Supporting Information

Impact of lowering fine particulate matter from major emission sources on mortality in Canada: a nationwide causal analysis

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Application of the g-formula

We outlined the algorithm for our application of the g-formula approach as follows:

Step 1, for each year between 2007 and 2016, model the conditional densities of time-varying $PM_{2.5}$ and all confounding variables using the whole sample, given covariate histories, in the following temporal ordering: (1) airshed; (2) community size; (3) urban form; (4) annual family income (in decile); (5) census-tract level ethnic concentration; (6) census-tract level deprivation index; (7) census-tract level instability measure; (8) census-tract level dependency measure; and (9) annual $PM_{2.5}$ exposure. Each variable was regressed against everything that came before it. Time-fixed covariates were included in all models.

Step 2, model the conditional probability (discrete hazard) of nonaccidental death at each year, given $PM_{2.5}$ and covariate histories, time-fixed covariates, and surviving and remaining uncensored to the previous time, using the whole sample.

Step 3, simulate a cohort followed between 2007 and 2016 under the intervention of interest as follows: (1) select a random sample (n=10,000) from the study population; (2) for each individual in the resample cohort and for 2007, set $PM_{2.5}$ and all other covariates to the observed values; (3) for each individual and for each year t from 2008 to 2016, predict time t covariates by applying coefficients estimated by covariate models in step 1 to data from times t-3, t-2, t-1, and t; (4) change time t covariate data as specified by the intervention of interest; (5) predict the probability of nonaccidental death between time t and t+1 by applying the coefficients estimated by outcome model in step 2 to data from times t-3, t-2, t-1, and t. Repeat (2) to (5) for each individual and for each year in the resampled cohort.

Step 4, estimate marginal estimate of the risk of nonaccidental death under the intervention as the average of the subject-specific risks in the resampled cohort.

Step 5, repeat steps 3 and 4 for each intervention of interest.

Step 6, repeat steps 3-5 on 200 nonparametric bootstrap resamples to construct the 95% confidence intervals (CI) for the risk difference and risk ratio of nonaccidental death with measures of comparison between two interventions.

Identifiability assumptions

Like any modern causal inference methods, the application of the g-formula relies on three identifiability assumptions (exchangeable, positivity, and consistency). Exchangeability assumes the absence of unmeasured confounding. This identifiability assumption is external to the data,[1-3] requiring us to make the assumption based on subject-matter knowledge about the $PM_{2.5}$-mortality relationship. To do this, we created a directed acyclic diagram (DAG) to conceptualize our subject-matter knowledge about the qualitative causal structure linking $PM_{2.5}$ exposure, nonaccidental death, and other measured and unmeasured covariates, according to the existing literature. Using the established graphic rules (*i.e.*, d-separation rules),[4] we carefully evaluated potential confounding variables to be considered in the analysis and the possible impact of unmeasured confounding (if any). As shown in the DAG (Appendix Figure S1), it is highly unlikely that unmeasured confounding would appreciably explain our observed association of changes in $PM_{2.5}$ exposure with changes in nonaccidental mortality. In addition, as described in our manuscript, we conducted a sensitivity analysis using Cox model to compare this study with the existing literature. We found that our estimated $PM_{2.5}$-mortality association was consistent with those reported elsewhere.[16-22] For example, in a recent large multiple-country cohort study, Strak *et al.* (2022) reported that each μg/m^3 increase in $PM_{2.5}$ exposure was associated with a hazard ratio of 1.02 (95% CI: 1.02 to 1.03) with nonaccidental mortality.[16] Similarly, in a large cohort study comprising 61 million adults in the continental U.S., Di *et al.* estimated that every μg/m^3 increase in $PM_{2.5}$ exposure was associated with a hazard ratio of 1.01 (95% CI: 1.01 to 1.01) with nonaccidental mortality.[17] To enhance communication about our causal theories with readers and to be explicit about our assumption about exchangeability, we presented this DAG in our manuscript.

