



# Modélisation hiérarchique et apprentissage statistique bayésien pour la prise en compte d'erreurs de mesure d'exposition complexes en épidémiologie des rayonnements ionisants.

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# Modélisation hiérarchique et apprentissage statistique bayésien pour la prise en compte d'erreurs de mesure d'exposition en épidémiologie des rayonnements ionisants

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Atelier SCIDONI, 12 Novembre 2020

## Context : Exposure measurement error in epidemiological studies

- Exposure measurement error is
  - ▶ ubiquitous
  - ▶ one of the most important source of uncertainty
- in epidemiological studies
- If not or only poorly accounted for, exposure measurement error may cause :
  - ▶ bias in risk estimates
  - ▶ a distortion of the exposure-risk relationship
  - ▶ a loss in power
- In retrospective cohort studies :
  - ▶ complex patterns of exposure measurement error
  - ▶ attenuation of the exposure-risk relationship for high exposure values [HertzPicciotto (1993), Stayner (2003)]
    - Suggested to be explained by the effect of measurement error

# Methods to account for measurement error

- Many methods for the correction of measurement error, like regression calibration and simulation extrapolation (SIMEX)
  - ▶ Lack of flexibility to account for complex measurement error
    - Measurement error in time-varying exposure variables
    - Combination of different types of measurement error
    - Heteroscedastic measurement error variances
    - Uncertainty in measurement error variance parameters
  - ▶ Potential lack of consistency in risk estimates in proportional hazards models [Bartlett and Keogh, 2016]
  - ▶ Disjoint steps to estimate true exposure and risk parameters
- Bayesian hierarchical models (also called multi-levels or random-effects models)
  - ▶ Provides a natural way of combining exposure and parameter uncertainty
  - ▶ Flexible approach to describe and account for complex measurement error
  - ▶ Allows for the joint estimation of true exposure and risk parameters
  - ▶ Allows to integrate external information through the specification of informative prior distributions to obtain more precise estimates

# Aims of the work

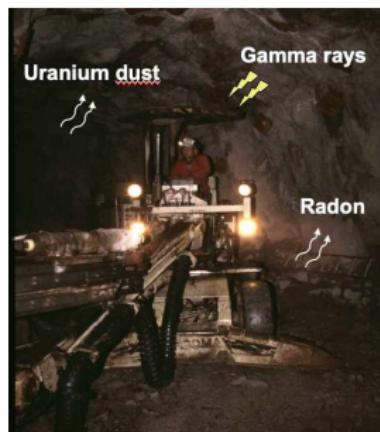
- ① Promote the use of **Bayesian hierarchical approach** to account for **complex** exposure measurement error in risk estimates in radiation epidemiology
  - ▶ Improved considerations of **uncertainties**
  - ▶ (Potentially) improved risk estimates in a **weakly informative context**
- ② Study the **impact** of different error structures on statistical inference
  - ▶ Simulation studies
  - ▶ Specific context of survival models with time-dependent covariates
- ③ Refine, if possible, the estimation of radiation-induced health risks at low doses
  - ▶ Réponses vis-à-vis de la stratégie scientifique de l'IRSN en radioprotection
    - Question 1 : Quels sont les effets d'une exposition à de faibles doses ?
    - Question 3 : Comment améliorer les concepts, méthodes et outils destinés à évaluer le risque suite aux expositions des travailleurs, de la population et des patients ?
- ④ Improve the knowledge about the shape of dose-response relationships
  - ▶ Réponses vis-à-vis des priorités scientifiques identifiées au niveau européen
    - Forme de la relation dose-réponse pour les cancers

