

Data analysis

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4/27/2023

##	id	gender	age	Z	time	status	shift	ARM
## 1	1	1	55.20165	1	47.88922	1	0.00000	Control
## 2	2	0	55.21952	1	60.00000	0	0.00000	Control
## 3	3	1	58.12572	0	49.93390	1	0.00000	Experimental
## 4	4	1	53.51899	1	56.75231	1	34.24845	Control
## 5	5	0	52.67932	0	50.13366	1	0.00000	Experimental
## 6	6	1	55.69778	1	47.75965	1	0.00000	Control

The following variables are needed in the dataset:

Z: indicating the treatment arm (with $Z = 1$: control and $Z = 0$: experimental)

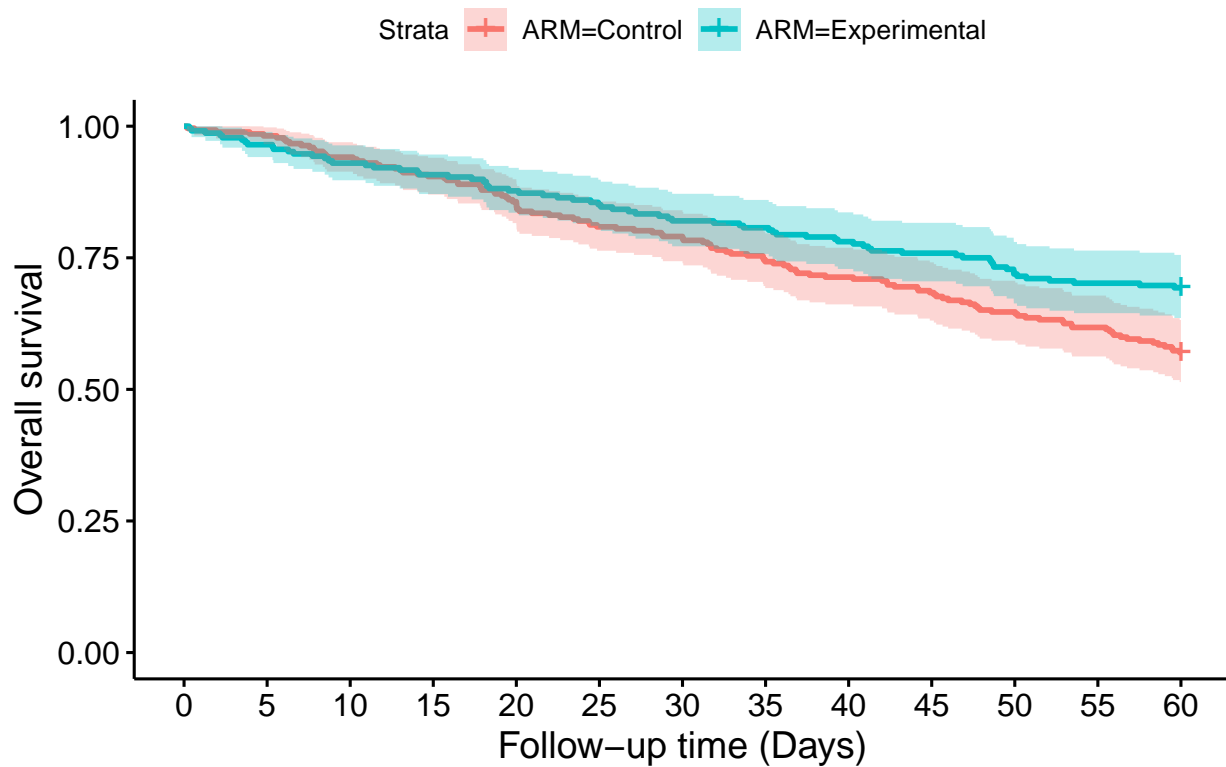
time: right-censored survival time

status: indication whether ($\text{status} = 1$) or not ($\text{status} = 0$) the patient had an event

shift: possible time of treatment crossover from one treatment to the other, 0 if the patient did not cross over

