1. Supplementary Methods

1.1. Data-generating distributions.

All covariates were generated as Bernoulli ($\mathcal{B}$) random variables with probabilities that were expit-linear functions of selected characteristics. In all scenarios, the coefficients of the equation for $H(t)$ were chosen so that approximately 50% of exposed workers experienced an intermediate health event by the end of follow-up. The coefficients of the outcome equations were chosen to permit a sufficiently large etiologic effect with which realistic effects could be compared.

Scenario 1. The data for each worker in this scenario was generated according to the following longitudinal structural equation model[12] for $t = 1, \dots, 20$ years of follow-up:

Susceptibility. $S \sim \mathcal{B}(0.50)$

Exposure. $E(t) = 1$ or 0, depending on intervention.

Intermediate health event. If $S = 0$ then $H(t) = 0$. If $H(t-1) = 1$ then $H(t) = 1$. Otherwise,

$$H(t) \sim \mathcal{B}\left\{expit\left(\beta_0^H + \beta_E^H \times \bar{E}(t)\right)\right\} = \mathcal{B}\left\{expit\left(-2.00 + 0.25 \times \bar{E}(t)\right)\right\}$$

$\bar{E}(t) = \sum_{k=1}^{t} E(k)$ denotes cumulative exposure in year t.

Employment status. Under the realistic intervention, $W(t) = 0$ if $H(t-1) = 1$. Otherwise $W(t) = 1$.

Outcome. If $S = 0$ then $Y(t) = 0$. Otherwise,

$$Y(t) \sim \mathcal{B}\left\{expit\left(\beta_0^Y + \beta_H^Y \times H(t) + \beta_E^Y \times \bar{E}(t)\right)\right\}$$
$$= \mathcal{B}\left\{expit\left(-7.00 + 1.50 \times H(t) + 0.25 \times \bar{E}(t)\right)\right\}. \quad (1)$$

Scenario 2. The outcome was generated as follows for susceptible workers:

$$Y(t) \sim \mathcal{B}\left\{expit\left(-7.00 + 3.00 \times H(t) + 0.25 \times \bar{E}(t)\right)\right\}.$$

If the outcome $Y(t)$ is generated as 1, all future outcome $Y(s)$ for time-points $s > t$ are set 1. The remaining equations were the same for this scenario as for the scenario 1.

Scenario 3. The intermediate health event was generated as follows:

If $H(t-10) = 1$ or $W(t-1) = 0$ then $W(t) = 0$. Otherwise $W(t) = 1$.

All other covariates were generated as in the scenario 1.

Scenario 4. While all remaining covariates were generated as in the scenario 1, health status for susceptible workers in this scenario was generated as follows:

$$H(1) \sim \mathcal{B}\left\{expit\left(-4.00 + 7.00 \times E(1)\right)\right\}, H(t > 1) = H(1).$$

1.2. Computing Intervention Effects.

Interventions and counterfactuals - We define static interventions $\{d_{s,1}, d_{s,0}\}$ that set binary exposure $E(t)$ to either 1 or 0, and $W(t)$ to 1 for all years between 1 and t. We denote $Y_{i,d_{s,1}}(t)$ and $Y_{i,d_{s,0}}(t)$ as the counterfactual outcomes that worker i would experience in year t if they were always at work, and respectively always exposed or unexposed. Counterfactual outcomes under each intervention were generated by setting nodes $E(t), W(t)$ in the system of equations above as specified by our interventions, sequentially for each subject i and year of follow-up t.

We define dynamic interventions $\{d_{d,1}, d_{d,0}\}$ that assign exposure according to employment status. Specifically, we define $d_{d,1}$ as an intervention that sets the exposure node $E(t)$ to 1 while a worker is actively employed ($W(t) = 1$). However, once the worker terminates employment ($W(t) = 0$), $d_{d,1}$ sets $E(t)$ to 0. Intervention $d_{d,0}$ assigns workers to no exposure before and after employment termination. The counterfactual outcomes $Y_{i,d_{d,1}}(t)$ and $Y_{i,d_{d,0}}(t)$ correspond to worker i's outcome in year t if they were always exposed and unexposed while at work, respectively.