## Motivating case study

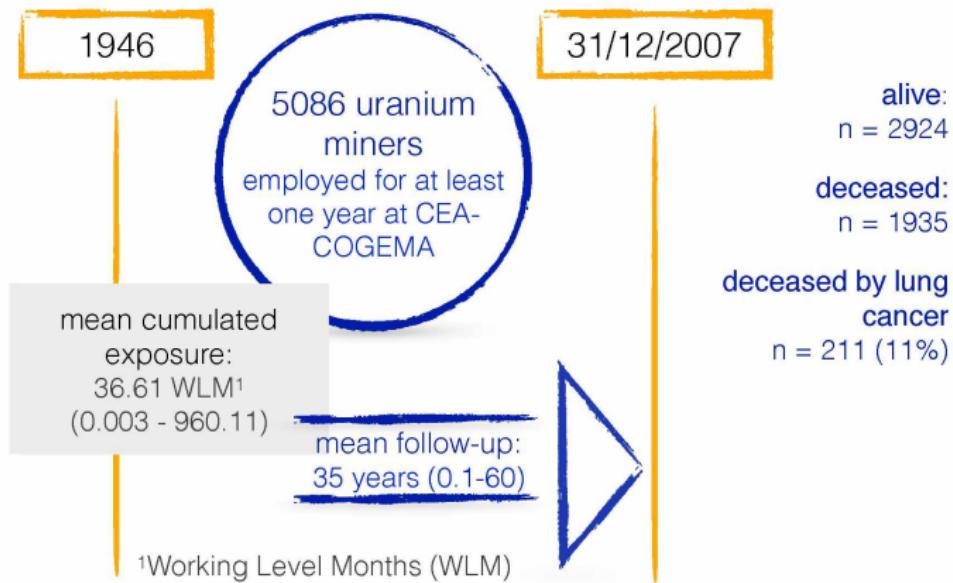
### Lung cancer and chronic low-dose exposure to radon

- Radon is a radioactive gas which presents the primary source of background radiation
- Radon is the second cause of lung cancer (after tobacco) [Samet and Eradze, 2000]

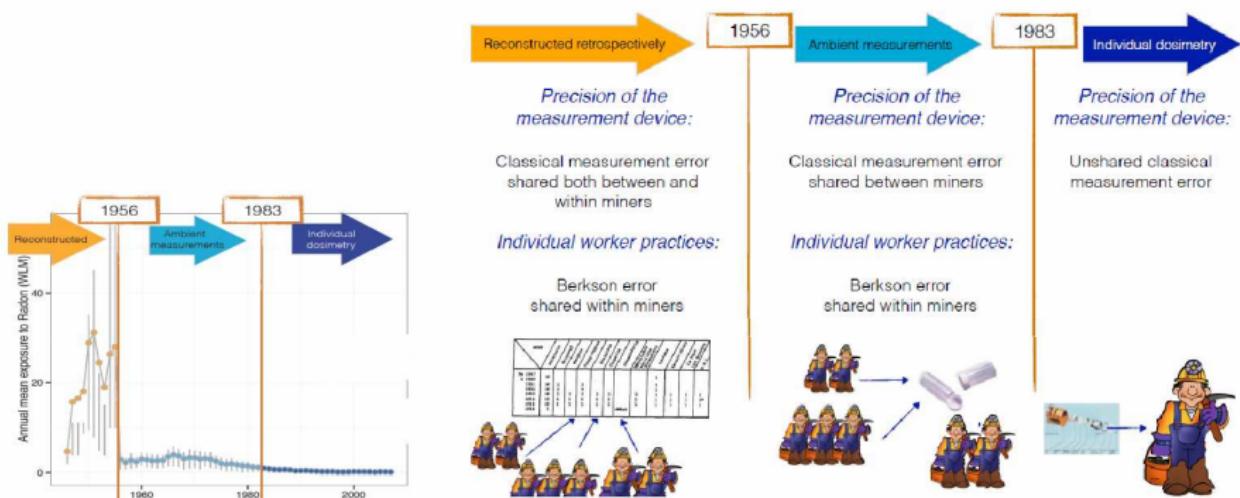
Thanks to an individual dosimetry collected over the entire career, the French cohort of uranium miners is a reference population for the study of the long-term health effects of chronic low-dose exposure to radon (Inhalation exposure)