The second assumption (positivity) posits that the probability of being exposed conditional on adjustment variables is greater than zero.[3] This assumption was well supported by the fact that this study comprised a very large population-based cohort (2.7 million adults) and that all the intervention strategies examined would lead to only modest changes in individuals' $PM_{2.5}$ exposures proportional to their observed exposure levels (ranging from ~1% to 14%, depending on year and source). The third assumption (consistency) further posits that the $PM_{2.5}$ exposure levels under comparison correspond to well-defined interventions.[2,3] This is indeed an important strength of this study. Previous studies often predicted sizable near-term reductions in the mortality effect of $PM_{2.5}$ based on unspecified interventions and under the assumption of instantaneously eliminating human-caused $PM_{2.5}$. In comparison, for our study interventions, we evaluated sustained and dynamic treatment regimes that comprised a sequence of actions across multiple strategies (*e.g.*, 25% incremental), emission sources (*e.g.*, transportation), and time periods. Our refined specifications of interventions were more supported by the data because the declines in ambient $PM_{2.5}$ in many developed countries including Canada have been progressive over last several decades and were largely driven by air quality regulations (and technology developments). Although we may further delineate the intervention specifications, for example, to require the potential reductions in transportation $PM_{2.5}$ by means of improving a given engine technology (*e.g.*, crankcase ventilation systems or diesel oxidation catalysts), it is reasonable to assume that these additional specifications would produce approximately equivalent results. Taken together, by focusing on more clearly defined interventions that correspond to complex but more realistic air quality actions, this study improved upon the previous studies by sharpening counterfactual contrasts in $PM_{2.5}$ exposures and mortality. This allowed for more meaningful interpretation of $PM_{2.5}$ reductions and changes in mortality risk.

We acknowledge that regardless of how much data are available, we cannot completely rule out the uncertainty about the identifiability assumptions. However, conditional on these identifiability assumptions (which are deemed reasonable in this study), our results derived from the g-formula approach can have causal interpretations.

Selected differences between the traditional Cox model and the g-formula

Compared with the Cox model, a notable strength of the g-formula approach is that it is highly flexible and can be used to evaluate a range of potential interventions. These include complex dynamic interventions that can comprise a sequence of actions over time, which cannot be evaluated by the traditional Cox model. In addition, the g-formula generates marginal effect measures that are directly interpreted as the contrasts between the risk that would have been observed if everyone in the entire population had been subject to an intervention regime of interest and the risk that would have been observed if all individuals had been subject to a different intervention regime (*e.g.*, the natural course). Such effect estimates are more useful for informing population-level interventions. Furthermore, the g-formula allows to yield the effect measures on the additive scale (in addition to the multiplicative scale). All of these characteristics are particularly relevant to the inferential goal of this study. An additional strength of the g-formula is that when the assumption that the covariates are independent of pollution does not hold, the Cox modeling approach would yield biased estimates but the g-formula approach would yield unbiased estimates.[24] Although this advantage is likely inconsequential in the present study given the relatively low $PM_{2.5}$ levels in Canada, in other regions with relatively high $PM_{2.5}$ levels, this aspect of the g-formula may be more important. For more details, please refer to Appendix Table S4.