Computing exposure effects - Denoting $d \in \{d_{s,0}, d_{s,1}, d_{d,0}, d_{d,1},\}$ as one of the four regimens of interest, we computed counterfactual survival curves for each regimen in d:

$$S_d(t) = \frac{\sum_{k=1}^{t} Y_{i,d}(k)}{n}.$$

The survival function $S_d(t)$ expresses the probability that a worker following regimen d has not yet experienced the outcome of interest by the end of year t. Cumulative incidence of the outcome (μ_d) under regimen d in year t was computed as:

$$\mu_d = 1 - S_d(t) = 1 - \frac{\sum_{k=1}^{t} Y_{i,d}(k)}{n}.$$

The static exposure effect, $\psi_s = \mu_{d_{s,1}} - \mu_{d_{s,0}}$, measures the risk difference (RD) contrasting the risk (cumulative incidence) of disease when a cohort is always at work and exposed to the risk when the same cohort is always at work but unexposed. The dynamic exposure effect, $\psi_d = \mu_{d_{d,1}} - \mu_{d_{d,0}}$, contrasts the risk of disease in a cohort that is always exposed while at work and the disease risk if the same cohort is unexposed while at work.

In order to contrast the effects of the two interventions in a scale that permitted comparison across scenarios, we computed the ratio of static and dynamic RDs, $R = \psi_s / \psi_d$. This ratio represents the factor by which the exposure effect decreased as a result of limiting exposure by early employment termination.

2. Supplementary Results

In the **Table S1** we present the distribution of selected variables by scenario and year of follow-up among workers following the always-exposed while at work dynamic regimen ($d_{d,1}$), We report the "always-exposed" arm because the distribution of covariates is similar in the "never-exposed" arm of the static and dynamic regimens. That is, differences in dynamic and static exposure effects are driven by the "always-exposed" arm of the two interventions. In addition, we report the distribution of covariates under the dynamic rather than static intervention to illustrate the attrition of susceptible workers out of the workforce over time. Susceptible workers remained at work, accumulated more exposure, leading to higher cumulative incidence of disease in Scenario 3. Since susceptible workers terminate employment for health reasons in Scenario 4, cumulative exposure and cumulative incidence of the outcome is lowest in this scenario.

Table S1. Distribution of simulated covariates in cohorts of workers always exposed while at work.

	Year of follow-up									
	t = 2	t = 4	t = 6	t = 8	t = 10	t = 12	t = 14	t = 16	t = 18	t = 20
Scenario 1[a]										
Susceptible, $\mathbb{E}[S]$	0.50	0.50	0.49	0.49	0.48	0.48	0.47	0.46	0.45	0.45
At work, $\mathbb{E}[W(t)]$	1.00	0.82	0.66	0.57	0.53	0.53	0.53	0.54	0.55	0.55
Cumulative exposure, $\mathbb{E}[\bar{E}(t)]$	2.00	3.72	5.12	6.30	7.39	8.46	9.56	10.69	11.85	13.04
In poor health, $\mathbb{E}[H(t)]$	0.09	0.27	0.40	0.46	0.48	0.47	0.47	0.46	0.45	0.45
Cumulative incidence, $\mathbb{E}[\bar{Y}(t)]$	0.00	0.01	0.02	0.03	0.04	0.05	0.07	0.08	0.09	0.11
Scenario 2[b]										
Susceptible, $\mathbb{E}[S]$	0.50	0.49	0.48	0.46	0.43	0.40	0.37	0.34	0.32	0.30
At work, $\mathbb{E}[W(t)]$	1.00	0.82	0.68	0.60	0.58	0.60	0.63	0.66	0.68	0.70
Cumulative exposure, $\mathbb{E}[\bar{E}(t)]$	2.00	3.73	5.17	6.44	7.67	8.98	10.40	11.92	13.54	15.24
In poor health, $\mathbb{E}[H(t)]$	0.09	0.26	0.38	0.43	0.43	0.40	0.37	0.34	0.32	0.30
Cumulative incidence, $\mathrm{E}[\bar{Y}(t)]$	0.00	0.02	0.05	0.10	0.15	0.20	0.25	0.29	0.32	0.35
Scenario 3[c]										
Susceptible, $\mathbb{E}[S]$	0.50	0.50	0.49	0.48	0.47	0.44	0.40	0.35	0.30	0.25
At work, $\mathbb{E}[W(t)]$	1.00	1.00	1.00	1.00	1.00	0.92	0.79	0.71	0.71	0.75
Cumulative exposure, $\mathbb{E}[\bar{E}(t)]$	2.00	4.00	6.00	8.00	10.00	11.92	13.56	15.05	16.57	18.23
In poor health, $\mathbb{E}[H(t)]$	0.09	0.27	0.40	0.46	0.46	0.44	0.40	0.35	0.30	0.25
Cumulative incidence, $\mathbb{E}[\bar{Y}(t)]$	0.00	0.01	0.02	0.04	0.08	0.14	0.22	0.30	0.36	0.42
Scenario 4[d]										
Susceptible, $\mathbb{E}[S]$	0.50	0.50	0.49	0.49	0.49	0.49	0.48	0.48	0.48	0.47
At work, $\mathbb{E}[W(t)]$	0.52	0.53	0.53	0.53	0.53	0.54	0.54	0.54	0.54	0.54
Cumulative exposure, $\mathbb{E}[\bar{E}(t)]$	1.52	2.58	3.65	4.73	5.81	6.91	8.01	9.12	10.23	11.33
In poor health, $\mathbb{E}[H(t)]$	0.48	0.47	0.47	0.47	0.47	0.46	0.46	0.46	0.46	0.46
Cumulative incidence, $\mathbb{E}[\bar{Y}(t)]$	0.01	0.01	0.02	0.02	0.03	0.03	0.04	0.04	0.05	0.06