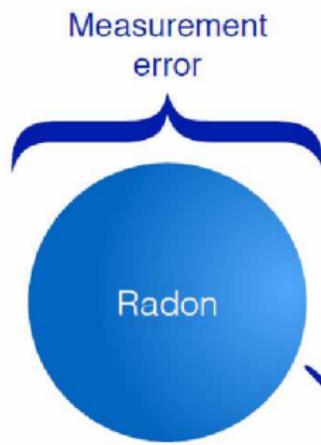
# The French cohort of uranium miners



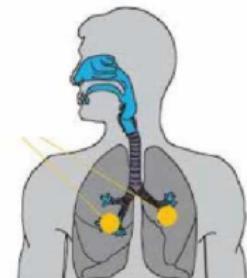
# Radon measurement error characteristics in the cohort



# Challenge



Obtain a measurement corrected estimate of the lung cancer risk associated with cumulative exposure to Radon



# Accounting for measurement error through a hierarchical structure

In a hierarchical framework, one can account for exposure measurement error combining the following submodels :

- Disease submodel
- Measurement submodel
- Exposure submodel

⇒ Joint modelling of all sub-models using conditional independence assumptions

[Richardson and Gilks, 1993]

⇒ Joint estimation of all unknown quantities

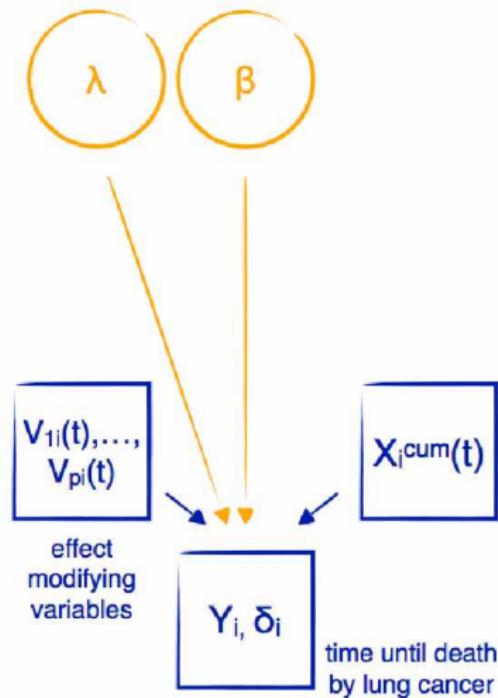
# The disease submodel

## Modelling failure times

- $Y_i = \min(T_i, C_i)$  is right-censored age at death by lung cancer
- $h_i(t) = h_0(t)(1 + \beta X_i^{\text{cum}}(t))$
- Suppose a piecewise constant model for  $h_0(t)$  with  $\lambda = (\lambda_1, \lambda_2, \lambda_3, \lambda_4)$

## Effect modifying variables

- Test the linearity of the exposure-risk relationship via piecewise linear models



## Measurement submodel $\mathcal{M}_2$

$Z_i^B(t)$  : estimated/observed exposure of individual  $i$  for year  $t$  of the calendar period B  
 $X_i^B(t)$  : "true" exposure of individual  $i$  for year  $t$  of the calendar period B  
 $U_i^B$  : error component for individual  $i$  and the period B (individual worker practices)

### First calendar period 1946-1955 :

- Berkson error shared within individuals :

- ▶  $X_i^1(t) = Z_i^1(t).U_i^1$
- ▶  $U_i^1 \sim \mathcal{LN}\left(-\frac{\sigma_{U_1}^2}{2}, \sigma_{U_1}^2\right)$  [Darby, 1998]
- ▶  $U_i^1 \perp\!\!\!\perp Z_i^1(t)$  and  $U_i^1 \perp\!\!\!\perp Y_i$
- ▶  $\mathbb{E}(X_i^1(t)|Z_i^1(t)) = Z_i^1(t)$
- ▶  $\sigma_{U_1}^2 = 0.86$  [Allodji et al., 2012]

### Second calendar period 1956-1982 :

- Berkson error shared within individuals :

