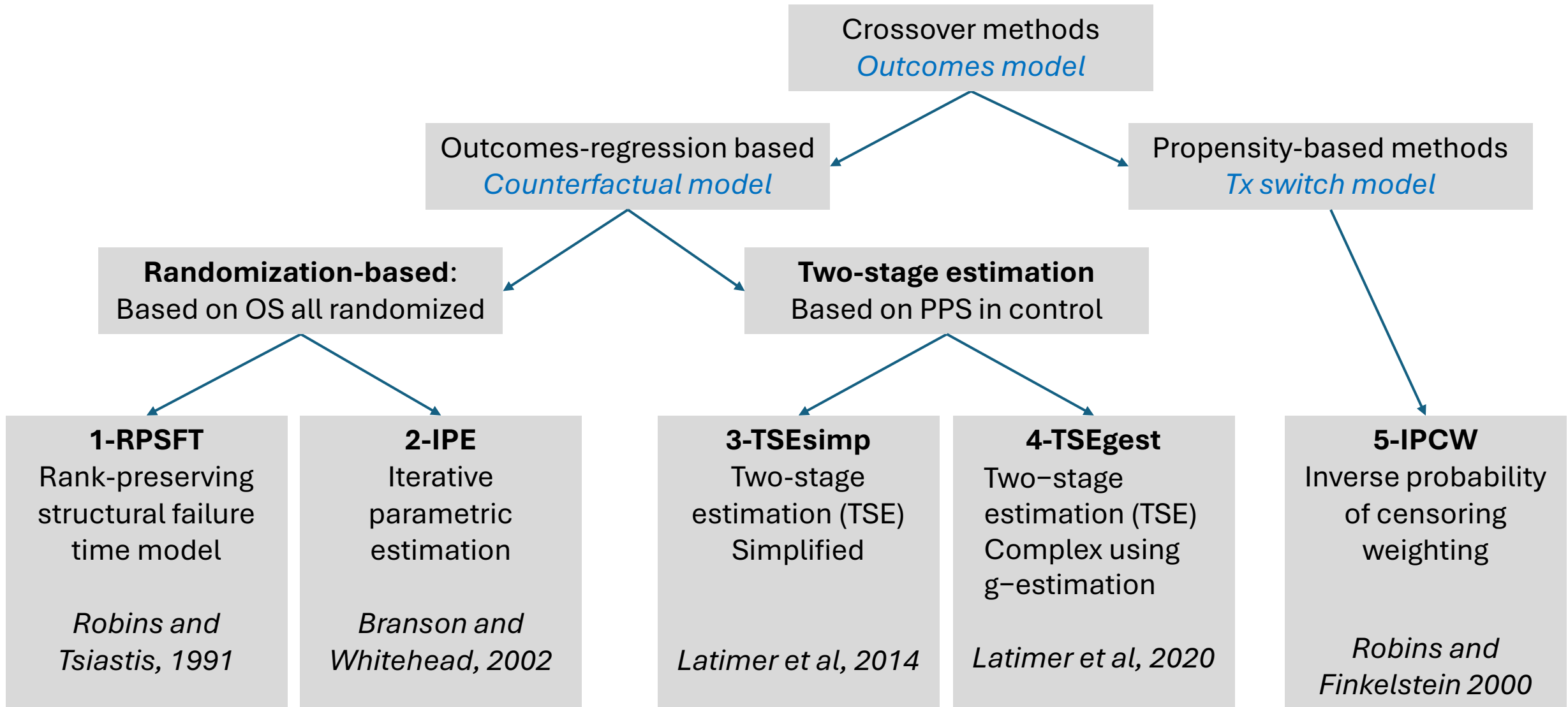


# When is crossover adjustment required?



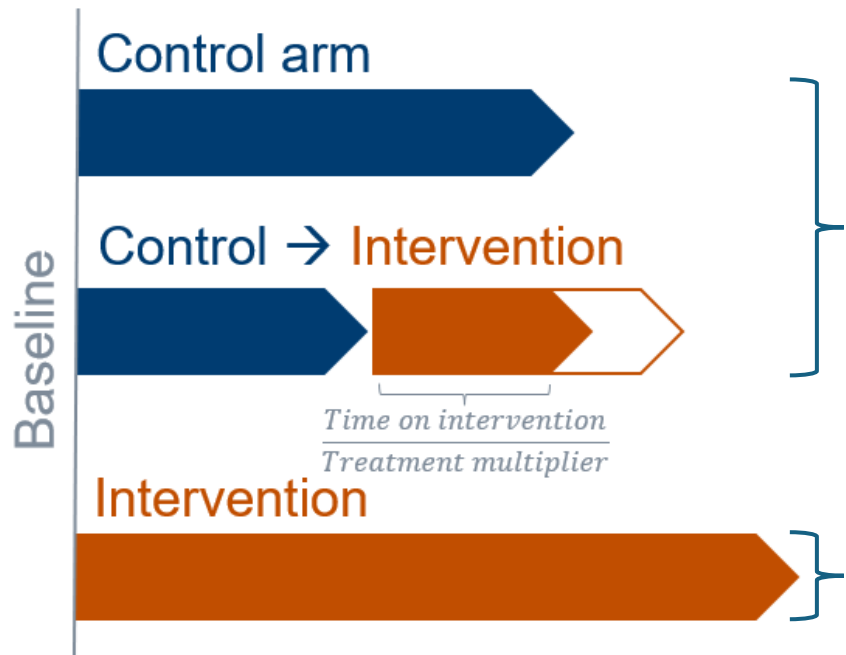
- We assume example from oncology with protocolized crossover at progression
- Crossover adjustment is required when investigational drug it is not considered a **realistic treatment pathway**
- Aim is to assess the *hypothetical* survival benefit for intervention versus control adjusted for crossover at progression assuming investigational drug not available outside of trial

# Crossover adjustment methods



# Outcomes vs. propensity-based methods

*Outcomes-regression based methods*

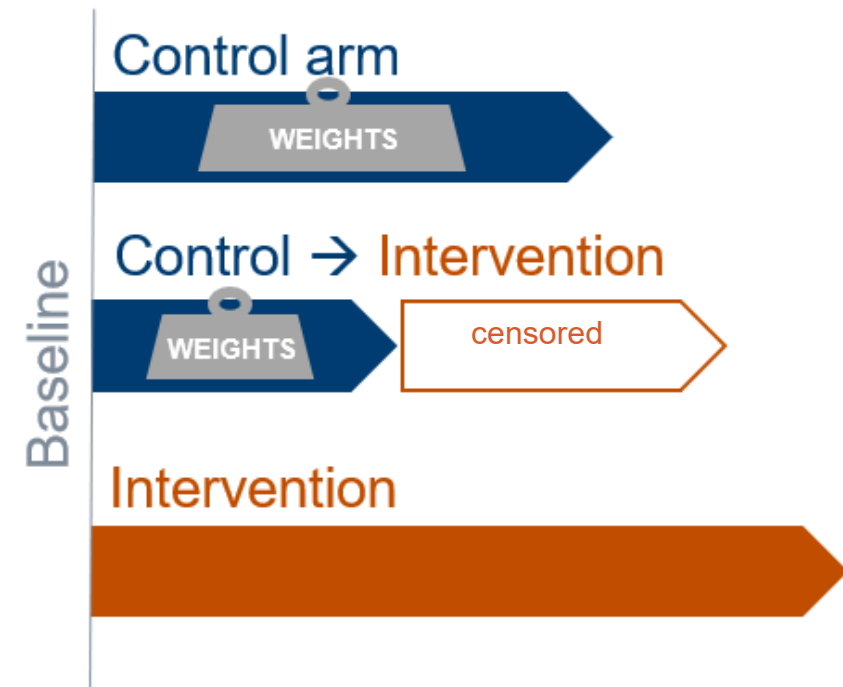


Observed control outcomes  
+  
Adjusted control outcomes  
vs.

Intervention outcomes

*Outcomes model:*  
HR Intervention vs. adjusted control outcomes  
(Weighted) Cox PH model