Syntax of R code for implementation of the g-formula approach

```
library(gfoRmula)
library(data.table)
library(survival)
library(Hmisc)
library(parallel)
library(dplyr)

########## Model code for Chen et al. ##########
### Impact of lowering fine particulate matter from major emission sources on
### mortality in Canada: a nationwide causal analysis

########## Variables ##########
### Baseline time-fixed variables
### X1-X4: cubic spline terms of age
### X5: sex
### X6: race/ethnicity
### X7: indigenous identity
### X8: landed immigrant status
### X9: years since in Canada
### X10: marital status
### X11: education
### X12: employment
```

```
### X13: occupation
### person_id: subject id

### Time-varying variables
### L1: airshed
### L2: community size
### L3: urban form
### L4: family income
### L5: ethnic concentration
### L6: material deprivation
### L7: residential instability
### L8: dependency
### A: annual PM2.5 (in log scale)
### Y: nonaccidental death
### time: follow up (in years)


########## Specify model for outcome ##########

outcome_model <- reformulate(c(
  ### exposure
  "I( log((exp(lag1_A)+exp(lag2_A)+exp(lag3_A))/3) )",

  ### baseline covariates
  "X1", "X2", "X3", "X4", "X5",
  "X10", 'X12', 'X13', 'X11',
  "X6", "X7", "X8", "I(X9 * X8)",

  ### time-varying covariates
  ### time-varying covariates are modeled using bounded normal likelihoods
  ### they are rounded to closest integer and specified as factors in the outcome regression model
  "as.factor(lag1_L1)", "as.factor(lag2_L1)", "as.factor(lag3_L1)",
  "as.factor(lag1_L2)", "as.factor(lag2_L2)", "as.factor(lag3_L2)",
  "as.factor(lag1_L3)", "as.factor(lag2_L3)", "as.factor(lag3_L3)",
  "as.factor(lag1_L4)", "as.factor(lag2_L4)",  "as.factor(lag3_L4)",
  "as.factor(lag1_L8)", "as.factor(lag2_L8)", "as.factor(lag3_L8)",
  "as.factor(lag1_L6)", "as.factor(lag2_L6)", "as.factor(lag3_L6)",
  "as.factor(lag1_L5)",  "as.factor(lag2_L5)", "as.factor(lag3_L5)",
  "as.factor(lag1_L7)", "as.factor(lag2_L7)", "as.factor(lag3_L7)",

  ### time
  "time", "I(time*time)",

  ### time - exposure interaction
  paste0("I( log((exp(lag1_A)+exp(lag2_A)+exp(lag3_A))/3) )", " : ", "factor(time)")),
```

```
  response = "Y")


########## Specify time-vayring covariates  ##########
### variable names
covnames <- c("L1", "L2", "L3",
              "L4", "L5",
              "L6", "L7", "L8",
              "A")

### model likelihoods
covtypes <- c("bounded normal", "bounded normal", "bounded normal",
              "bounded normal", "bounded normal",
              "bounded normal", "bounded normal", "bounded normal",
              "normal")

### name labels
covlabels <- covnames
names(covlabels) <- c("Airshed", "Community size", "Urban form",
                      "Family Income", "Ethnic concentration",
                      "Material deprivation", "Residential instability", "Dependency",
                      "PM2.5")

### regression models
tv_cov_models <- list(covmodels = c(

  ### model for airshed
  L1 ~ X1 + X2 + X3 + X4 +
    X10 + X12 + X11 + X13 +
    X5 +
    X6 + X7 + X8 + I(X9 * X8) +
    lag1_L1 + lag2_L1 + lag3_L1 +
    lag1_L2 + lag2_L2 + lag3_L2 +
    lag1_L3 + lag2_L3 + lag3_L3 +
    lag1_L4 + lag2_L4 + lag3_L4 +
    lag1_L5 + lag2_L5 + lag3_L5 +
    lag1_L6 + lag2_L6 + lag3_L6 +
    lag1_L7 + lag2_L7 + lag3_L7 +
    lag1_L8 + lag2_L8 + lag3_L8 +
    lag1_A + lag2_A + lag3_A +
    time + I(time * time),

  ### model for CMA/CA size
  L2 ~ X1 + X2 + X3 + X4 +
    X10 + X12 + X11 + X13 +
```

```
  X5 +
  X6 + X7 + X8 + I(X9 * X8) +
  L1 + lag1_L1 + lag2_L1 + lag3_L1 +
  lag1_L2 + lag2_L2 + lag3_L2 +
  lag1_L3 + lag2_L3 + lag3_L3 +
  lag1_L4 + lag2_L4 + lag3_L4 +
  lag1_L5 + lag2_L5 + lag3_L5 +
  lag1_L6 + lag2_L6 + lag3_L6 +
  lag1_L7 + lag2_L7 + lag3_L7 +
  lag1_L8 + lag2_L8 + lag3_L8 +
  lag1_A + lag2_A + lag3_A +
  time + I(time * time),

### model for L3 form characteristics
L3 ~ X1 + X2 + X3 + X4 +
  X10 + X12 + X11 + X13 +
  X5 +
  X6 + X7 + X8 + I(X9 * X8) +