- ▶  $X_i^2(t) = Z_i^2(t).U_i^2$
- ▶  $U_i^2 \sim \mathcal{LN}\left(-\frac{\sigma_{U_2}^2}{2}, \sigma_{U_2}^2\right)$
- ▶  $U_i^2 \perp\!\!\!\perp Z_i^2(t)$  and  $U_i^2 \perp\!\!\!\perp Y_i$
- ▶  $\mathbb{E}(X_i^2(t)|Z_i^2(t)) = Z_i^2(t)$
- ▶  $\sigma_{U_2}^2 = 0.15$  [Allodji et al., 2012]

Third calendar period 1983-2007 : Classical measurement error **neglected** (magnitude of error much smaller than in earlier periods)

## Measurement submodel $\mathcal{M}_3$ + Exposure submodel

=> Refined measurement submodel only for the first calendar period 1946-1955

$X_{ij}^1(t)$  : "true" exposure of individual  $i$  for year  $t$ , given that he worked in mine  $j$

$Z_j^1$  : estimated mean exposure for one month of work in mine  $j$  (1946-1955)

$T_{ij}(t)$  : Time in months spent by individual  $i$  in mine  $j$  during year  $t$

$\xi_j$  : "true" mean exposure for one month of work in mine  $j$  (1946-1955)

$U_i^1$  : error component for individual  $i$  over the period 1946-1955

$U_j^1$  : error component for all miners working in mine  $j$  over the period 1946-1955

- Berkson error shared within individuals :

- ▶  $X_{ij}^1(t) = \xi_j \cdot T_{ij}(t) \cdot U_i^1$
- ▶  $U_i^1 \sim \mathcal{LN}\left(-\frac{\sigma_{U_1}^2}{2}, \sigma_{U_1}^2\right)$
- ▶  $\mathbb{E}(X_{ij}^1(t)|\xi_j, T_{ij}(t)) = \xi_j \cdot T_{ij}(t)$

- Classical measurement error shared both within and between miners

- ▶  $Z_j^1 = \xi_j \cdot U_j^1$
- ▶  $U_j^1 \sim \mathcal{LN}\left(-\frac{\sigma_{U_*}^2}{2}, \sigma_{U_*}^2\right)$
- ▶  $U_j^1 \perp \xi_j$