Data

Overall survival



Adding an indicator for crossover

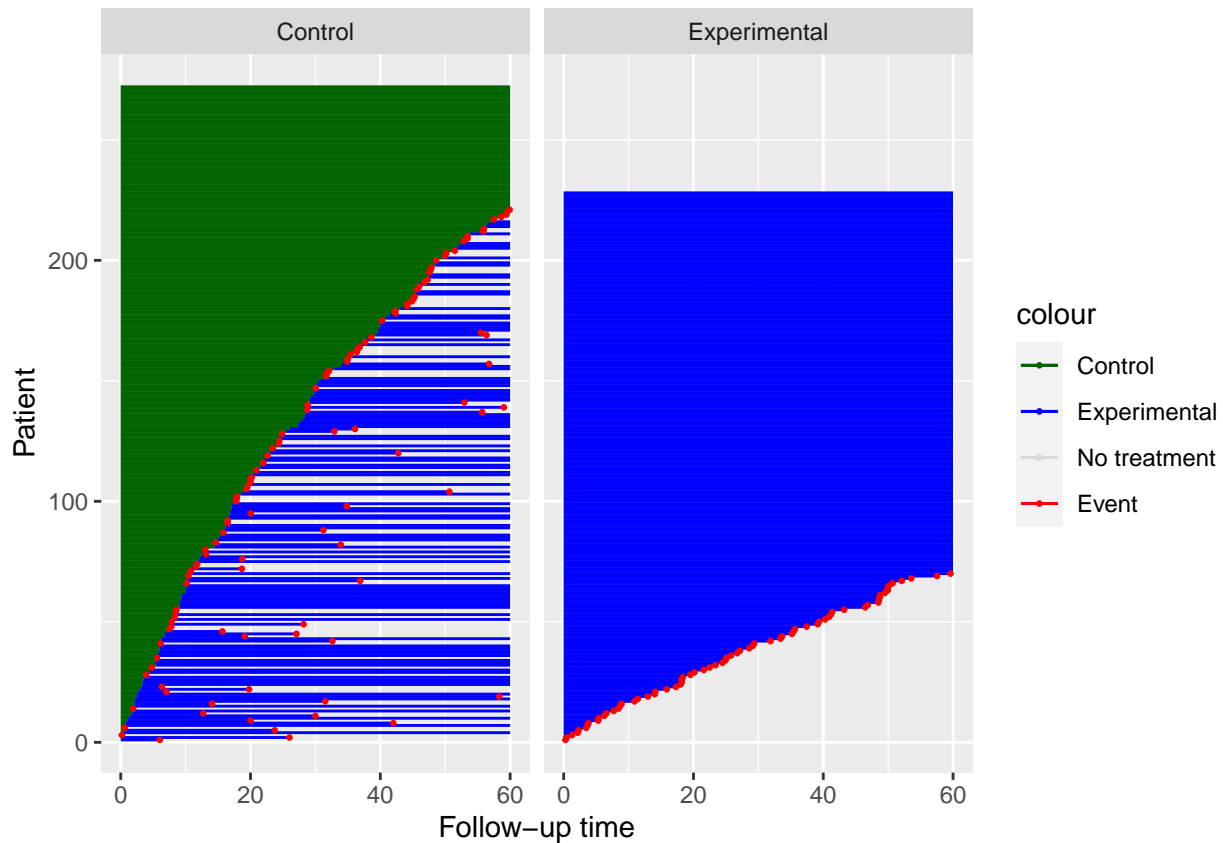
```
data$CO.indicator = ifelse(data$shift>0,yes="Yes",no="No") #Variable to indicate whether or not the pat  
table(data$ARM)
```

```
##  
##      Control Experimental  
##      272          228
```

```
table(data$ARM,data$CO.indicator)
```

```
##  
##              No Yes  
## Control      132 140  
## Experimental 228  0
```

Patient pathway plot



Data analysis on Overall Survival endpoint

Treatment-policy estimand

```
## Additive Aalen Model
##
## Test for nonparametric terms
##
## Test for non-significant effects
##      Supremum-test of significance p-value H_0: B(t)=0
## (Intercept)                8.31                0
##
## Test for time invariant effects
##      Kolmogorov-Smirnov test p-value H_0:constant effect
## (Intercept)                0.0256                0.546
##      Cramer von Mises test p-value H_0:constant effect
## (Intercept)                0.0108                0.386
##
## Parametric terms :
##      Coef.      SE Robust SE      z  P-val lower2.5% upper97.5%
## const(Z) 0.00297 0.00112    0.00112 2.66 0.00777  0.000775   0.00517
##
## Call:
## aalen(formula = Surv(time, status) ~ const(Z), data = data)
```

Wald type standard error and confidence interval

```
## Additive Aalen Model
##
## Test for nonparametric terms
##
## Test for non-significant effects
##      Supremum-test of significance p-value H_0: B(t)=0
## (Intercept)          8.31          0
##
## Test for time invariant effects
##      Kolmogorov-Smirnov test p-value H_0:constant effect
## (Intercept)          0.0256          0.546
##      Cramer von Mises test p-value H_0:constant effect
## (Intercept)          0.0108          0.386
##
## Parametric terms :
##      Coef.      SE Robust SE      z      P-val lower2.5% upper97.5%
## const(Z) 0.00297 0.00112    0.00112 2.66 0.00777 0.000775 0.00517
##
## Call:
## aalen(formula = Surv(time, status) ~ const(Z), data = data)

##      Estimand      Estimator Measure Value SE.type      SE
## const(Z) Treatment policy Additive Hazards Model      beta 0.003      Wald 0.001
##      p      LB      UB
## const(Z) 0.008 0.001 0.005

##      Estimand      Estimator
## const(Z) Treatment policy Additive Hazards Model
## const(Z)1 Treatment policy Additive Hazards Model
##      Measure Value SE.type      SE
## const(Z)      beta 0.003      Wald 0.001
## const(Z)1 Relative risk of surviving (exp. vs control) 1.195      Wald 0.080
##      p      LB      UB
## const(Z) 0.008 0.001 0.005
## const(Z)1 0.008 1.048 1.363
```

Score type standard error and confidence interval

Estimate β by minimizing the score equations

```
hazards = hazards.marginal(data)
beta = beta.estimate.itt(data=data,lower=-0.01,upper=0.01,hazards=hazards) #the lower and upper bounds
beta
```

```
## [1] 0.002977041
```

Now we estimate the p-value

```
fit.ivsacim = ivsacim(time=data$time, event=data$status, instrument=data$Z, IV_valid = TRUE, treatment_
fit.ivsacim.by_prod = fit.ivsacim$by_prod
stime = fit.ivsacim$stime
```

```
p.value = p.itt.score(fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,stime=stime,hazards=hazards)
p.value
```

```
## [1] 0.00520822
```

SE for β :

```
beta.se = beta.itt.se.function(fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,beta.est=beta,hazards=
beta.se
```

```
## [1] 0.001098524
```

Now we determine a 95% CI by minimising the quadratic difference between the p-value and 5%

```
LB = beta.bound.itt(lower=beta-10*beta.se,upper=beta,fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,
UB = beta.bound.itt(lower=beta,upper=beta+10*beta.se,fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,
```

```
##               Estimand               Estimator
## const(Z)   Treatment policy Additive Hazards Model
## const(Z)1  Treatment policy Additive Hazards Model
## 1          Treatment policy Additive Hazards Model
## 11         Treatment policy Additive Hazards Model
##                                     Measure Value SE.type    SE
## const(Z)                                     beta 0.003    Wald 0.001
## const(Z)1 Relative risk of surviving (exp. vs control) 1.195    Wald 0.080
## 1                                     beta 0.003    Score 0.001
## 11         Relative risk of surviving (exp. vs control) 1.195    Score 0.079
##               p      LB      UB
## const(Z)   0.008 0.001 0.005
## const(Z)1  0.008 1.048 1.363
## 1          0.005 0.001 0.005
## 11         0.005 1.054 1.366
```