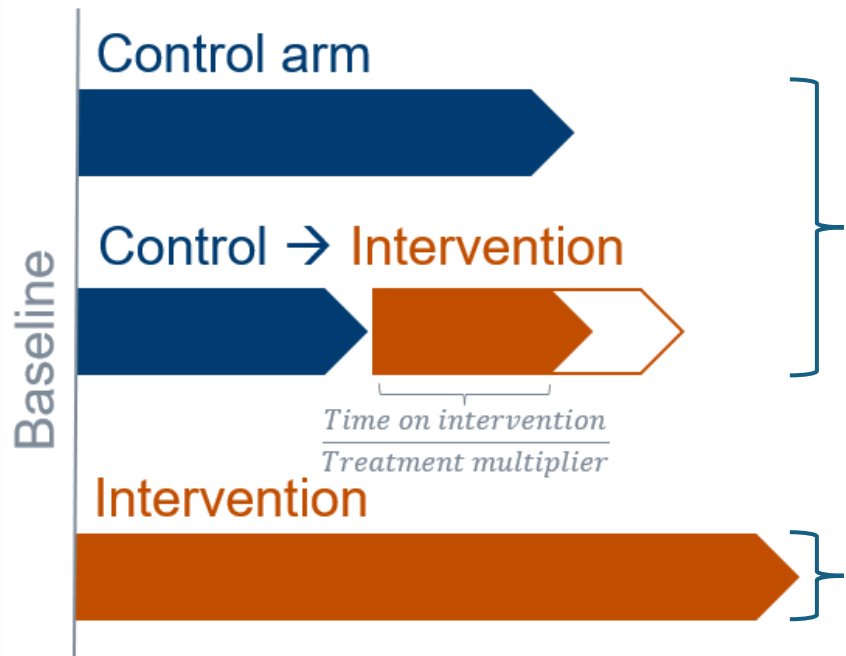
*Propensity-based methods*





# Outcomes vs. propensity-based methods

## Outcomes-regression based methods



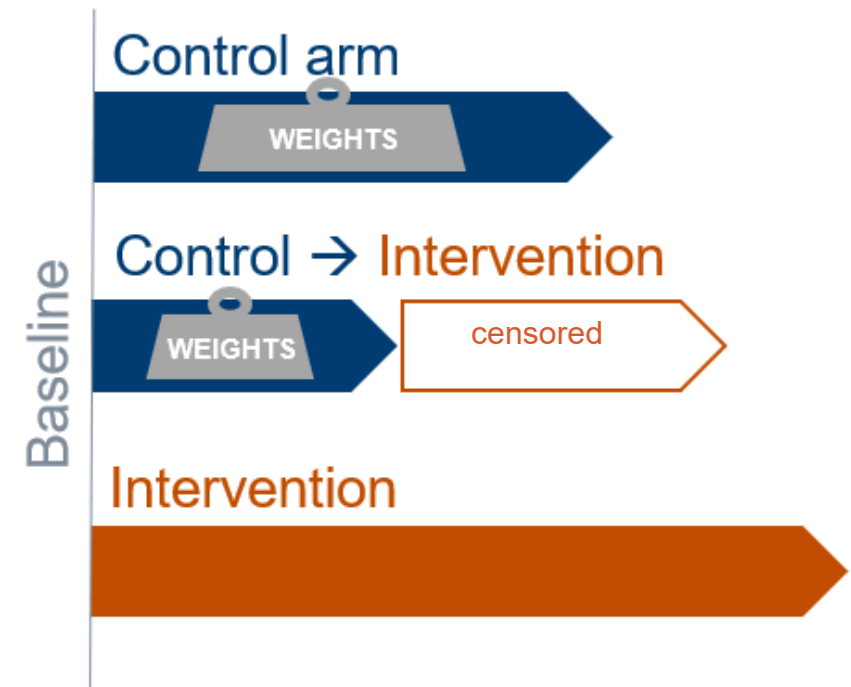
Observed control outcomes  
+  
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Intervention outcomes

### Outcomes model:

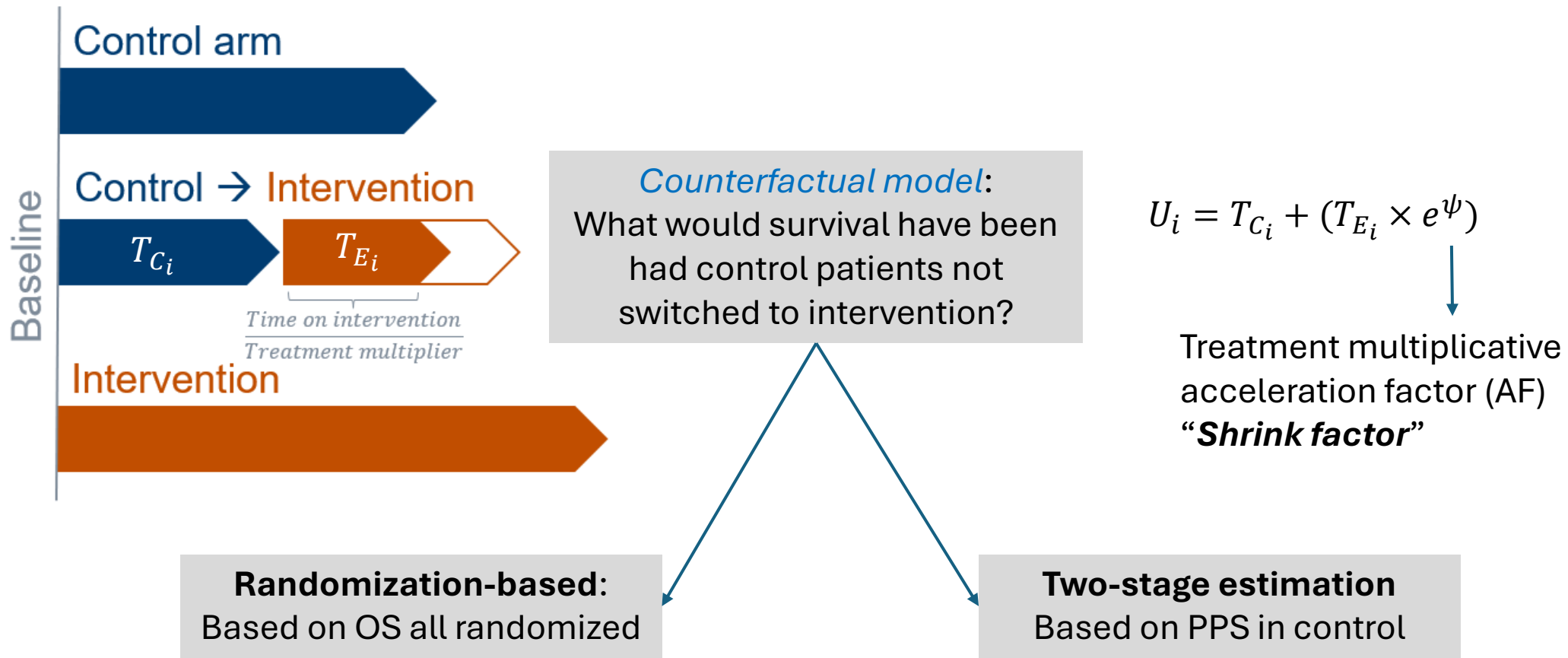
HR Intervention vs. adjusted control outcomes  
(Weighted) Cox PH model

## Propensity-based methods



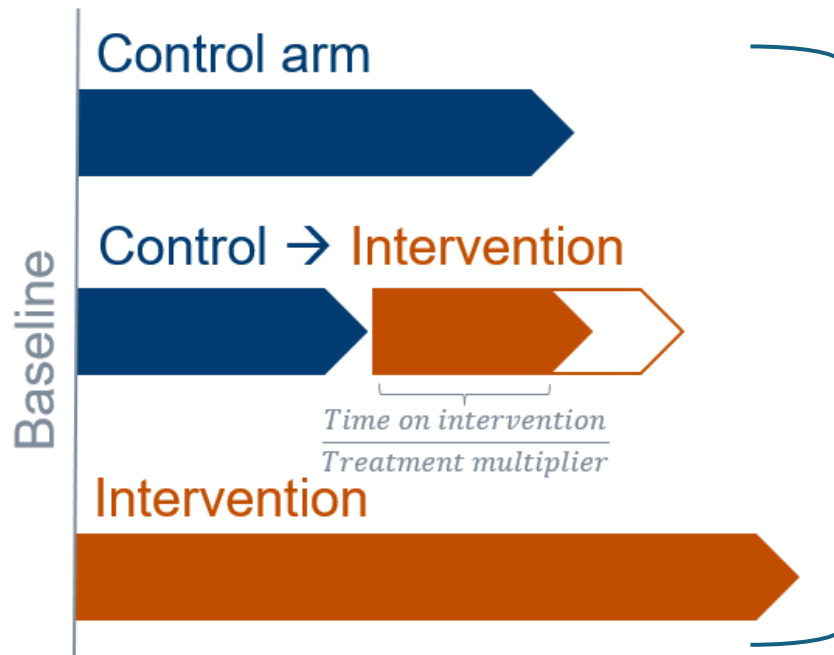
# Counterfactual model

Outcomes-regression based methods



# Randomization-based methods: 1-RPSFT & 2-IPE

Outcomes-regression based methods



For each individual in RCT:

$$U_i = T_{C_i} + (T_{E_i} \times e^\psi)$$

Counterfactual model  
Randomization-based  
methods

**1-RPSFT**  
G-  
estimation  
(non-  
parametric)

\*No  
Covariates

**2-IPE**  
Failure time  
model  
(parametric)

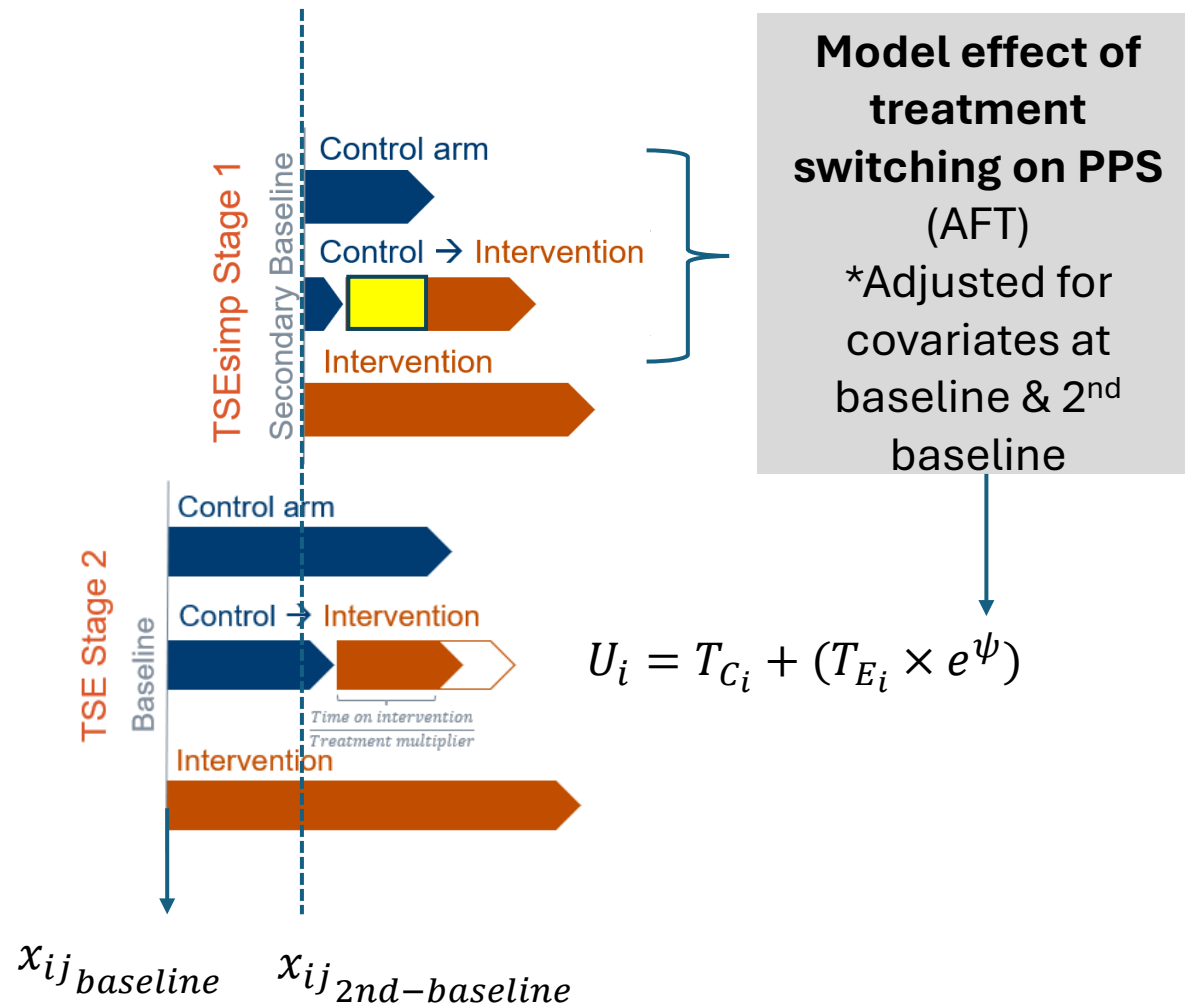
\*No  
Covariates

Assumptions:

1. Common treatment effect
2. The only difference between randomized groups is the treatment received (i.e. independence between randomised groups and potential outcomes)
3. Parametric assumptions for IPE

*Estimates value for  $\psi$  that produces the most similar untreated survival times between randomized groups*

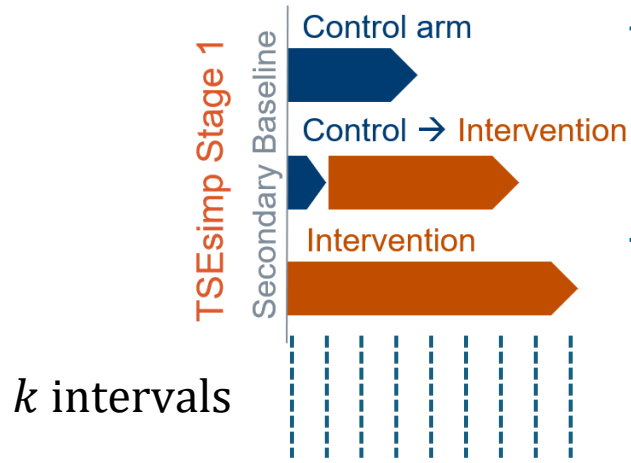
# Two-stage estimation: 3-TSEsimp



## Assumptions:

1. Switching at or after a disease-related secondary baseline time-point
2. No unmeasured confounding
3. If switching happens after the secondary baseline, no time-dependent confounding between secondary baseline and time of switch

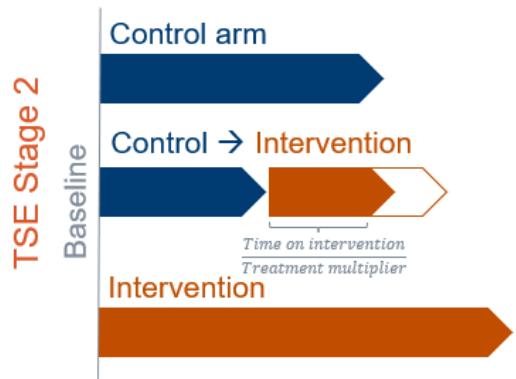
# Two-stage estimation: 4-TSEgest



**G-estimation & Treatment switch model**  
\*Adjusted for covariates at baseline & time-varying covariates

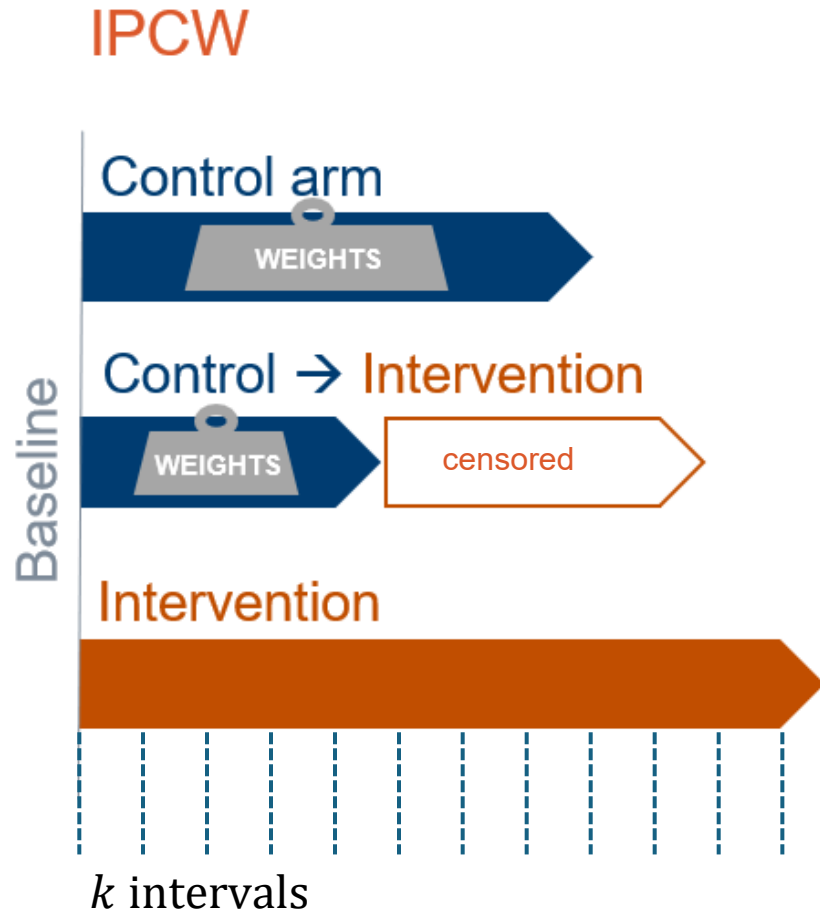
$$\text{logit}(p(E_{ik})) = \alpha PPS_{i,\psi} + \sum_j \beta_j x_{ijk}$$

$$U_i = T_{C_i} + (T_{E_i} \times e^\psi)$$



- Assumptions:**
1. No unmeasured confounding
  - If no secondary baseline, assumes independence between switch status and potential outcomes, conditional on variables measured at baseline and overtime

# Propensity-based method: 5-IPCW



## *Tx switching model*

Weights estimated using mixed effect logistic regression  
 \*Adjusted for baseline and time-varying covariates (k intervals)

## *Assumptions:*

1. No unmeasured confounding

$$W(t) = \prod_{k=0}^t \frac{\Pr[C(k) = 0 | \bar{C}(k-1) = 0, \bar{A}(k-1), V, T > k]}{\Pr[C(k) = 0 | \bar{C}(k-1) = 0, \bar{A}(k-1), \bar{L}(k), T > k]}$$