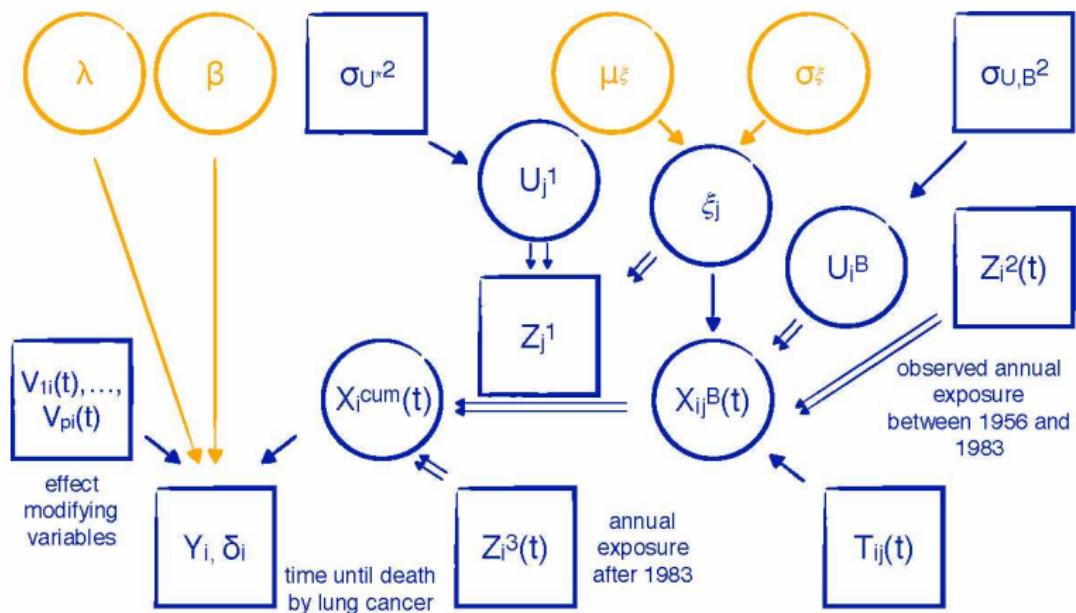
- The exposure model

- ▶  $\xi_j \sim \mathcal{LN}(\mu_\xi, \sigma_\xi)$

$\sigma_{U_1}^2$  and  $\sigma_{U_*}^2$  fixed according to [Allodji et al., 2012] + sensitivity analysis



# Directed Acyclic Graph



# Bayesian inference

- Informative prior distributions for the  $\lambda$  parameters defining the baseline hazard function  $h_0(t)$ 
  - ▶ External information : lung cancer mortality in the general French male population between 1968 and 2005
- Complex joint posterior distribution  $\theta = (\beta, \lambda, \mu_\xi, \sigma_\xi, \xi, U)$   
=> Adaptive Metropolis-Within-Gibbs algorithm developed and tested in Python
- About 6,000 (Model  $M_3$ ) latent exposure variables to update at each iteration of the MCMC algorithm  
=> High-dimensional posterior distribution
- Idea 1 => Block updating of  $U$ ; after defining 239 homogeneous groups of miners (hierarchical clustering) based on information on :
  - ▶ Mine location
  - ▶ Type of mine
  - ▶ Job type
- Idea 2 => Update  $\log(X)$  instead of  $X$  in order to respect the constraint  $X > 0$  and to improve convergence

# Simulation study : Do shared and unshared errors have the same impact on risk estimation when assuming survival disease models ?

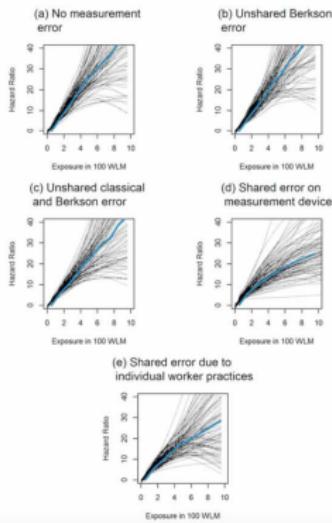
- Simulation of survival times and exposure measurement errors when assuming  $\beta = 5$  (Excess Hazard Ratio (EHR)),  $\beta = 2$  (Cox) and  $\sigma = 0.9$
- Radon exposure data of the French cohort of uranium miners
- Bayesian inference of an EHR or a Cox model without accounting for error

Type of error		EHR			Cox		
		$\hat{\beta}$	Relative bias	Coverage rate	$\hat{\beta}$	Relative bias	Coverage rate
unshared	Berkson	4.65	-0.07	0.91	1.25	-0.38	0.00
	classical	4.34	-0.13	0.78	0.83	-0.59	0.00
between	Berkson	4.69	-0.06	0.93	1.25	-0.38	0.00
	classical	4.44	-0.11	0.85	0.80	-0.60	0.00
within	Berkson	3.98	-0.20	0.73	0.76	-0.62	0.00
	classical	3.03	-0.39	0.13	0.39	-0.81	0.00
none		4.90	-0.02	0.96	1.96	-0.02	0.95

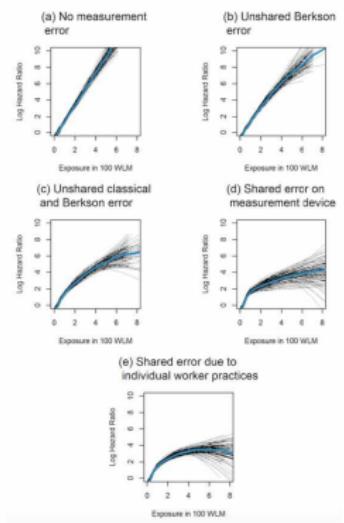
# Simulation study : Can error structures that occur in retrospective studies cause an attenuation of the exposure-risk relationship ?