Using Instrumental Variables (g-estimation): method by Ying and Tchetgen Tchetgen 2022

(No baseline covariates are included)

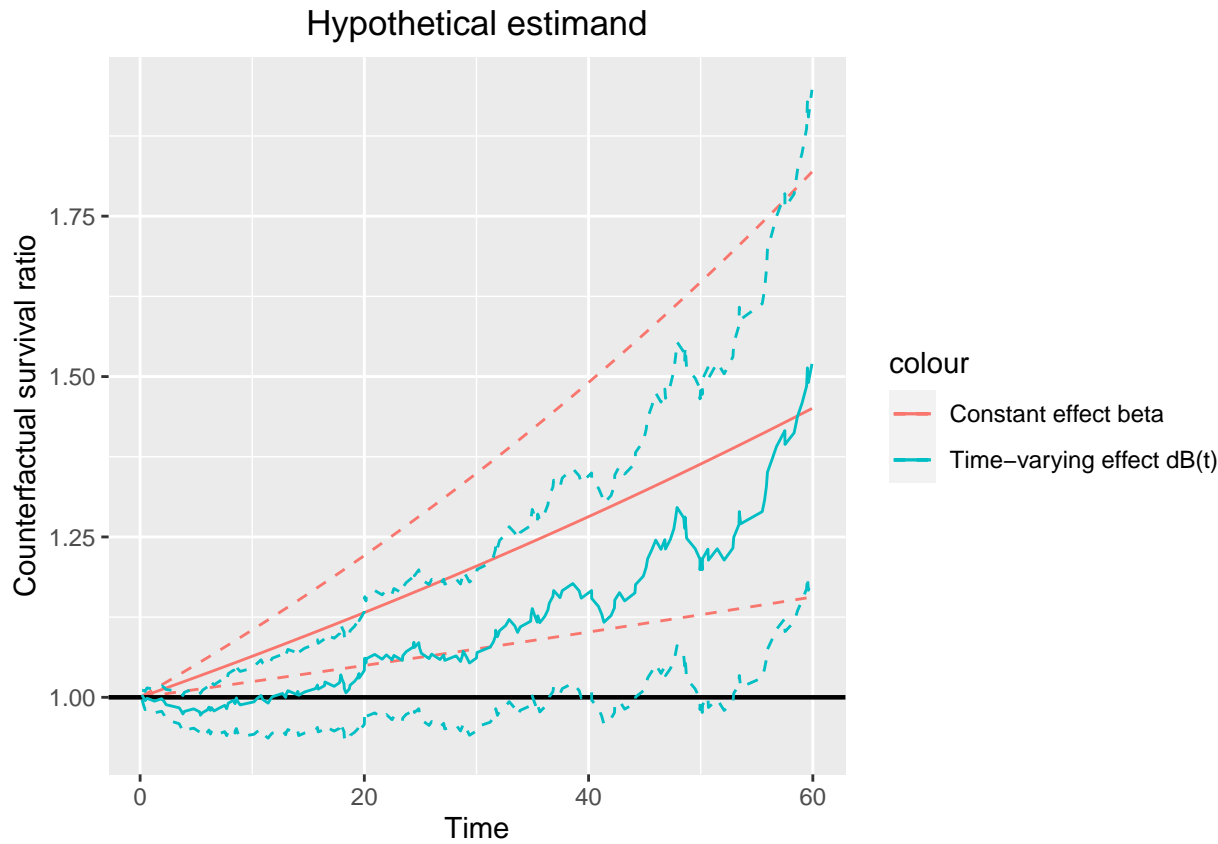
```
library(ivsacim) #install this package first if needed
fit.ivsacim <- ivsacim(time=data$time, event=data$status, instrument=data$Z, IV_valid = TRUE, treatment_
summary(fit.ivsacim)
```

```
##
## Instrumental Variables Structural Additive Cumulative Intensity Model with a Valid IV
##
## Test for non-significant exposure effect. H_0: B_D(t) = 0
```

```
##
##      Supremum-test pval
## Exposure      0
##
##
## Goodness-of-fit test for constant effects model. H_0: B_D(t) = beta_D * t
##      Supremum-test pval
##      0.114
##
## Constant effect model: B_D(t) = beta_D * t
##      coef se(coef) z-value p-value
## Exposure      0.0062  0.00193    3.22  0.0013
##
```

```
p.value = summary(fit.ivsacim)$pval_beta_D
```

Hypothetical survival risk ratio over time:



##	Estimand	Estimator
## const(Z)	Treatment policy	Additive Hazards Model
## const(Z)1	Treatment policy	Additive Hazards Model
## 1	Treatment policy	Additive Hazards Model
## 11	Treatment policy	Additive Hazards Model
## 12	Hypothetical estimand	ivsacim
## 13	Hypothetical estimand	ivsacim
##		Measure Value

```
## const(Z)                                beta 0.003
## const(Z)1          Relative risk of surviving (exp. vs control) 1.195
## 1                                beta 0.003
## 11          Relative risk of surviving (exp. vs control) 1.195
## 12                                beta 0.006
## 13          Relative risk of surviving (always exp. vs always control) 1.450
##          SE.type    SE      p    LB    UB
## const(Z)      Wald 0.001 0.008 0.001 0.005
## const(Z)1      Wald 0.080 0.008 1.048 1.363
## 1              Score 0.001 0.005 0.001 0.005
## 11              Score 0.079 0.005 1.054 1.366
## 12              Wald 0.002 0.001 0.002 0.010
## 13              Wald 0.168 0.001 1.156 1.819
```