[a] Scenario 1: The intermediate health had a moderate effect on the outcome, it could occur in any year t, and the intermediate health event in year $t-1$ predicted leaving work in year t.

[b] Scenario 2: The intermediate health event had a stronger effect on the outcome than in Scenario 1. All other relationships between variables were as in Scenario 1.

[c] Scenario 3: The intermediate health event in year $t-10$ predicted leaving work in year t. All other relationships between variables were as in Scenario 1.

[d] Scenario 4: The intermediate health event could only occur during the first year, $t = 1$. All other relationships between variables were as in Scenario 1.

2. Simulation Code

```
#==============================================================================#
#               INSTALL PACKAGES AND LOAD LIBRARIES                            #
#==============================================================================#
install.packages("simcausal")
install.packages("doParallel")
install.packages("data.table")
install.packages("ggplot2")
install.packages("gridExtra")

library(simcausal)
library(doParallel)
library(data.table)
library(ggplot2)
library(gridExtra)
#============================================================================#
#             SET OUTPUT DIRECTORY AND GLOBAL VARIABLES                      #
#============================================================================#
registerDoParallel(cores = detectCores())
'%+%'      <- function(a,b) paste0(a,b)
tmax       <- 20
vecfun.add("pmax")
vecfun.add("psum")
set.seed(12345)
dir = getwd() #Assign directory to which figures/tables are saved.
```

```
#=====================================================#
# PLOT SURVIVAL CURVES                                #
#=====================================================#
# A helper function that plots etiologic and          #
# realistic survival estimates                        #
#=====================================================#

PlotSurv <- function (ETI.E0, ETI.E1, REA.E0, REA.E1, minsurv){

   Year = c(1:length(ETI.E0))
   dall <- data.table(rbind(data.table(Year = Year, Intervention = "Static",  Exposure = "Unexposed", St=ETI.E0),
                 data.table(Year = Year, Intervention = "Static",  Exposure = "Exposed",   St=ETI.E1),
                 data.table(Year = Year, Intervention = "Dynamic", Exposure = "Unexposed", St=REA.E0),
                 data.table(Year = Year, Intervention = "Dynamic", Exposure = "Exposed",   St=REA.E1)))


   gplota.1 <- ggplot() + theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank(),
                        panel.background = element_blank(), axis.line = element_line(colour = "black"),
                        axis.title.x = element_text(size=12),
                        axis.text.x  = element_text(angle=90, vjust=0.5, size=12),
                        axis.title.y = element_text(size=12),
                        axis.text.y  = element_text(angle=90, vjust=0.5, size=12),
                        plot.title   = element_text(face="bold", hjust = 0.5, vjust=2.12, size=14),
                        strip.background = element_rect(colour="black", fill="white"),
                        legend.position="right")+
    geom_line(data = dall, aes(x = Year, y = St,   color = Intervention,   linetype = Exposure))+
    scale_linetype_manual(values=c("twodash", "dotted"))+
    scale_color_manual(values=c('black','#999999'))+
    ylab('Survival Probability') +
    xlab('Years Since Hire') +
    ylim(minsurv, 1);
    print(gplota.1)
   return(gplota.1)
  }
```

```
#======================================================#
# COMPUTE COUNTERFACTUAL SURVIVAL                      #
#======================================================#