- Bayesian inference of **natural cubic splines** without accounting for exposure measurement error to study the shape of the exposure-response relationship

EHR with  $\beta = 5$



Cox with  $\beta = 2$



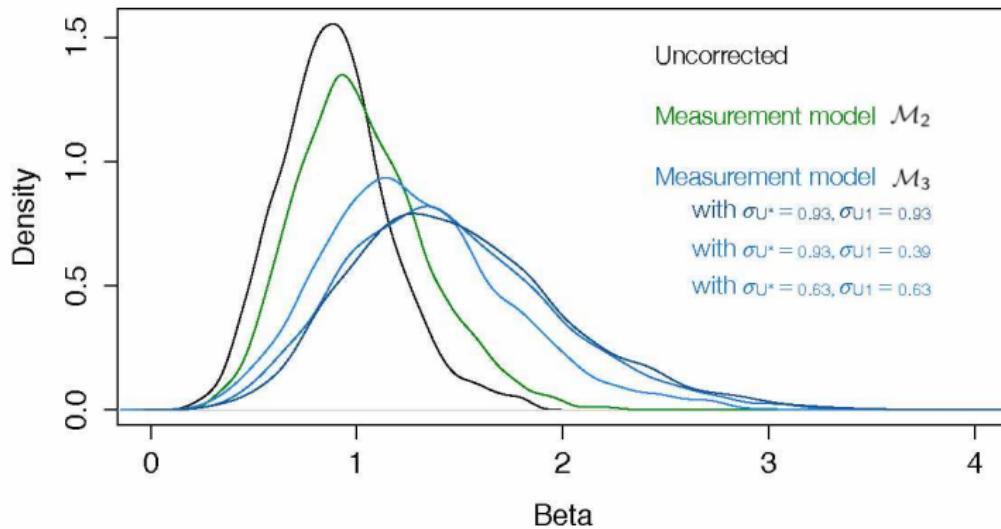
# Application to the French cohort of uranium miners

Posterior medians and 95% Credible Intervals for the risk coefficient of death by lung cancer due to radon exposure

Model	Uncorrected	Measurement model	Measurement model	Uncorrected
	Full cohort	$M_2$ Full cohort	$M_3$ Full cohort	
	EHR per 100 WLM	EHR per 100 WLM	EHR per 100 WLM	EHR per 100 WLM
Linear				
	0.87 [0.42;1.50]	0.99 [0.49;1.71]	1.44 [0.66;2.69]	2.75 [1.18; 5.32]
Piecewise linear				
<50 WLM	2.57 [1.18;4.57]	3.05 [1.10;3.54]	2.70 [0.95;5.11]	3.20 [0.80;7.03]
$\geq 50$ WLM	0.30 [-0.15;0.98]	0.44 [-0.13;1.11]	1.00 [-0.04;2.95]	2.82 [0.19;8.14]