$C(k)$ : whether switching has occurred at the end of interval  $k$ ,

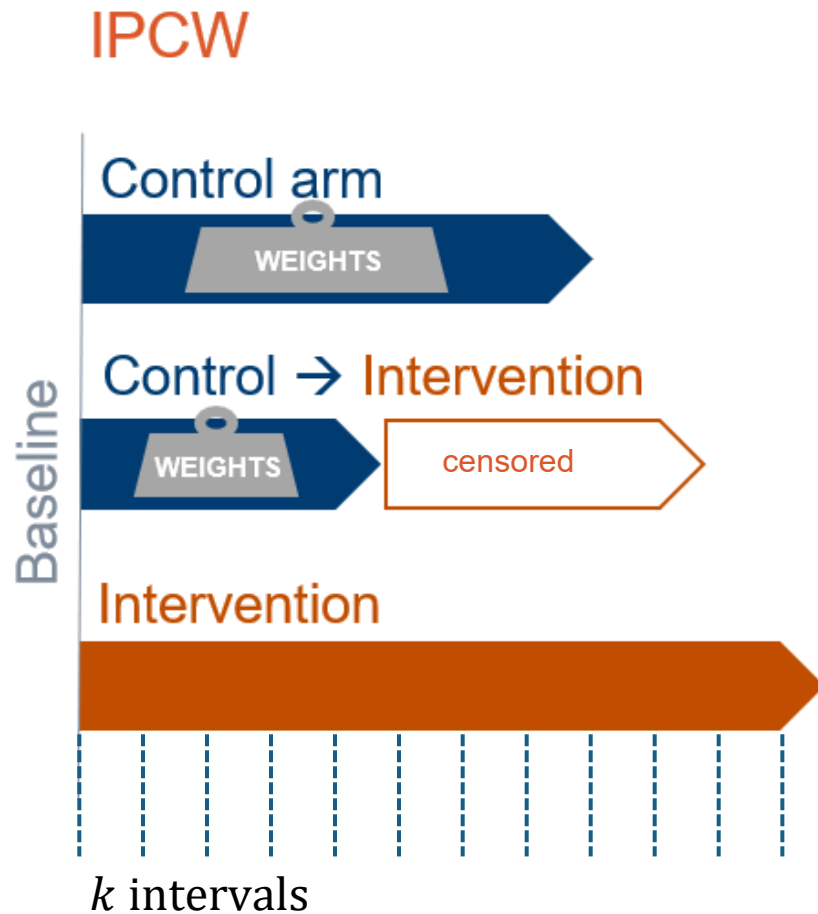
$\bar{C}(k-1)$ : switching history up to end of the previous interval

$\bar{A}(k-1)$ : treatment history up to end of the previous interval

$V$ : array of baseline covariates

$\bar{L}(k)$ : history of time-varying covariates including  $V$

# Propensity-based method: 5-IPCW



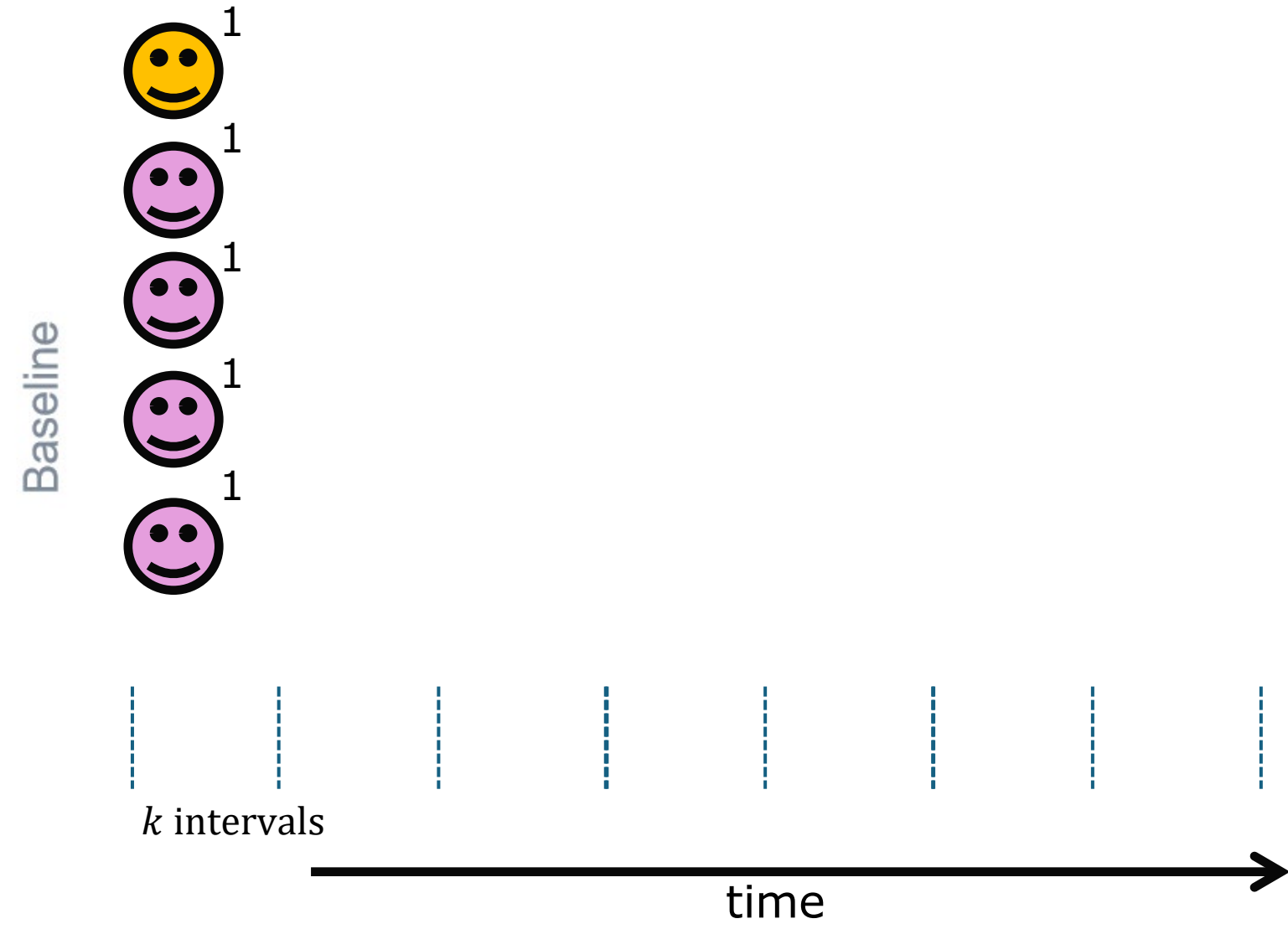
Easiest to think of this as an extension to the simple per-protocol censoring analysis.

## Four steps:

1. Censor switchers at point of switch
2. Model probability of switching according to baseline and time-dependent characteristics (e.g. ECOG, HRQoL, lesion size)
3. Use probabilities to compute weights (e.g. upweight people who have similar characteristics to switchers but *didn't* switch). Weight equals the “inverse probability of not switching”
4. Use weights in a survival analysis to remove selection bias associated with censoring