Score (Sandwich estimator) β estimate:

```
fit.ivsacim.by_prod = fit.ivsacim$by_prod
stime = fit.ivsacim$stime
beta = beta.estimate.iv.score(fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,lower=-0.01,upper=0.01,
beta
```

```
## [1] 0.005421263
```

Next, we estimate the SE of β using the Sandwich estimator

```
beta.se = beta.iv.se(fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,beta.est=fit.ivsacim.by_prod$bet
beta.se
```

```
## [1] 0.002738459
```

Now we estimate the p-value

```
p.value = p.iv.score(fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,stime=stime)
p.value
```

```
## [1] 0.02272636
```

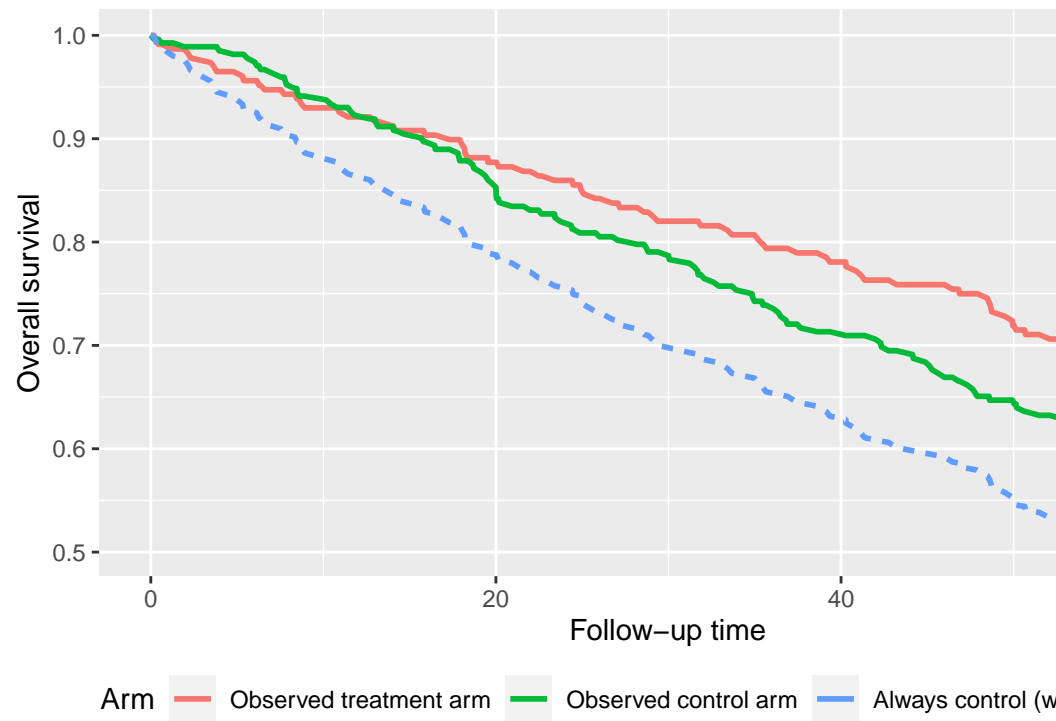
Now we determine a 95% CI by minimising the quadratic difference between the p-value and 5%

```
LB = beta.bound.iv(lower=beta-10*beta.se,upper=beta,fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,s
UB = beta.bound.iv(lower=beta,upper=beta+10*beta.se,fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,s
```

```
##          Estimand          Estimator
## const(Z)      Treatment policy Additive Hazards Model
## const(Z)1      Treatment policy Additive Hazards Model
## 1              Treatment policy Additive Hazards Model
## 11              Treatment policy Additive Hazards Model
## 12      Hypothetical estimand          ivsacim
## 13      Hypothetical estimand          ivsacim
## 14      Hypothetical estimand          ivsacim
```

```
## 15      Hypothetical estimand      ivsacim
##
## const(Z)      beta 0.003
## const(Z)1      Relative risk of surviving (exp. vs control) 1.195
## 1      beta 0.003
## 11      Relative risk of surviving (exp. vs control) 1.195
## 12      beta 0.006
## 13      Relative risk of surviving (always exp. vs always control) 1.450
## 14      beta 0.005
## 15      Relative risk of surviving (always exp. vs always control) 1.384
## SE.type SE p LB UB
## const(Z) Wald 0.001 0.008 0.001 0.005
## const(Z)1 Wald 0.080 0.008 1.048 1.363
## 1 Score 0.001 0.005 0.001 0.005
## 11 Score 0.079 0.005 1.054 1.366
## 12 Wald 0.002 0.001 0.002 0.010
## 13 Wald 0.168 0.001 1.156 1.819
## 14 Score 0.003 0.023 0.001 0.009
## 15 Score 0.227 0.023 1.052 1.759
```

Observed and hypothetical survival curves



Hypothetical survival curve

Observed — Observed - - Predicted

One-step estimator

1. Initial estimate for β using the IV estimator of Ying and Tchetgen Tchetgen


```
library(ivsacim)
fit.ivsacim <- ivsacim(time=data$time, event=data$status, instrument=data$Z, IV_valid = TRUE, treatment,
summary(fit.ivsacim)
```

```
##
## Instrumental Variables Structural Additive Cumulative Intensity Model with a Valid IV
##
## Test for non-significant exposure effect. H_0: B_D(t) = 0
##
##          Supremum-test pval
## Exposure          0.002
##
##
## Goodness-of-fit test for constant effects model. H_0: B_D(t) = beta_D * t
##          Supremum-test pval
##          0.106
##
## Constant effect model: B_D(t) = beta_D * t
##          coef se(coef) z-value p-value
## Exposure    0.0062  0.00193    3.22  0.0013
##
```

```
beta.start = fit.ivsacim$beta_D
stime = fit.ivsacim$stime
```