# A helper function that computes counterfactual       #
# survival after the counterfactual outcomes are       #
# generated.                                           #
#======================================================#
CFSurvival <- function(DT){
  X       <-  data.table(DT)
  npats   <-  length(unique(X$ID))
  sumY    <-  X[, sum(Y), by = t];
  cumsumY <-  sumY[,cumsum(V1)]
  ST      <-  1-cumsumY/npats;
  return(ST)
}

#======================================================#
#   COMPUTE COUNTERFACTUAL STATIC SURVIVAL             #
#======================================================#
# Function that generates counterfactual outcomes      #
# under interventions that set exposure and prevent    #
# leaving work, and computes the counterfactual        #
# survival.                                            #
#======================================================#

CF_STATIC <- function(DAG,NFULL){
  act_ET <-c(
    node("W", t = 1:tmax, distr = "rconst", const = 1),
    node("E", t = 1:tmax, distr = "rconst", const = abar))
  ETDact   <-  DAG + action("W1E0", nodes = act_ET, abar = 0) +
    action("W1E1", nodes = act_ET, abar = 1)
  CFData    <-  sim(ETDact,actions = c("W1E0","W1E1"), n = NFULL, wide = FALSE)
  CFST      <-  lapply(CFData, function(x) CFSurvival(x));
  ATE       <- (1-CFST$W1E1[tmax]) - (1-CFST$W1E0[tmax])
  return(list(E0   = CFST$W1E0,   E1   = CFST$W1E1, ATE = ATE))
}
```

```
#=====================================================#
#   COMPUTE COUNTERFACTUAL DYNAMIC SURVIVAL           #
#=====================================================#
# Function that generates counterfactual outcomes     #
# under interventions that set exposure while at work #
# and computes the counterfactual survival.           #
#=====================================================#
CF_DYNAMIC <- function(DAG,NFULL){
  act_REAL <-c(node("E", t = 1:tmax, distr = "rconst", const = ifelse(W[t] == 1, abar, 0)))
REALDact   <-  DAG + action("E0", nodes = act_REAL, abar = 0) +
    action("E1", nodes = act_REAL, abar = 1)
  CFData    <-  sim(REALDact,actions = c("E0","E1"), n = NFULL, wide = FALSE)
  CFST      <-  lapply(CFData, function(x) CFSurvival(x));
  ATE       <- (1-CFST$E1[tmax]) - (1-CFST$E0[tmax])
  return(list(E0   = CFST$E0,   E1   = CFST$E1, ATE = ATE))
}

#========================================================#
#     DEFINE DATA GENERATING DISTRIBUTIONS               #
#========================================================#
#Function that defines the data-generating distributions #
#for all scenarios. Scenario 1 (DAG1) serves as default. #
#Other scenarios are generated by changing a single      #
#relatinship from scenario 1.                            #
#========================================================#

generate_DAGs <- function() {
    require("simcausal")

    pS     <- 0.50 #prevalence of susceptability
    EonY   <- 0.25 #effect of each year of exposure on outcome
    EonH   <- 0.25 #effect of each year of exposure on health status

    ##########################################################
    # BASE CASE (SCENARIO 1)                                 #
    # 1) Health Status has a moderate effect on the outcome  #
    # 2) Cummulative exposure predicts health status         #
    # 3) Health status in year t-1 predicts at work in year t #
    ##########################################################
```

```
H.1      <- substitute(plogis(-5.00))                          #health status in year 1.
H.t.1    <- substitute(plogis(-2.00 + EonH*Ebar[t]))           #health status in years>1, scenario 1.
E.gt1    <- substitute(plogis(-1.00 + 2.00*E[t-1]))            #exposure years>1.
Y.t.1    <- substitute(plogis(-7.00 + 1.5*H[t] + EonY*Ebar[t]))  #outcome during all years, scenario 1.


D1   <- DAG.empty() +