  L1 + lag1_L1 + lag2_L1 + lag3_L1 +
  L2 + lag1_L2 + lag2_L2 + lag3_L2 +
  lag1_L3 + lag2_L3 + lag3_L3 +
  lag1_L4 + lag2_L4 + lag3_L4 +
  lag1_L5 + lag2_L5 + lag3_L5 +
  lag1_L6 + lag2_L6 + lag3_L6 +
  lag1_L7 + lag2_L7 + lag3_L7 +
  lag1_L8 + lag2_L8 + lag3_L8 +
  lag1_A + lag2_A + lag3_A +
  time + I(time * time),

### model for income decile
L4 ~ X1 + X2 + X3 + X4 +
  X10 + X12 + X11 + X13 +
  X5 +
  X6 + X7 + X8 + I(X9 * X8) +
  L1 + lag1_L1 + lag2_L1 + lag3_L1 +
  L2 + lag1_L2 + lag2_L2 + lag3_L2 +
  L3 + lag1_L3 + lag2_L3 + lag3_L3 +
  lag1_L4 + lag2_L4 + lag3_L4 +
  lag1_L5 + lag2_L5 + lag3_L5 +
  lag1_L6 + lag2_L6 + lag3_L6 +
  lag1_L7 + lag2_L7 + lag3_L7 +
  lag1_L8 + lag2_L8 + lag3_L8 +
  lag1_A + lag2_A + lag3_A +
  time + I(time * time),
```

```
### model for ethnic concentration
L5 ~  X1 + X2 + X3 + X4 +
  X10 + X12 + X11 + X13 +
  X5 +
  X6 + X7 + X8 + I(X9 * X8) +
  L1 + lag1_L1 + lag2_L1 + lag3_L1 +
  L2 + lag1_L2 + lag2_L2 + lag3_L2 +
  L3 + lag1_L3 + lag2_L3 + lag3_L3 +
  L4 + lag1_L4 + lag2_L4 + lag3_L4 +
  lag1_L5 + lag2_L5 + lag3_L5 +
  lag1_L6 + lag2_L6 + lag3_L6 +
  lag1_L7 + lag2_L7 + lag3_L7 +
  lag1_L8 + lag2_L8 + lag3_L8 +
  lag1_A + lag2_A + lag3_A +
  time + I(time * time),

### model for material deprivation
L6 ~  X1 + X2 + X3 + X4 +
  X10 + X12 + X11 + X13 +
  X5 +
  X6 + X7 + X8 + I(X9 * X8) +
  L1 + lag1_L1 + lag2_L1 + lag3_L1 +
  L2 + lag1_L2 + lag2_L2 + lag3_L2 +
  L3 + lag1_L3 + lag2_L3 + lag3_L3 +
  L4 + lag1_L4 + lag2_L4 + lag3_L4 +
  L5 + lag1_L5 + lag2_L5 + lag3_L5 +
  lag1_L6 + lag2_L6 + lag3_L6 +
  lag1_L7 + lag2_L7 + lag3_L7 +
  lag1_L8 + lag2_L8 + lag3_L8 +
  lag1_A + lag2_A + lag3_A +
  time + I(time * time),

### model for residential instability
L7 ~ X1 + X2 + X3 + X4 +
  X10 + X12 + X11 + X13 +
  X5 +
  X6 + X7 + X8 + I(X9 * X8) +
  L1 + lag1_L1 + lag2_L1 + lag3_L1 +
  L2 + lag1_L2 + lag2_L2 + lag3_L2 +
  L3 + lag1_L3 + lag2_L3 + lag3_L3 +
  L4 + lag1_L4 + lag2_L4 + lag3_L4 +
  L5 + lag1_L5 + lag2_L5 + lag3_L5 +
  L6 + lag1_L6 + lag2_L6 + lag3_L6 +
  lag1_L7 + lag2_L7 + lag3_L7 +
  lag1_L8 + lag2_L8 + lag3_L8 +
```

```
    lag1_A + lag2_A + lag3_A +
    time + I(time * time),

  ### model for dependency
  L8 ~ X1 + X2 + X3 + X4 +
    X10 + X12 + X11 + X13 +
    X5 +
    X6 + X7 + X8 + I(X9 * X8) +
    L1 + lag1_L1 + lag2_L1 + lag3_L1 +
    L2 + lag1_L2 + lag2_L2 + lag3_L2 +
    L3 + lag1_L3 + lag2_L3 + lag3_L3 +
    L4 + lag1_L4 + lag2_L4 + lag3_L4 +
    L5 + lag1_L5 + lag2_L5 + lag3_L5 +
    L6 + lag1_L6 + lag2_L6 + lag3_L6 +
    L7 + lag1_L7 + lag2_L7 + lag3_L7 +
    lag1_L8 + lag2_L8 + lag3_L8 +
    lag1_A + lag2_A + lag3_A +
    time + I(time * time),

  ### model for PM2.5 exposure
  A ~ X1 + X2 + X3 + X4 +
    X10 + X12 + X11 + X13 +
    X5 +
    X6 + X7 + X8 + I(X9 * X8) +
    L1 + lag1_L1 + lag2_L1 + lag3_L1 +
    L2 + lag1_L2 + lag2_L2 + lag3_L2 +
    L3 + lag1_L3 + lag2_L3 + lag3_L3 +
    L4 + lag1_L4 + lag2_L4 + lag3_L4 +
    L5 + lag1_L5 + lag2_L5 + lag3_L5 +
    L6 + lag1_L6 + lag2_L6 + lag3_L6 +
    L7 + lag1_L7 + lag2_L7 + lag3_L7 +
    L8 + lag1_L8 + lag2_L8 + lag3_L8 +
    lag1_A + lag2_A + lag3_A +
    time + I(time * time)
))


########## Specify intervention functions ##########

### sr_t0_run is for x% incremental mitigation strategy
sr_t0_run <- function(newdf, pool, intvar, intvals, time_name, t) {
  prop_reduce <- intvals[[2]]
  n_red <- (1 / prop_reduce) - 1
  src_name <- paste0("p_", intvals[[1]], "_", t)
```

```
  if (t >= 0  & t <= n_red) {
    newdf[, (intvar) := log(exp(get(intvar)) - (exp(get(intvar)) * (get(src_name) * prop_reduce)))]
  }
  if (t == (n_red + 1)) {
    newdf[, (intvar) := log(exp(get(intvar)) - (exp(get(intvar)) *
                                               (get(src_name) * (get(src_name) *
                                                                 (1 %% prop_reduce)))))]
  }
}

### sr_phased_50 is for 50% phased mitigation strategy
sr_phased_50 <- function(newdf, pool, intvar, intvals, time_name, t) {
  src_name <- paste0("p_", intvals[[1]], "_", t)