2. Calculate score function for every patient, evaluated in the initial β estimate and take the sample average.

```
#Z.formula=Z~1 #use this if you dont want to condition on baseline covariates
#L.values=c() #use this if you dont want to condition on baseline covariates
Z.formula=Z~gender+age #change the names of the baseline covariates
L.values=c("gender","age") #change the names of the baseline covariates

fit.ivsacim.by_prod = fit.ivsacim$by_prod
stime = fit.ivsacim$stime
#Sample average of the score function, evaluated in beta.start
av = av.function(fit.ivsacim.by_prod = fit.ivsacim.by_prod,data=data,beta.start=beta.start,stime=stime
av
```

```
## [1] -0.008687571
```

3. Calculate the derivative of the score function for every patient, evaluated in the initial β estimate and take the sample average.

```
## [1] -8.231402
```

4. Update the initial β estimate

```
beta.update = beta.start - av/av.deriv
beta.update
```

```
## [1] 0.005147617
```

```
beta = beta.update
```

Now we estimate the p-value

```
p.value = p.score(fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,stime=stime,Z.formula=Z.formula,L.v  
p.value
```

```
## [1] 0.04847756
```

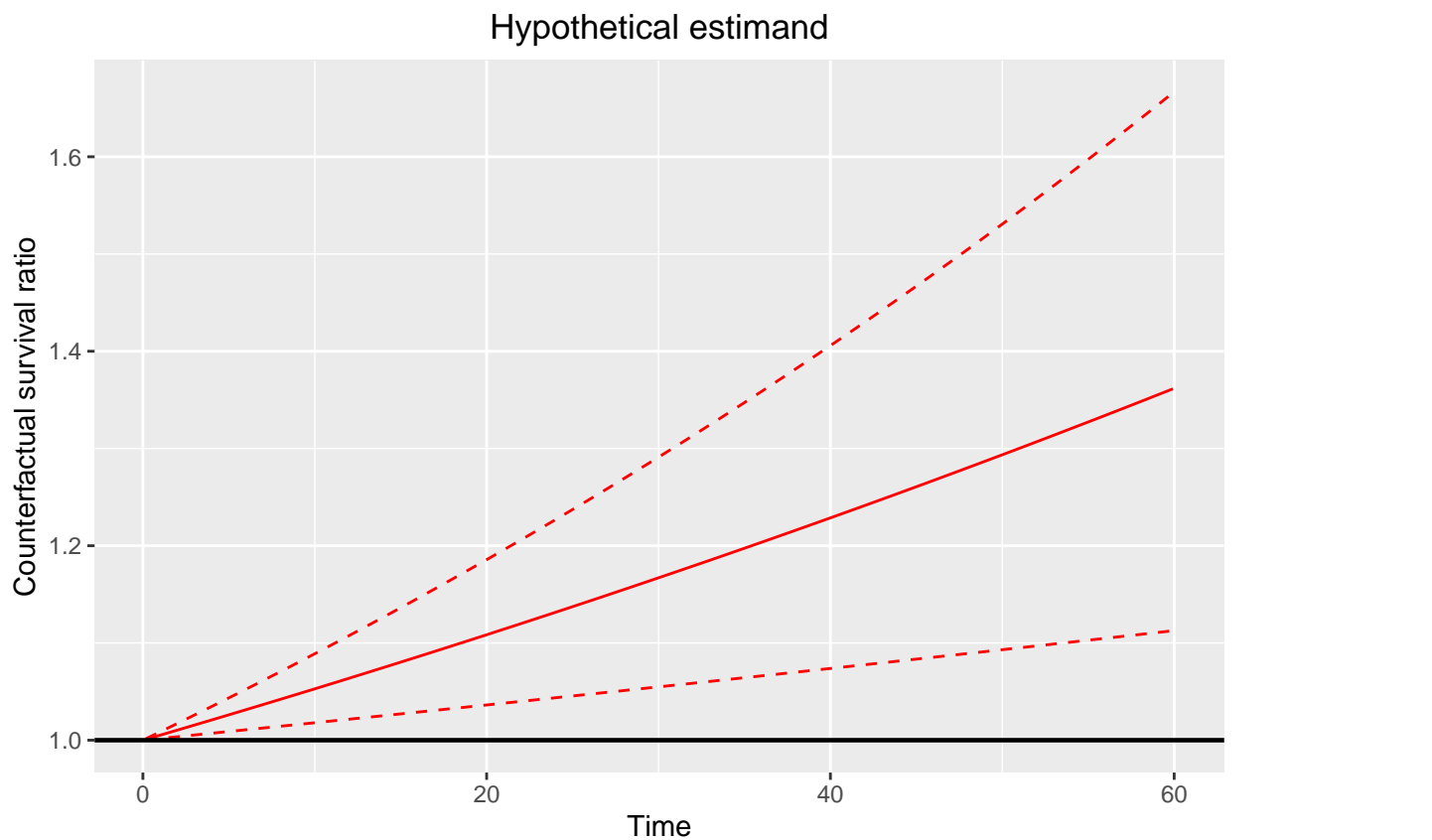
SE for β :

```
beta.se = beta.se.function(fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,beta.est=beta,Z.formula=Z.  
beta.se
```

```
## [1] 0.001718241
```