  node("S",       t=1,      distr = "rbern",      prob  = pS)+
  node("W",       t=1,      distr = "rconst",     const = 1)+
  node("E",       t=1,      distr = "rbern",      prob  = 0.5)+
  node("Ebar",    t=1,      distr = "rconst",     const = E[1])+
  node("H",       t=1,      distr = "rbern",      prob  = ifelse(S[t]==1,.(H.1),0)) +
  node("Y",       t=1,      distr = "rbern",      prob  = ifelse(S[t]==1,.(Y.t.1),0), EFU=TRUE)+

  node("S",       t=2:tmax,  distr = "rconst",     const = S[t-1])+
  node("W",       t=2:tmax,  distr = "rbern",      prob = ifelse(W[t-1] == 0, 0, ifelse(H[t-1]==1,0,1)))+
  node("E",       t=2:tmax,  distr = "rbern",      prob  = .(E.gt1))+
  node("Ebar",    t=2:tmax,  distr = "rconst",     const = Ebar[t-1] + E[t])+
  node("H",       t=2:tmax,  distr = "rbern",      prob  = ifelse(H[t-1] == 1, 1, ifelse(S[t]==1,.(H.t.1),0)))+
  node("Y",       t=2:tmax,  distr = "rbern",      prob  = ifelse(S[t]==1,.(Y.t.1),0), EFU=TRUE)
DAG1 <- set.DAG(D1)

#########################################################
# SCENARIO 2                                            #
# 1) Health Status has a strong effect on the outcome   #
#########################################################
Y.t.2    <- substitute(plogis(-7.00 + 3.0*H[t] + EonY*Ebar[t]))  #outcome during all years, scenario 2.
D2    <- D1+
       node("Y",       t=1:tmax,  distr = "rbern",      prob  = ifelse(S[t]==1,.(Y.t.2),0), EFU=TRUE)
DAG2 <- set.DAG(D2)

#########################################################
# SCENARIO 3                                            #
# 3) Health status in year t-10 predicts at-work in year t  #
#########################################################
D3    <- D1 +
       node("W",       t=1:10,     distr = "rconst",    const = 1) +
       node("W",       t=11:tmax,  distr = "rbern",     prob = ifelse(W[t-1] == 0, 0, ifelse(H[t-10]==1,0,1)))
DAG3 <- set.DAG(D3)
```

```
    ########################################################
    # SCENARIO  4                                          #
    # 2) Exposure in t=1 predicts health status            #
    ########################################################
    H.1.4    <- substitute(plogis(-4.00 + 7.00*E[t]))  #health status in years 1, scenario 5.

    D4    <- D1 +
      node("H",       t=1,      distr = "rbern",       prob  = ifelse(S[t]==1,.(H.1.4),0))+
      node("H",       t=2:tmax, distr = "rconst",      const = ifelse(H[t-1] == 1, 1, 0))
    DAG4 <- set.DAG(D4)

    return(list(DAG1   = DAG1,   DAG2   = DAG2,   DAG3  = DAG3,   DAG4 = DAG4))
}
```

```
#==============================================================================#
#                        MAIN FUNCTION CALLS                                   #
#==============================================================================#
# 1) GENERATE nsims COHORTS, EACH CONSISTING OF nobs WORKERS                   #
# 2) COMPUTE SURVIVAL CURVES UNDER STATIC AND DYNAMIC INTERVENTIONS           #
# 3) COMPUTE EXPOSURE EFFECTS: RD=(1-S_1(t))-(1-S_0(t))                        #
# 4) GENERATE FIGURES AND SUMMARY TABLES                                       #
#==============================================================================#

  DAGs   <- generate_DAGs(); #list of data-generating functions
  nobs   <- 50000      #number of workers in each cohort
  nsims  <- 500        #nubmer of simulated datasets

  ##############################################################
  # Simulate cohorts and compute survival/exposure effects     #
  #for each cohort.                                             #
  ##############################################################
  # registerDoParallel(cores = 1)
  survEst <- foreach(t.counter = icount(nsims), .combine = "cbind") %dopar% {
   message("sim N: " %+% t.counter)