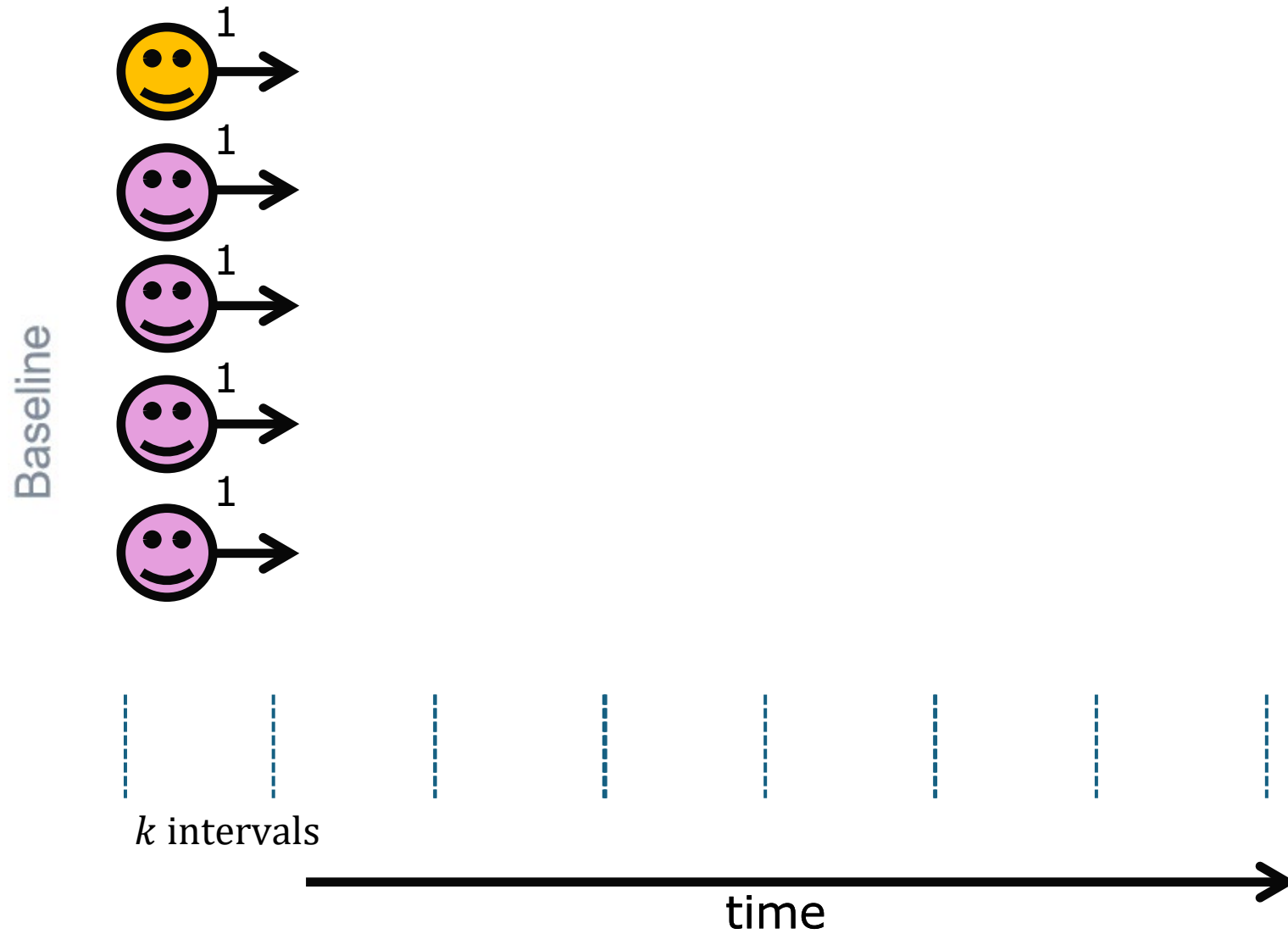


# Propensity-based method: 5-IPCW

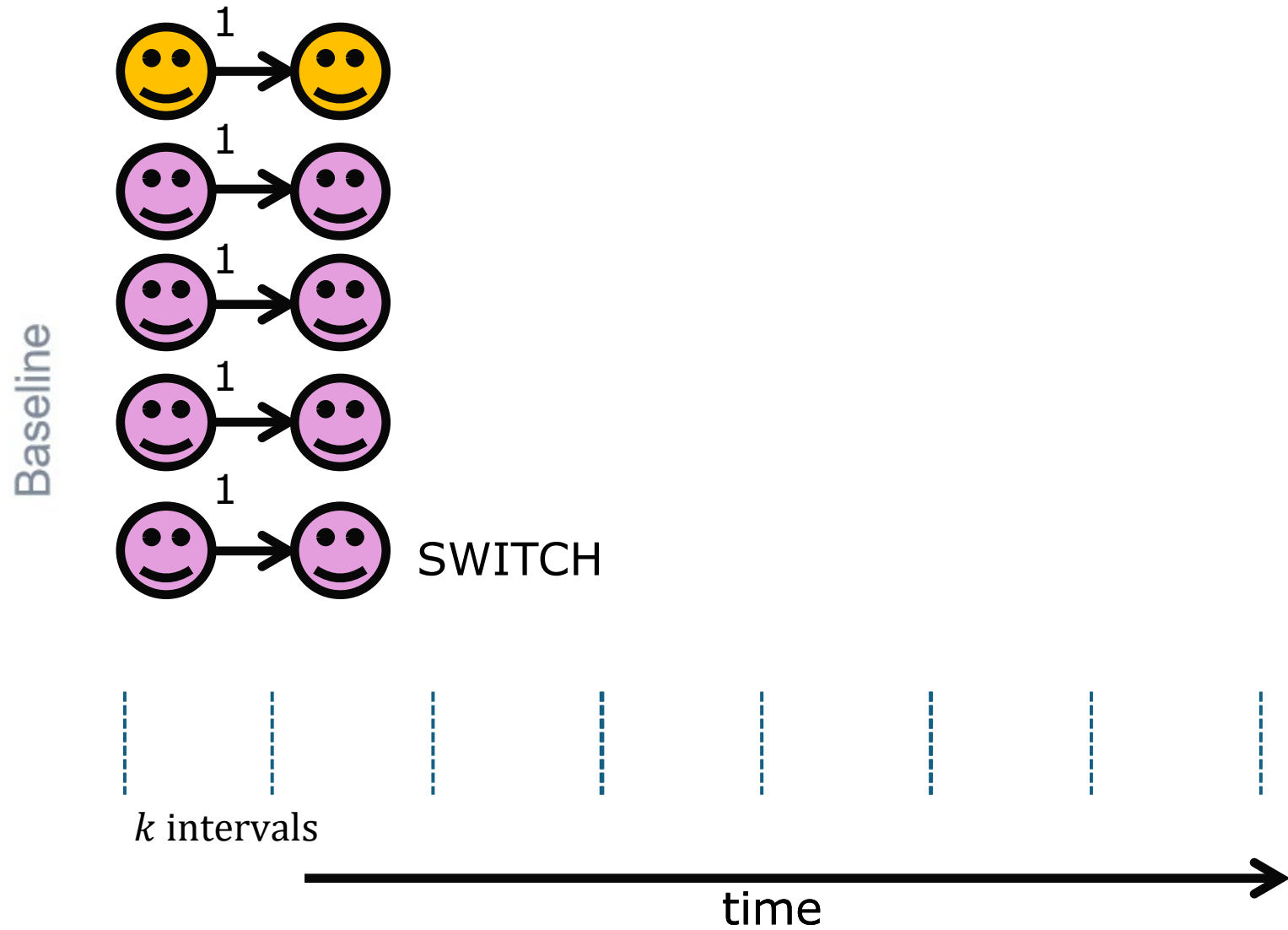




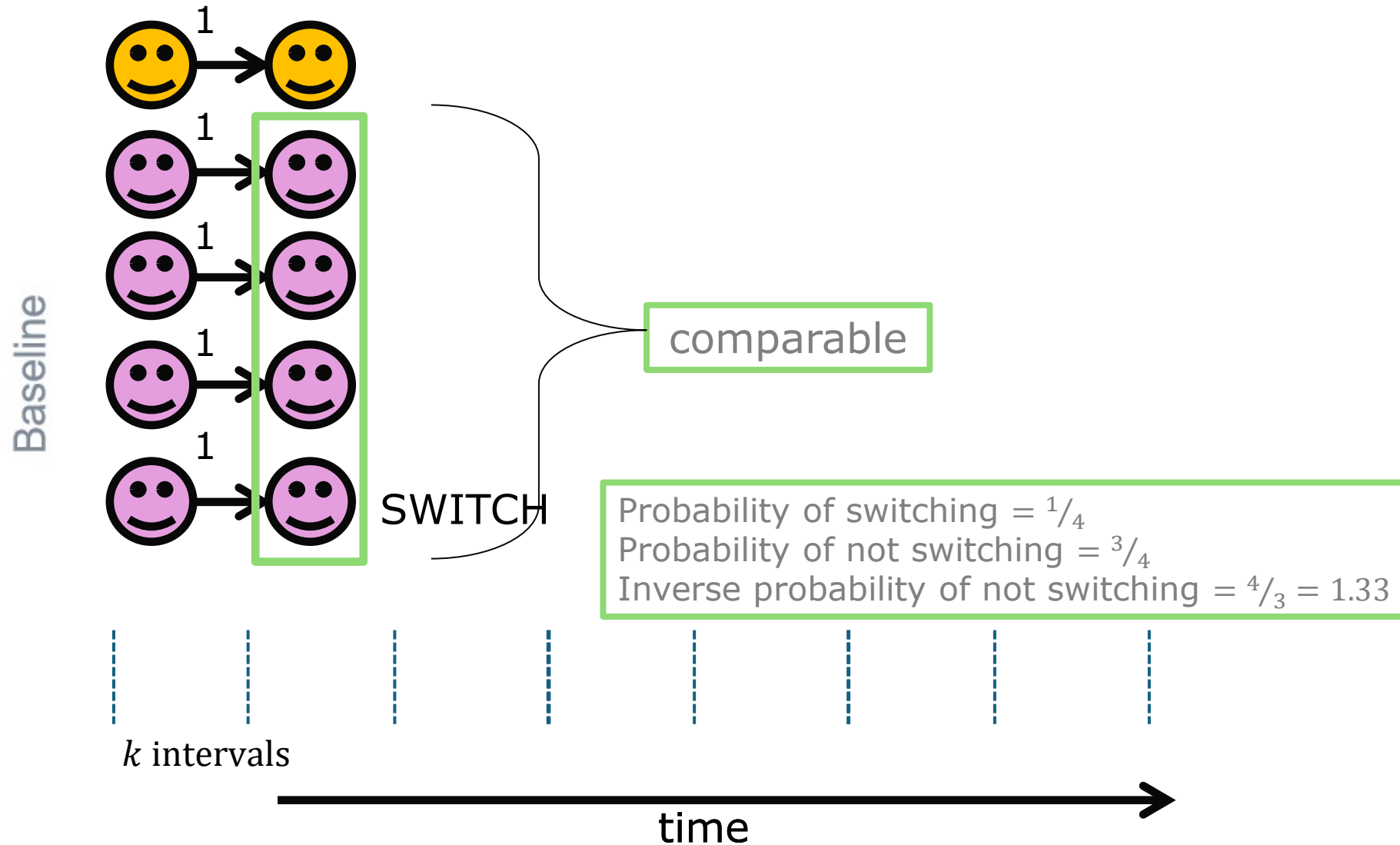
# Propensity-based method: 5-IPCW



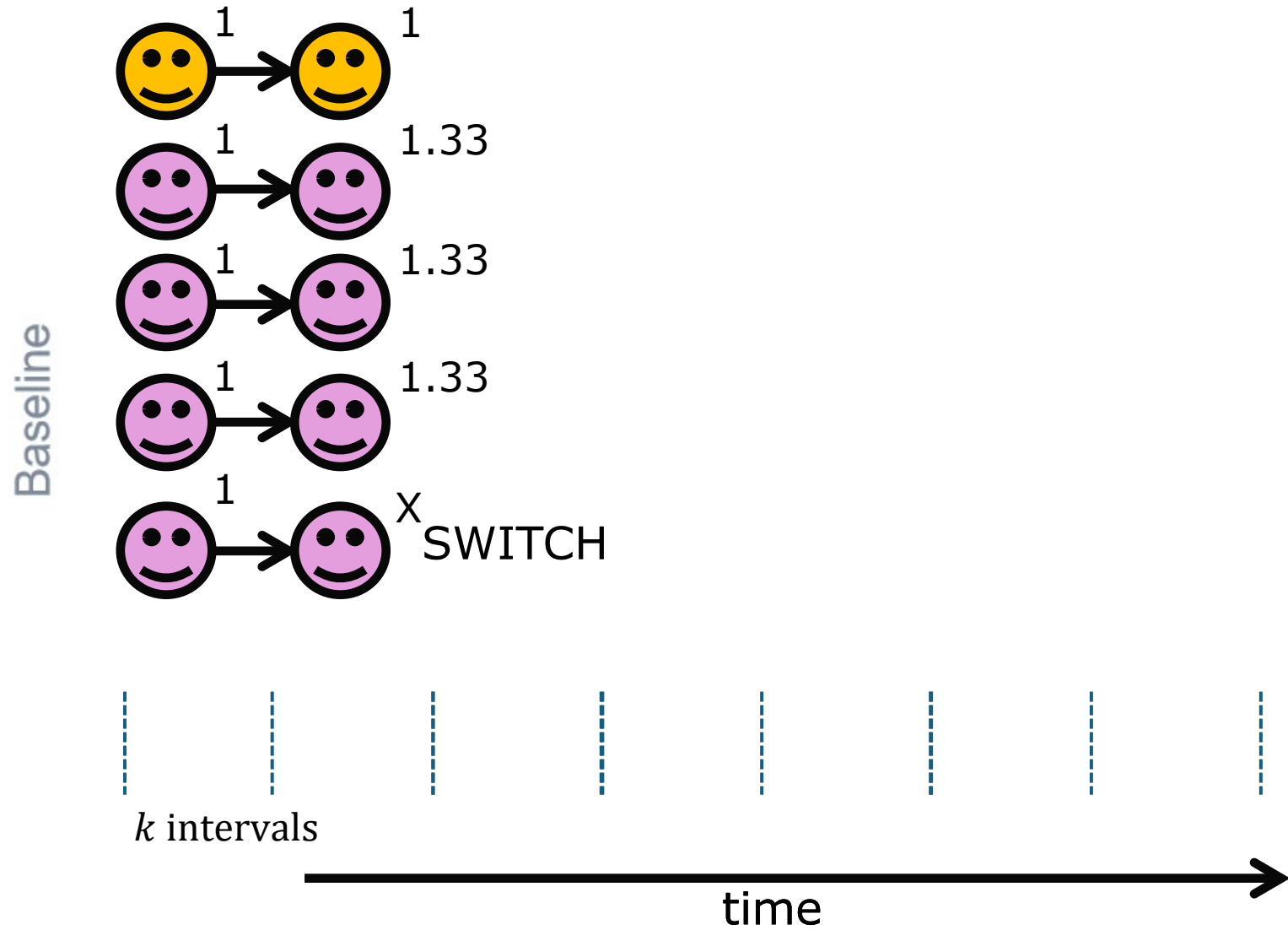
# Propensity-based method: 5-IPCW



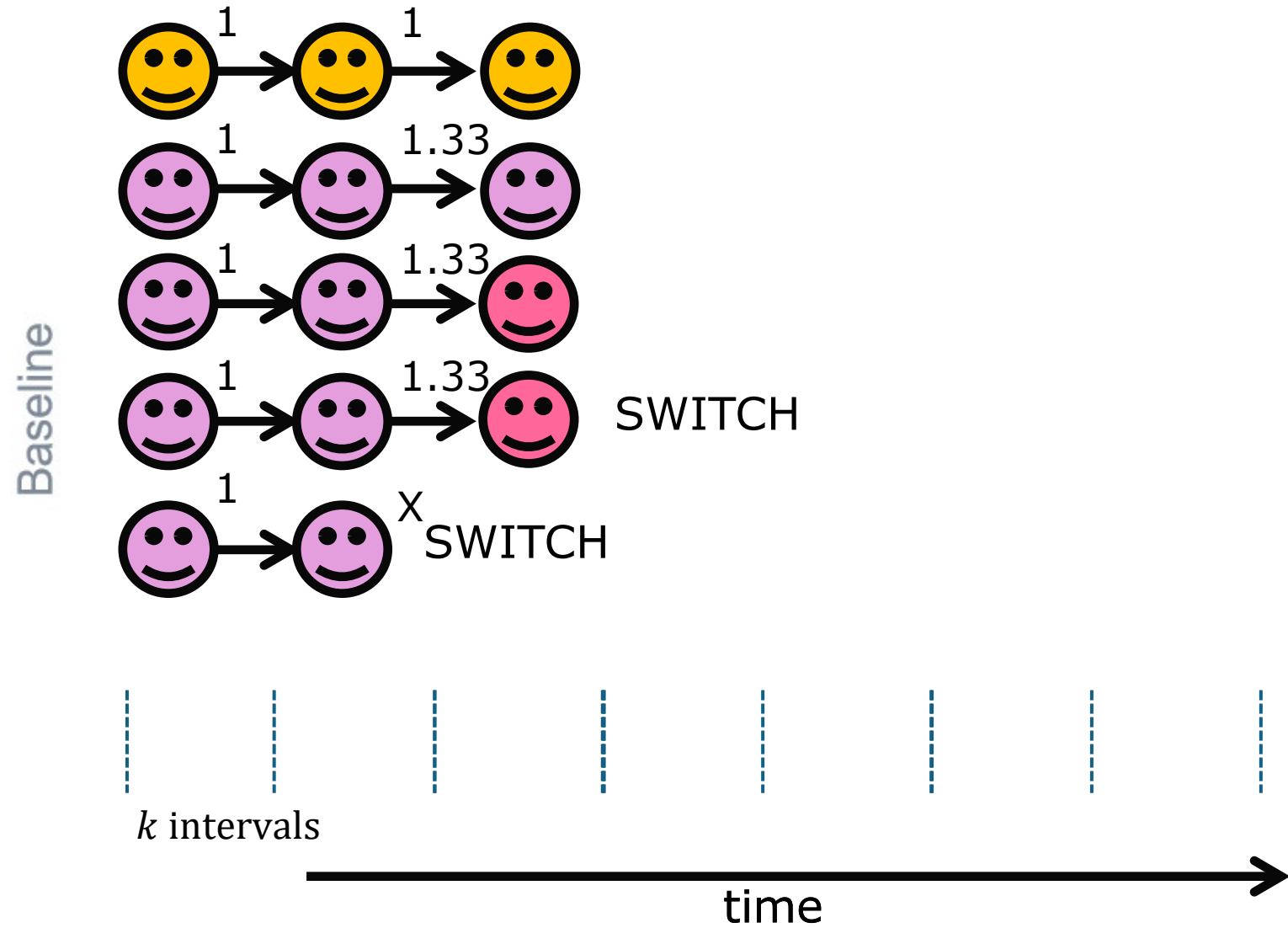
# Propensity-based method: 5-IPCW



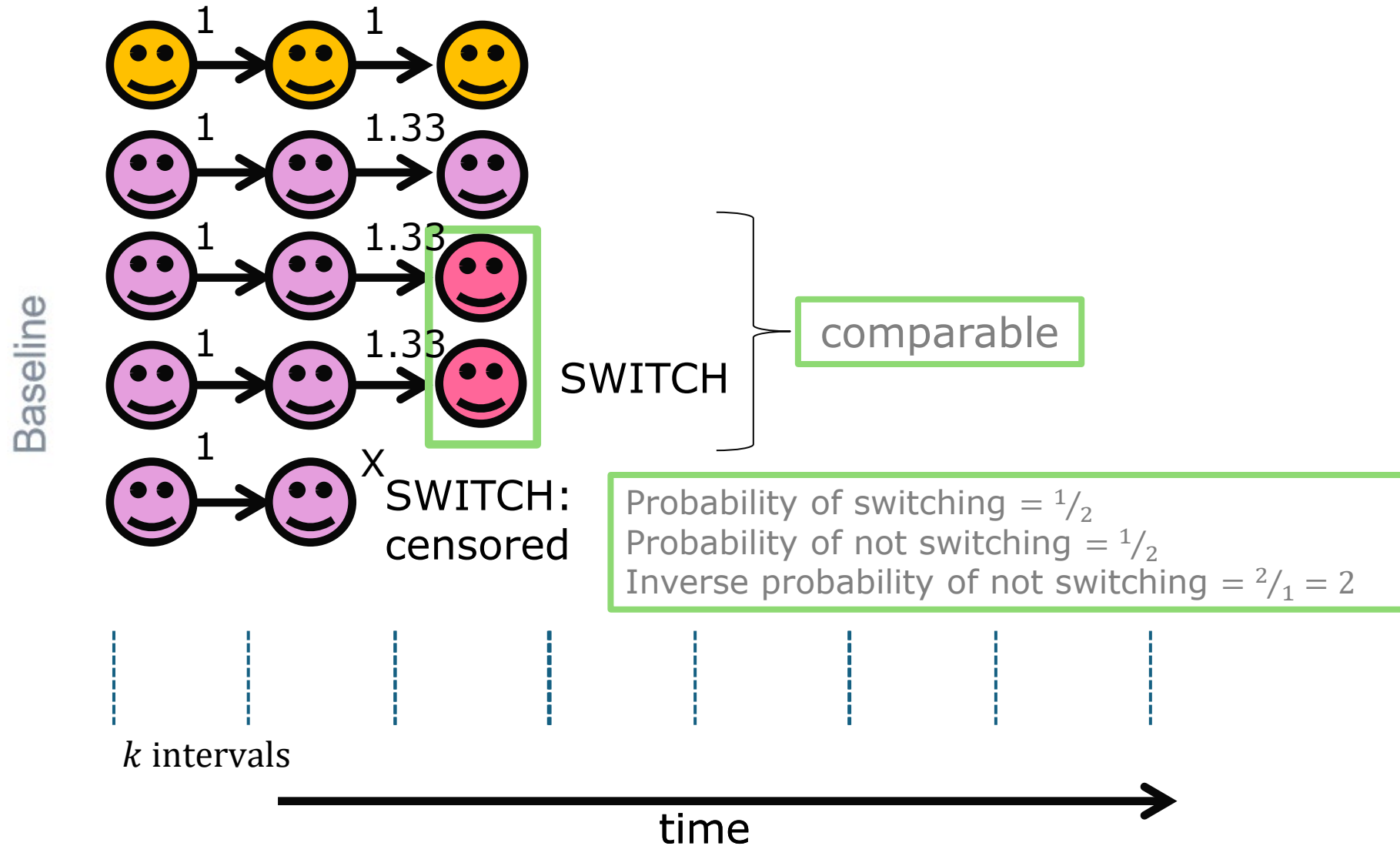
# Propensity-based method: 5-IPCW



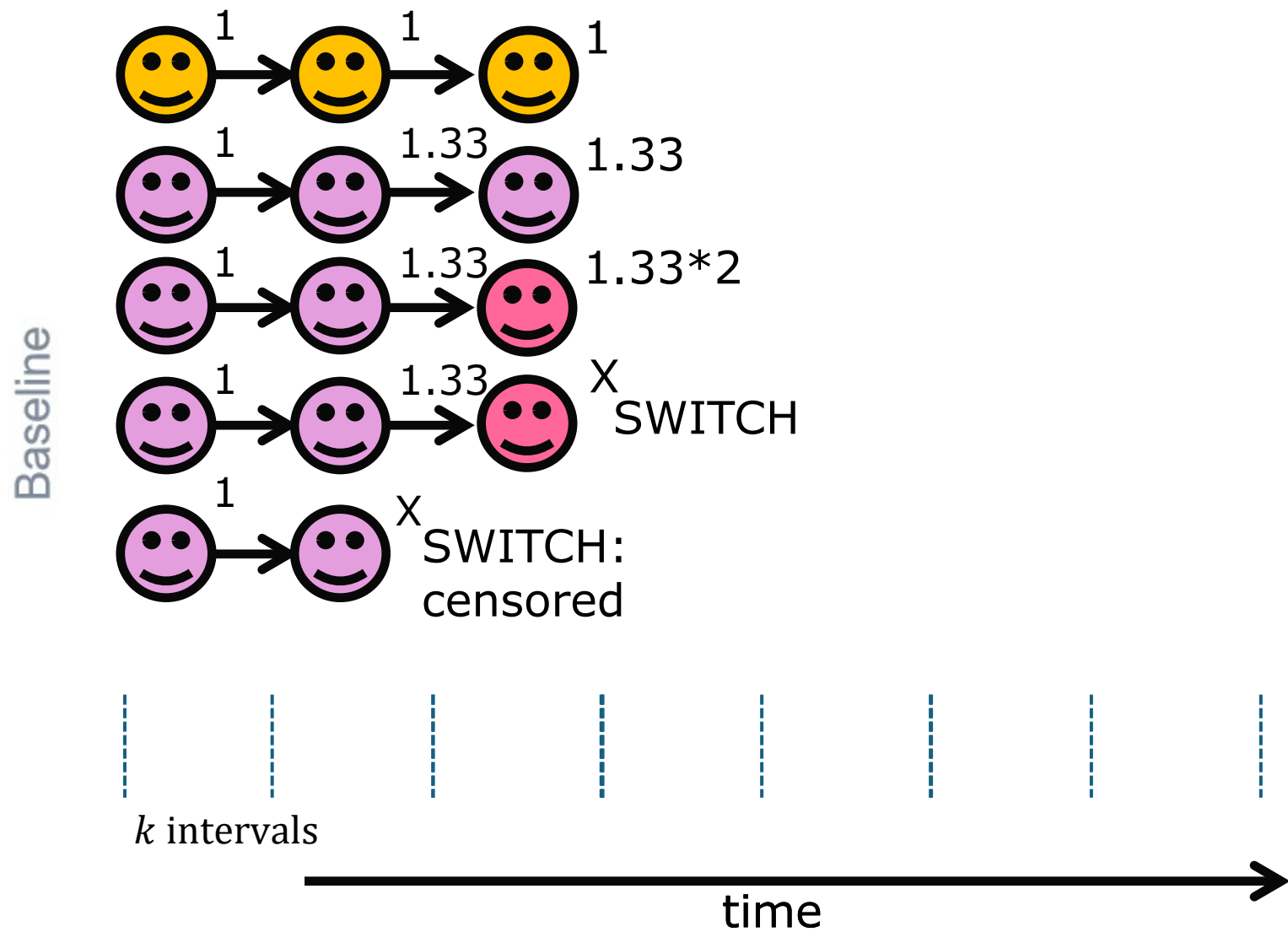
# Propensity-based method: 5-IPCW



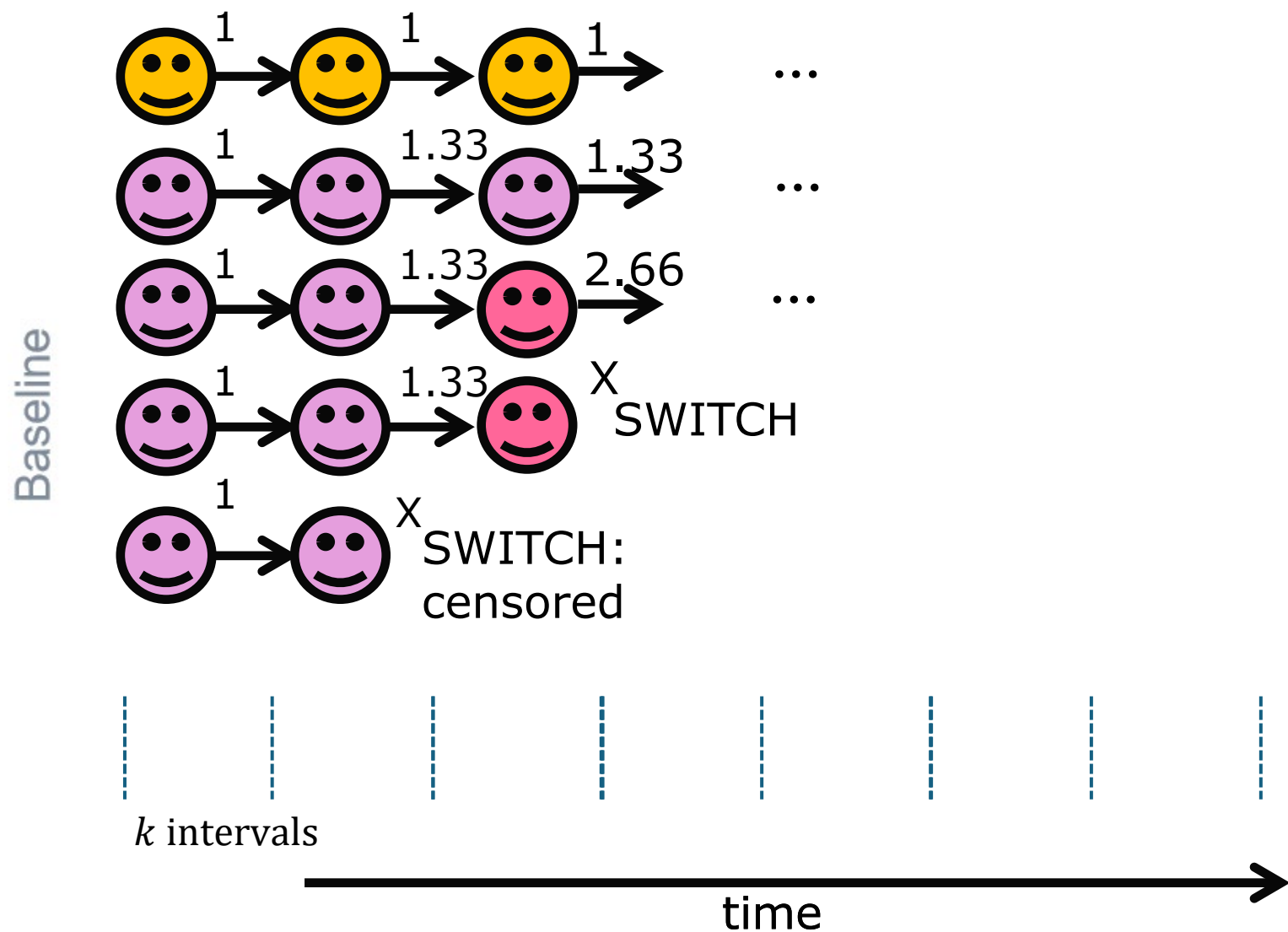
# Propensity-based method: 5-IPCW



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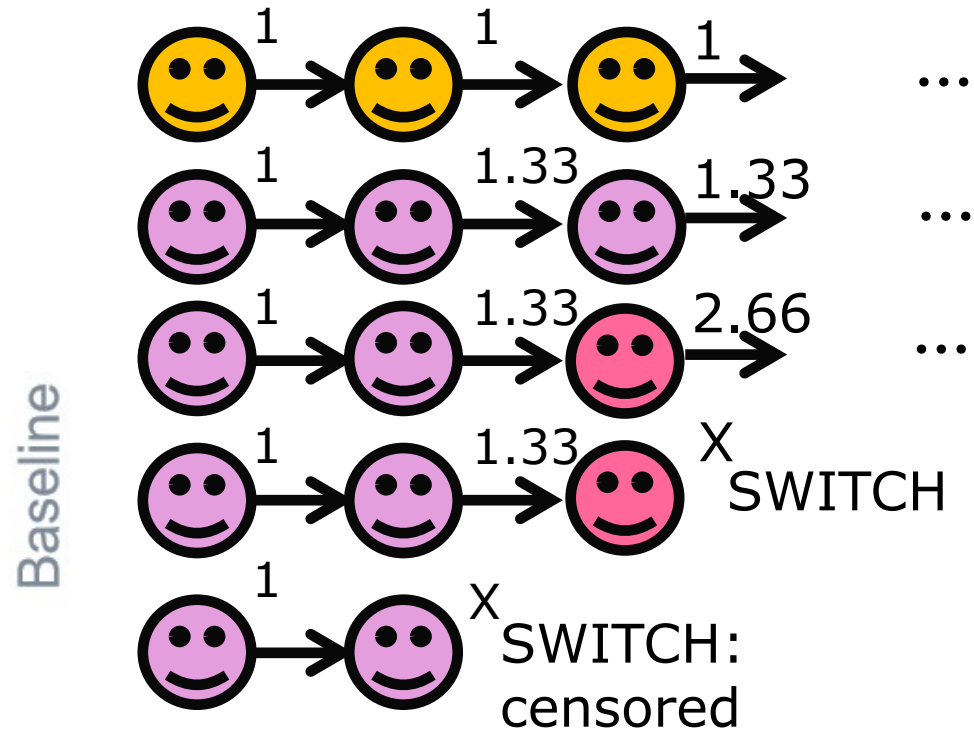


# Propensity-based method: 5-IPCW





# Propensity-based method: 5-IPCW

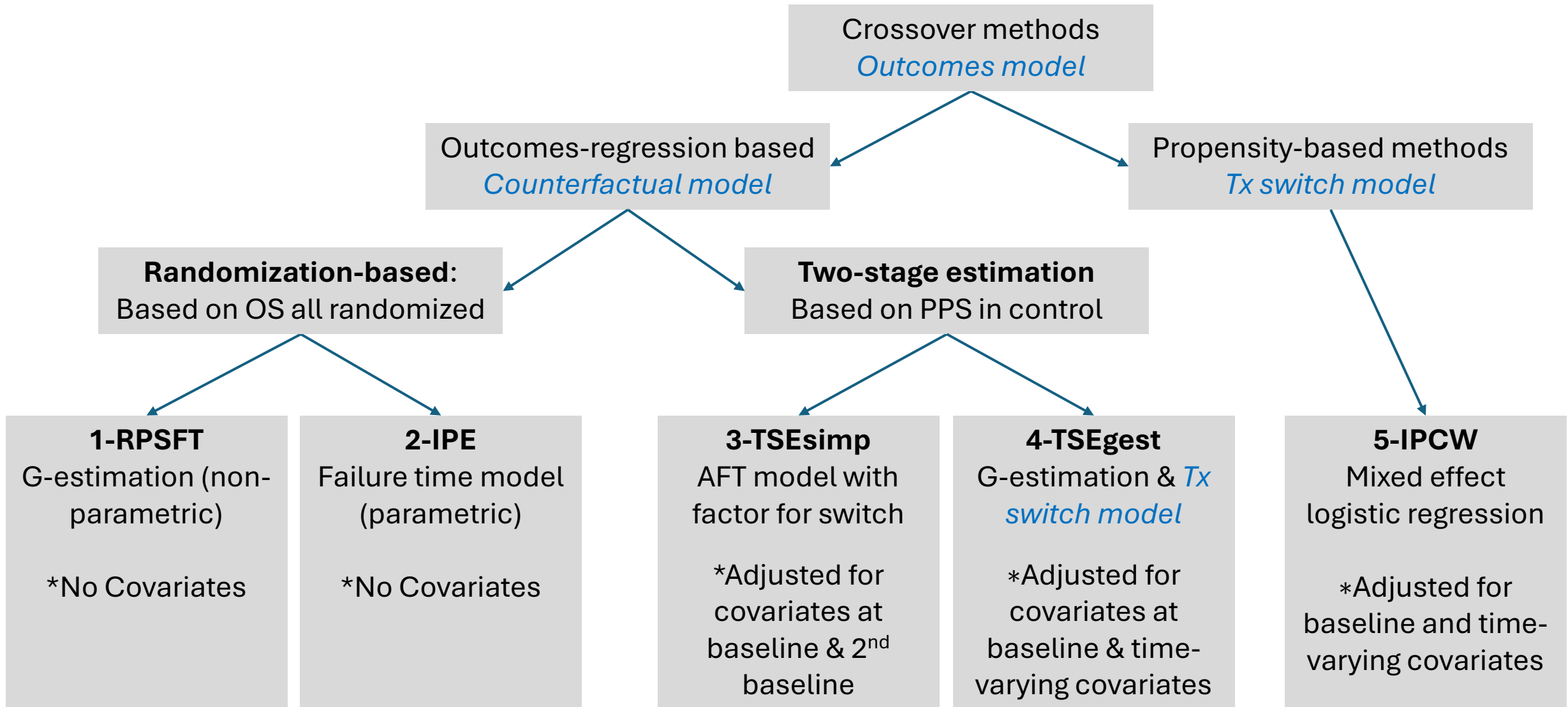


- We need to be able to distinguish which patients who have not switched are similar to those who have switched