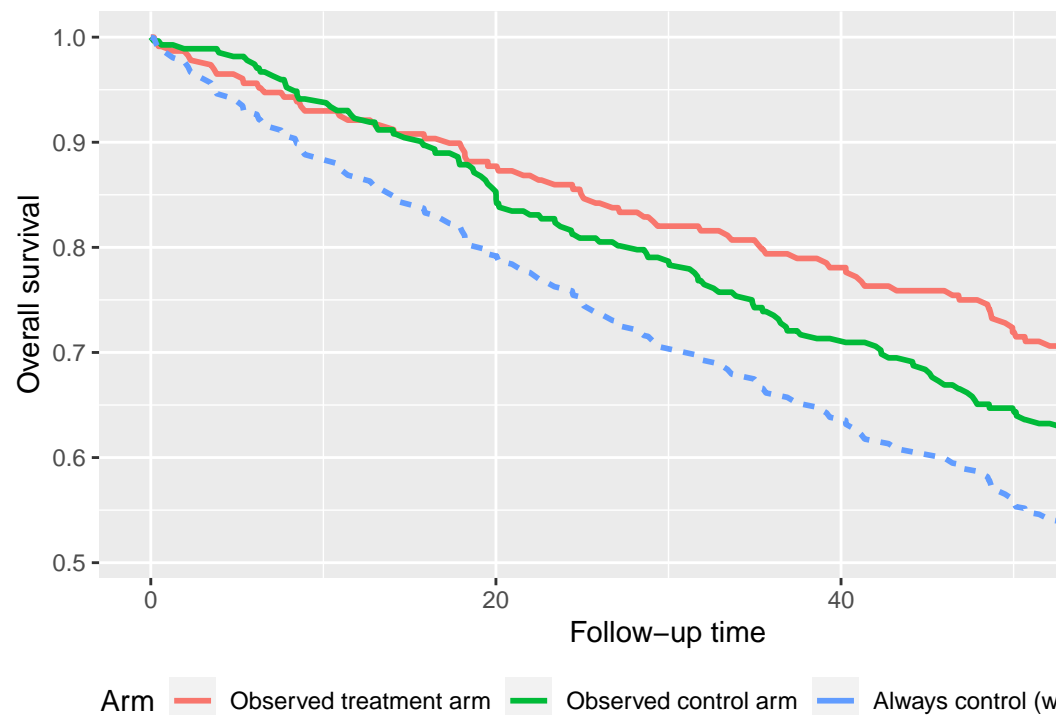
Now we determine a 95% CI by minimising the quadratic difference between the p-value and 5%

```
LB = beta.bound(lower=beta-10*beta.se,upper=beta,fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,stim  
UB = beta.bound(lower=beta,upper=beta+10*beta.se,fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,stim
```



	Estimand	Estimator	
## const(Z)	Treatment policy	Additive Hazards Model	
## const(Z)1	Treatment policy	Additive Hazards Model	
## 1	Treatment policy	Additive Hazards Model	
## 11	Treatment policy	Additive Hazards Model	
## 12	Hypothetical estimand	ivsacim	
## 13	Hypothetical estimand	ivsacim	
## 14	Hypothetical estimand	ivsacim	
## 15	Hypothetical estimand	ivsacim	
## 16	Hypothetical estimand	Onestep	
## 17	Hypothetical estimand	Onestep	
##			Measure Value
## const(Z)			beta 0.003
## const(Z)1	Relative risk of surviving (exp. vs control)		1.195
## 1			beta 0.003
## 11	Relative risk of surviving (exp. vs control)		1.195
## 12			beta 0.006
## 13	Relative risk of surviving (always exp. vs always control)		1.450
## 14			beta 0.005
## 15	Relative risk of surviving (always exp. vs always control)		1.384
## 16			beta 0.005
## 17	Relative risk of surviving (always exp. vs always control)		1.361
##	SE.type	SE	p LB UB
## const(Z)	Wald	0.001	0.008 0.001 0.005
## const(Z)1	Wald	0.080	0.008 1.048 1.363
## 1	Score	0.001	0.005 0.001 0.005
## 11	Score	0.079	0.005 1.054 1.366
## 12	Wald	0.002	0.001 0.002 0.010
## 13	Wald	0.168	0.001 1.156 1.819
## 14	Score	0.003	0.023 0.001 0.009
## 15	Score	0.227	0.023 1.052 1.759
## 16	Score	0.002	0.048 0.000 0.009
## 17	Score	0.140	0.048 1.001 1.718

Observed and hypothetical survival curves



Hypothetical survival curve

Observed — Observed - - Predicted

One-step estimator with hazard

1. Initial estimate for β using the IV estimator of Ying and Tchetgen Tchetgen

```
library(ivsacim)
fit.ivsacim <- ivsacim(time=data$time, event=data$status, instrument=data$Z, IV_valid = TRUE, treatment=
summary(fit.ivsacim)
```

```
##
## Instrumental Variables Structural Additive Cumulative Intensity Model with a Valid IV
##
## Test for non-significant exposure effect. H_0: B_D(t) = 0
##
##      Supremum-test pval
## Exposure      0
##
##
## Goodness-of-fit test for constant effects model. H_0: B_D(t) = beta_D * t
##      Supremum-test pval
##      0.109
##
## Constant effect model: B_D(t) = beta_D * t
##      coef se(coef) z-value p-value
## Exposure  0.0062  0.00193   3.22  0.0013
##
```

```
beta.start = fit.ivsacim$beta_D
stime = fit.ivsacim$stime
```

2. Calculate score function for every patient, evaluated in the initial β estimate and take the sample average.

```
hazards = hazards.conditional(data,T.formula = T.formula)

fit.ivsacim.by_prod = fit.ivsacim$by_prod
stime = fit.ivsacim$stime
#Sample average of the score function, evaluated in beta.start
av = av.function.hazard(fit.ivsacim.by_prod = fit.ivsacim.by_prod,data=data,beta.start=beta.start,stime=stime)
av
```

```
## [1] -0.009675167
```

3. Calculate the derivative of the score function for every patient, evaluated in the initial β estimate and take the sample average.

```
## [1] -8.252618
```

4. Update the initial β estimate

```
beta.update = beta.start - av/av.deriv
beta.update
```

```
## [1] 0.005030659
```

```
beta = beta.update
```

Now we estimate the p-value

```
p.value = p.score.hazard(fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,stime=stime,Z.formula=Z.formula)
p.value
```

```
## [1] 0.007696374
```