   ETIST  <- lapply(DAGs, function(x) CF_STATIC(x, nobs))
   REAST  <- lapply(DAGs, function(x) CF_DYNAMIC(x, nobs))
   return(list(
    ETI.1.E0   = ETIST$DAG1$E0,   ETI.1.E1   = ETIST$DAG1$E1,   ETI.1.ATE   = ETIST$DAG1$E0 - ETIST$DAG1$E1,
    ETI.2.E0   = ETIST$DAG2$E0,   ETI.2.E1   = ETIST$DAG2$E1,   ETI.2.ATE   = ETIST$DAG2$E0 - ETIST$DAG2$E1,
    ETI.3.E0   = ETIST$DAG3$E0,   ETI.3.E1   = ETIST$DAG3$E1,   ETI.3.ATE   = ETIST$DAG3$E0 - ETIST$DAG3$E1,
    ETI.4.E0   = ETIST$DAG4$E0,   ETI.4.E1   = ETIST$DAG4$E1,   ETI.4.ATE   = ETIST$DAG4$E0 - ETIST$DAG4$E1,

    REA.1.E0   = REAST$DAG1$E0,   REA.1.E1   = REAST$DAG1$E1,   REA.1.ATE   = REAST$DAG1$E0 - REAST$DAG1$E1,
    REA.2.E0   = REAST$DAG2$E0,   REA.2.E1   = REAST$DAG2$E1,   REA.2.ATE   = REAST$DAG2$E0 - REAST$DAG2$E1,
    REA.3.E0   = REAST$DAG3$E0,   REA.3.E1   = REAST$DAG3$E1,   REA.3.ATE   = REAST$DAG3$E0 - REAST$DAG3$E1,
    REA.4.E0   = REAST$DAG4$E0,   REA.4.E1   = REAST$DAG4$E1,   REA.4.ATE   = REAST$DAG4$E0 - REAST$DAG4$E1
    ))
}
```

```
###########################################
# Average survival, effects, effect ratio and differences          #
# across the nsim cohorts for each scenario and generate a    #
# table                                                                                                   #
###########################################
m<- data.frame(apply(survEst, 1, function(x) apply(t(data.frame(x)),2,mean)))
#write.csv(m,paste0(dir,"All_Results.csv")) #save the results for each simulated cohort/scenario
t1a <- rbind(round(m$ETI.1.ATE, 2), round(m$REA.1.ATE, 2), RAT.1 = round(m$ETI.1.ATE, 2)/round(m$REA.1.ATE, 2),
          round(m$ETI.2.ATE, 2), round(m$REA.2.ATE, 2), RAT.2 = round(m$ETI.2.ATE, 2)/round(m$REA.2.ATE, 2),
          round(m$ETI.3.ATE, 2), round(m$REA.3.ATE, 2), RAT.3 = round(m$ETI.3.ATE, 2)/round(m$REA.3.ATE, 2),
          round(m$ETI.4.ATE, 2), round(m$REA.4.ATE, 2), RAT.4 = round(m$ETI.4.ATE, 2)/round(m$REA.4.ATE, 2))
 colnames(t1a) <- c(paste0("t",seq(1,tmax)));
 t1b <- rbind(data.frame(SCENARIO = "1", INT = "ETIOLOGIC"),
           data.frame(SCENARIO = "1", INT = "DYNAMIC"),
           data.frame(SCENARIO = "1", INT = "RD_RAT"),
           data.frame(SCENARIO = "2", INT = "ETIOLOGIC"),
           data.frame(SCENARIO = "2", INT = "DYNAMIC"),
           data.frame(SCENARIO = "2", INT = "RD_RAT"),
           data.frame(SCENARIO = "3", INT = "ETIOLOGIC"),
           data.frame(SCENARIO = "3", INT = "DYNAMIC"),
           data.frame(SCENARIO = "3", INT = "RD_RAT"),
           data.frame(SCENARIO = "4", INT = "ETIOLOGIC"),
           data.frame(SCENARIO = "4", INT = "DYNAMIC"),
           data.frame(SCENARIO = "4", INT = "RD_RAT"))
  t1 <- cbind(t1b,t1a);
  #selcols      <- c("SCENARIO","INT",paste0("t",seq(2,tmax, by=2)))
  #write.csv(t1[,selcols],paste0(dir,"Table_1.csv"))
```

```
############################################
# Plot average survival, for each scenario, and as grid for      #
# each of the three comparisons.                                            #
############################################
#Compute min survival. Used to set ylim in all figures           #
minsurv <- round(min(m$ETI.1.E1, m$ETI.2.E1, m$ETI.3.E1, m$ETI.4.E1, na.rm=TRUE)-0.1,1)
#minsurv <- 0.5

###########################
# First each scenario                        #
###########################
SCENARIO_1 <- PlotSurv(m$ETI.1.E0, m$ETI.1.E1, m$REA.1.E0, m$REA.1.E1, minsurv)
SCENARIO_2 <- PlotSurv(m$ETI.2.E0, m$ETI.2.E1, m$REA.2.E0, m$REA.2.E1, minsurv)
SCENARIO_3 <- PlotSurv(m$ETI.3.E0, m$ETI.3.E1, m$REA.3.E0, m$REA.3.E1, minsurv)
SCENARIO_4 <- PlotSurv(m$ETI.4.E0, m$ETI.4.E1, m$REA.4.E0, m$REA.4.E1, minsurv)

print(SCENARIO_1 + ggtitle("Scenario 1"))
print(SCENARIO_2 + ggtitle("Scenario 2"))