# Sensitivity to the error variance parameters

Posterior distribution for  $\beta$

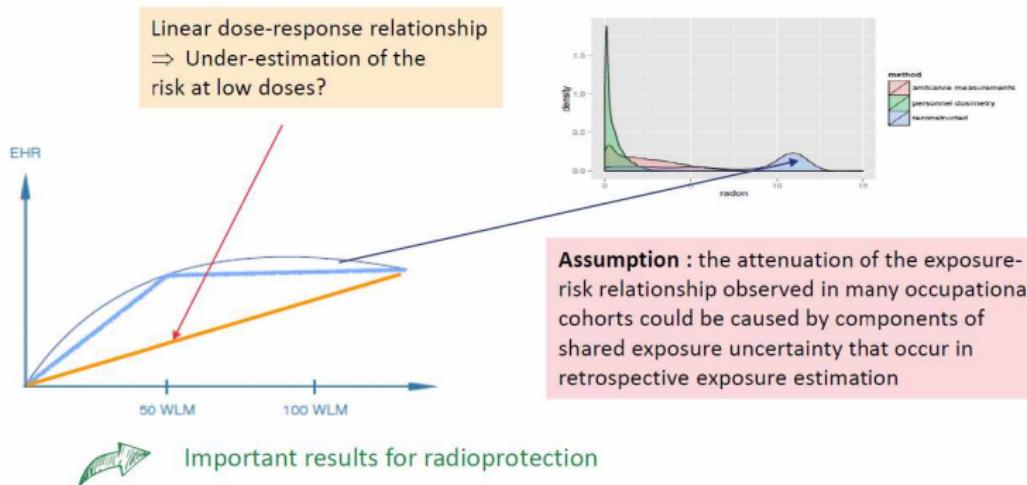


## Conclusions (1/2)

- First application of the Bayesian hierarchical approach to account for exposure measurement error in radiation epidemiology
- We also extended the proposed hierarchical models to account for left-censored and missing exposure data prone to exposure measurement error
  - ▶ Belloni M, Guienneuc C, Rage E, Ancelet S. (2020) *A Bayesian hierarchical approach to account for left-censored and missing exposure data prone to classical measurement error when analyzing lung cancer mortality due to  $\gamma$ -rays in the French cohort of uranium miners.* Radiat Environ Biophys; 59 :423-437.
- Application to the French cohort of uranium miners
  - ▶ When accounting for a combination of shared Berkson and classical measurement error
    - We observed a marked increase in the risk coefficient estimated in the linear EHR model
    - There was a less pronounced attenuation of the exposure-risk relationship
  - ▶ When accounting for unshared measurement error, we do not observe a substantial difference between corrected and uncorrected risk estimates (results not shown)
    - Hoffmann S, Rage E, Laurier D, Laroche P, Guienneuc C, Ancelet S. (2017) *Accounting for Berkson and classical measurement error in radon exposure assessment using a Bayesian structural approach in the analysis of lung cancer mortality in the French cohort of uranium miners.* Radiat Res; 187(2) :196-209.

## Conclusions (2/2)

- Results on simulated data
  - ▶ Measurement error shared within individuals can cause more bias in risk estimation than unshared measurement error or shared measurement error between individuals when assuming survival disease sub-models (New result)



- ▶ Hoffmann S, Laurier D, Rage E, Guihenneuc C, Ancelet S. (2018) *Shared and unshared measurement error in occupational cohort studies and their effects on statistical inference in proportional hazards models*. Plos One ; 13(2) :e0190792.

## Limitations & Perspectives

- Corrected risk coefficients sensitive to measurement error variance parameters
- Adaptive Metropolis-Within-Gibbs algorithm => Very time-consuming to explore high-dimensional posterior distributions
  - ▶ Hamiltonian Monte-Carlo ? Variational Bayes ? Other Bayesian learning approaches ?
  - ▶ Future application to a joint cohort of about 70000 uranium miners (French, Czech, German) in the subtask 6.4.1 of the RadoNorm European project
- Robustness to measurement and/or exposure model misspecification ? ⇒ To check !
- Bayesian model selection for high-dimensional hierarchical models ?

## Evénements à venir

- Atelier Statistique SFdS : "Apprentissage statistique des modèles à variables latentes"

- ▶ En distanciel les **7, 8, 9, 10, 11 décembre 2020 (9h-13h30)**
- ▶ Animé par Estelle KUHN (INRAE), Maud DELATTRE (INRAE) et Sophie DONNET (INRAE)
- ▶ Inscription payante (tarifs réduits) avant le 30 novembre 2020 !



- Journée AppliBUGS

- ▶ Séminaire scientifique sur les techniques et (surtout) l'application des méthodes statistiques bayésiennes dans divers domaines
- ▶ En distanciel les **17 et 18 décembre 2020 (9h-12h30)**
- ▶ Programme de la journée disponible sur "<http://genome.jouy.inra.fr/applibugs/applibugs.rencontres.html>"
- ▶ Séminaire gratuit mais inscription obligatoire



Pour plus d'infos, me contacter par email à [sophie.ancelet@irsn.fr](mailto:sophie.ancelet@irsn.fr) !