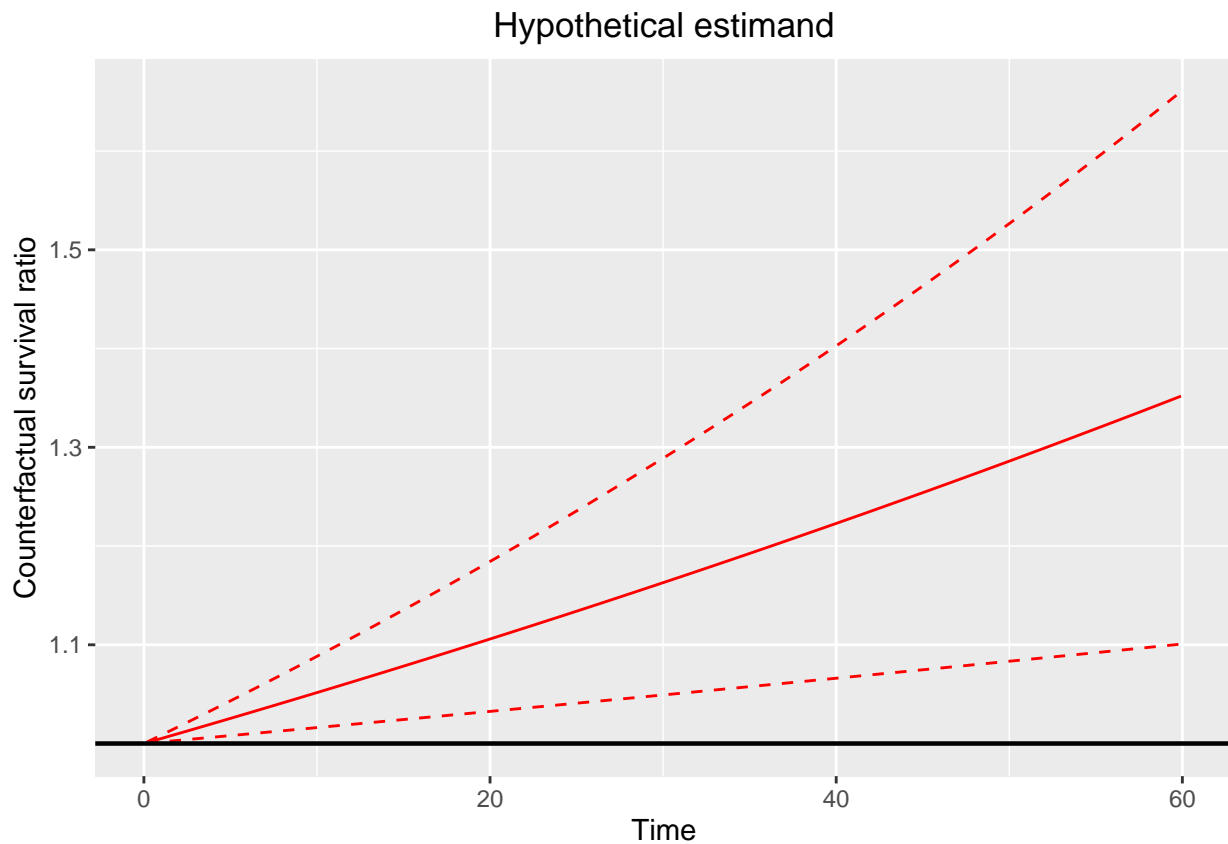
SE for β :

```
beta.se = beta.se.function.hazard(fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=data,beta.est=beta,Z.formula=Z.formula)
beta.se
```

```
## [1] 0.001749919
```

Now we determine a 95% CI by minimising the quadratic difference between the p-value and 5%