print(SCENARIO_3 + ggtitle("Scenario 3"))
print(SCENARIO_4 + ggtitle("Scenario 4"))
# Save figures as pdfs.
# pdf(paste0(dir,"Scenario1_SURV.pdf")); print(SCENARIO_1 + ggtitle("Scenario 1")); dev.off()
# pdf(paste0(dir,"Scenario2_SURV.pdf")); print(SCENARIO_2 + ggtitle("Scenario 2")); dev.off()
# pdf(paste0(dir,"Scenario3_SURV.pdf")); print(SCENARIO_3 + ggtitle("Scenario 3")); dev.off()
# pdf(paste0(dir,"Scenario4_SURV.pdf")); print(SCENARIO_4 + ggtitle("Scenario 4")); dev.off()
```

```
##########################
# Then each comparison                    #
##########################

##########################################
# Comparison 1: evaluates the role of the strength of the     #
#             association between intermediate health               #
#             status and outcome. It compares the base case       #
#             (scenarios 1,moderate effect), to scenario 2            #
#             (strong effect).                                                        #
##########################################
title1  <- "Moderate effect of health status \non the outcome."
title2  <- "Strong effect of health status \non the outcome."
p1      <-  SCENARIO_1 + ggtitle(title1) + theme(plot.title = element_text(hjust = 0.5));
p2      <-  SCENARIO_2 + ggtitle(title2) + theme(plot.title = element_text(hjust = 0.5));
grid.arrange(p1, p2, ncol = 2)
#pdf(paste0(dir,"Contrast_1_2.pdf")); grid.arrange(p1, p2, ncol = 2);    dev.off()

##########################################
# Comparison 2: evaluates the role of timing of the              #
#             relationship between the onset of symptoms         #
#             of adverse health event and leaving work.             #
#             It compares scenario 1 in which health status        #
#             in year t predicts leaving work in the next             #
#             year (t+1), to scenario 3 in which health               #
#             status in year t predicts leaving work 10               #
#             years later (t+10).                                                    #
##########################################
title1a <-  "Health status in year t-1 \npredicts leaving work in year t."
title3  <-  "Health status in year t-10 \npredicts leaving work in year t."
p1a     <-  SCENARIO_1 + ggtitle(title1a) + theme(plot.title = element_text(hjust = 0.5));
p3      <-  SCENARIO_3 + ggtitle(title3)  + theme(plot.title = element_text(hjust = 0.5));
grid.arrange(p1a, p3, ncol = 2)
#pdf(paste0(dir,"Contrast_1_3.pdf")); grid.arrange(p1a, p3, ncol = 2);    dev.off()
```

```
##############################################
  # Comparison 3: evaluates the role of timing of the            #
  #           relationship between exposure and the adverse      #
  #           health event. It compares scenario 1 in which      #
  #           cumulative exposure predicts the health status     #
  #           to scenario 4 in which health status serves as     #
  #           a screen: only exposure in first year affects      #
  #           health status in the first year. Workers that      #
  #           do not experience adverse events in the first      #
  #           year, are not at risk of experiencing them         #
  #           later.                                             #
  ##############################################
  title1b  <- "Cumulative exposure \npredicts health status in all years."
  title4   <- "Adverse health event occurs \nin the first year of exposure. "
  p1b      <- SCENARIO_1 + ggtitle(title1b) + theme(plot.title = element_text(hjust = 0.5));
  p4       <- SCENARIO_4 + ggtitle(title4) + theme(plot.title = element_text(hjust = 0.5));
  grid.arrange(p1b, p4, ncol = 2)
  #pdf(paste0(dir,"Contrast_1_4.pdf")); grid.arrange(p1b, p4, ncol = 2);    dev.off()
```