## Practical problems

- Data collection over time
- Missing data
- Model convergence
- High weights

# Crossover adjustment methods



# Comparing crossover adjustment methods

		Randomization-based		Two-stage estimation		Propensity-based
	Requirement	1-RPSFT	2-IPE <sup>b</sup>	3-TSEsimp	4-TSEgest	5-IPCW
Model	Model for counterfactual survival	Y	Y	Y	Y	
	Model for effect of treatment switching on PPS			Y	Y	
	Model for treatment switching				Y	Y
	Model for outcomes (Cox model)	Y	Y	Y	Y	Y
Data	Survival from full RCT including intervention arm	Y	Y			
	Date of secondary baseline			Y	Y	
	Baseline covariates that impact switch or outcome			Y	Y	Y
	Covariates (baseline or secondary baseline) that impact switch or PPS			Y	Y	
	Sufficient data on non-switchers with characteristics similar to switchers to upweight (i.e., sufficiently large N/ low crossover)					Y
	Time-varying covariates that influence switch or outcome				Y	Y
Assumption	Common treatment effect (regardless time)	Y	Y			
	Randomized groups independent from potential outcomes	Y	Y			
	No unmeasured confounding			Y	Y	Y
	Switch occurs at secondary baseline			Y	optional	
	No time-dependent confounding (secondary baseline → switch)			Y		

**Notes:** Adapted from Box 1 Latimer et al. 2020. <sup>6</sup> **Abbreviations:** IPCW, inverse probability of censoring weights; IPE, iterative parameter estimation; RPSFT, rank preserving structural failure time; TSEgest, two-stage estimation involving g-estimation; TSEsimp, simplified two-stage estimation. <sup>b</sup> Requires additional assumption regarding appropriate parametric distribution as compared to RPSFT; \* If secondary baseline not assumed, requires assumption of independence between switch status and potential outcomes, conditional on variables measured at baseline and over time.



# Conclusions

- Multiple methods, each relying on different set of assumptions
- Challenging to determine which assumptions are most plausible
- Availability of data covariates over time important for TSE and IPCW methods
- If high degree of crossover and/or limited sample size IPCW estimates may be biased
- When re-censoring is introduced (methods using counterfactual model) limits available follow-up, which can impact extrapolations in cost-effectiveness model



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# Poll Question 1

**How should you select the most appropriate crossover adjustment method?**

- A. Based on what methods were pre-specified
- B. Based on the plausibility of assumptions from a clinical perspective
- C. Based on the characteristics of the data
- D. Ideally, all of the above