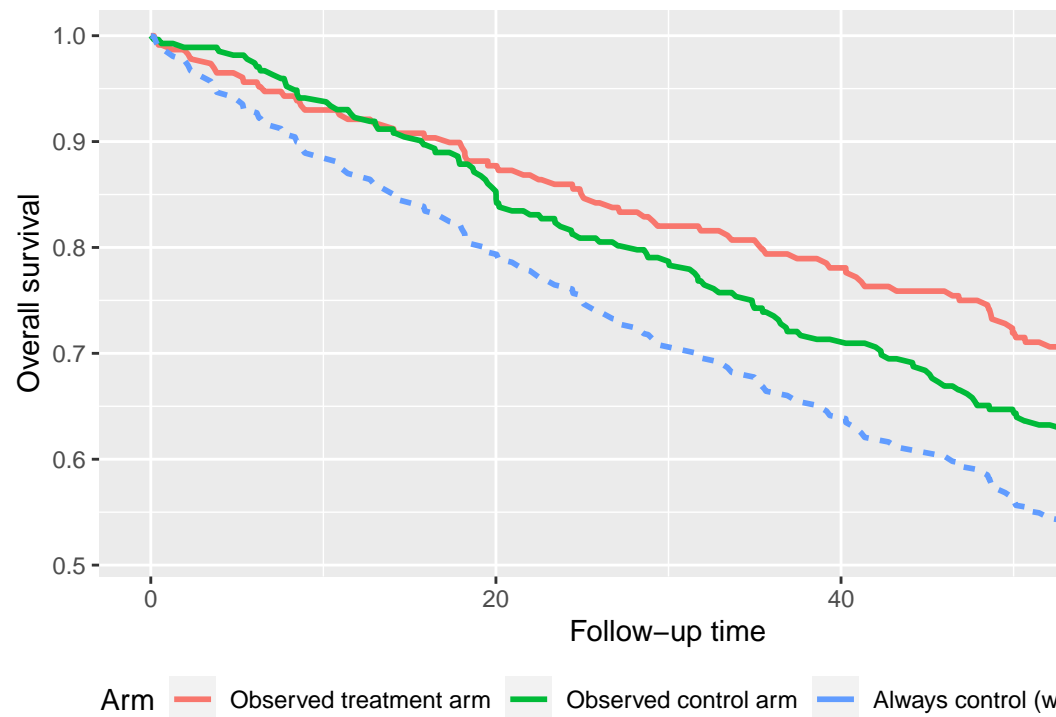
```
LB = beta.bound.hazard(lower=beta-10*beta.se,upper=beta,fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=da
UB = beta.bound.hazard(lower=beta,upper=beta+10*beta.se,fit.ivsacim.by_prod=fit.ivsacim.by_prod,data=da
```



```
##                               Estimand           Estimator
## const(Z)      Treatment policy Additive Hazards Model
## const(Z)1     Treatment policy Additive Hazards Model
## 1             Treatment policy Additive Hazards Model
## 11            Treatment policy Additive Hazards Model
## 12            Hypothetical estimand                    ivsacim
## 13            Hypothetical estimand                    ivsacim
## 14            Hypothetical estimand                    ivsacim
## 15            Hypothetical estimand                    ivsacim
## 16            Hypothetical estimand                    Onestep
## 17            Hypothetical estimand                    Onestep
## 18            Hypothetical estimand    Onestep with hazard
## 19            Hypothetical estimand    Onestep with hazard
##
##                               Measure Value
## const(Z)                                beta 0.003
## const(Z)1      Relative risk of surviving (exp. vs control) 1.195
## 1                                beta 0.003
## 11      Relative risk of surviving (exp. vs control) 1.195
## 12                                beta 0.006
## 13      Relative risk of surviving (always exp. vs always control) 1.450
## 14                                beta 0.005
## 15      Relative risk of surviving (always exp. vs always control) 1.384
## 16                                beta 0.005
```

```
## 17      Relative risk of surviving (always exp. vs always control) 1.361
## 18                                          beta 0.005
## 19      Relative risk of surviving (always exp. vs always control) 1.352
##      SE.type      SE      p      LB      UB
## const(Z)      Wald 0.001 0.008 0.001 0.005
## const(Z)1      Wald 0.080 0.008 1.048 1.363
## 1      Score 0.001 0.005 0.001 0.005
## 11      Score 0.079 0.005 1.054 1.366
## 12      Wald 0.002 0.001 0.002 0.010
## 13      Wald 0.168 0.001 1.156 1.819
## 14      Score 0.003 0.023 0.001 0.009
## 15      Score 0.227 0.023 1.052 1.759
## 16      Score 0.002 0.048 0.000 0.009
## 17      Score 0.140 0.048 1.001 1.718
## 18      Score 0.002 0.008 0.001 0.009
## 19      Score 0.142 0.008 1.085 1.670
```

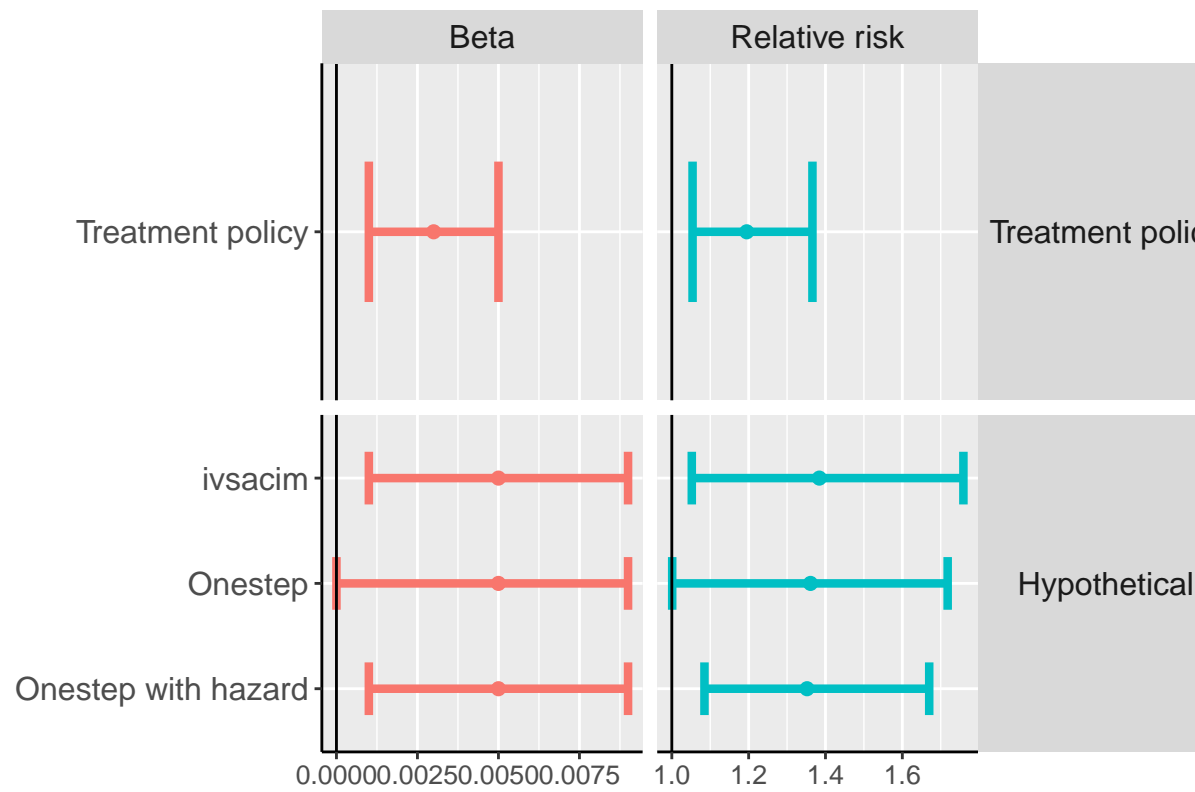
Observed and hypothetical survival curves



Hypothetical survival curve

Observed — Observed - - Predicted

Results on overall survival endpoint



Plot of the results