  prop_reduce <- 0.5

  ## set intervention at time = 0 and time = 5
  if (t == 0 | t == 5) {
    newdf[, (intvar) := log(exp(get(intvar)) - (exp(get(intvar)) * (get(src_name) * prop_reduce)))]
  }
}

### sr_phased_25 is for 25% phased mitigation strategy
sr_phased_25 <- function(newdf, pool, intvar, intvals, time_name, t) {
  src_name <- paste0("p_", intvals[[1]], "_", t)
  prop_reduce <- 0.25

  ## set intervention at time = 0, 3, 6, and 9
  if (t == 0 | t == 3 | t == 6 | t == 9) {
    newdf[, (intvar) := log(exp(get(intvar)) - (exp(get(intvar)) * (get(src_name) * prop_reduce)))]
  }
}

### sr_t0 is idealistic zero-out mitigation strategy
sr_t0 <- function(newdf, pool, intvar, intvals, time_name, t) {
  prop_reduce <- intvals[[2]]

  ## set intervention at time = 0
  if (t == 0) {
    src_name <- paste0("p_", intvals[[1]], "_", t)
    newdf[, (intvar) := log(exp(get(intvar)) - (exp(get(intvar)) * (get(src_name) * prop_reduce)))]
  }
}


### specify interventions (use agriculture “AG” as an example)
```

```
interventions <- list(

  ### 25% incremental interventions
  list(c(sr_t0_run, "AG", 0.25))
)

### specify names for the interventions
pnames_int <- c('p_AG')
int_descript <- c(paste0("inc25_", pnames_int))

### specify variable that is intervened upon
intvars <- list("A")


########## Specify customized lag function and convert to factor ##########

lag1_round <- function(pool, histvars, time_name, t, id_name){

  current_ids <- unique(pool[get(time_name)==t][[id_name]])

  lapply(histvars, FUN = function(histvar) {
    i <- 1

    pool[get(time_name)==t,
         (paste0("lag1_round_", histvar)) :=
           ifelse((round(tapply(pool[get(id_name) %in% current_ids &
                                       get(time_name) == t-i][[histvar]],
                                pool[get(id_name) %in% current_ids &
                                       get(time_name) == t-i][[id_name]],
                                FUN=min), 0)) >= 1,
                  round(tapply(pool[get(id_name) %in% current_ids &
                                      get(time_name) == t-i][[histvar]],
                               pool[get(id_name) %in% current_ids &
                                      get(time_name) == t-i][[id_name]],
                               FUN=min), 0),
                  1)]
  })
}

lag2_round <- function(pool, histvars, time_name, t, id_name){

  current_ids <- unique(pool[get(time_name)==t][[id_name]])

  lapply(histvars, FUN = function(histvar) {
    i <- 2
```

```
    pool[get(time_name)==t,
         (paste0("lag2_round_", histvar)) :=
           ifelse((round(tapply(pool[get(id_name) %in% current_ids &
                                       get(time_name) == t-i][[histvar]],
                                pool[get(id_name) %in% current_ids &
                                       get(time_name) == t-i][[id_name]],
                                FUN=min), 0)) >= 1,
                  round(tapply(pool[get(id_name) %in% current_ids &
                                      get(time_name) == t-i][[histvar]],
                               pool[get(id_name) %in% current_ids &
                                      get(time_name) == t-i][[id_name]],
                               FUN=min), 0),
                  1)]
  })
}

lag3_round <- function(pool, histvars, time_name, t, id_name){

  current_ids <- unique(pool[get(time_name)==t][[id_name]])

  lapply(histvars, FUN = function(histvar) {
    i <- 3

    pool[get(time_name)==t,
         (paste0("lag3_round_", histvar)) :=
           ifelse((round(tapply(pool[get(id_name) %in% current_ids &
                                       get(time_name) == t-i][[histvar]],
                                pool[get(id_name) %in% current_ids &
                                       get(time_name) == t-i][[id_name]],
                                FUN=min), 0)) >= 1,
                  round(tapply(pool[get(id_name) %in% current_ids &
                                      get(time_name) == t-i][[histvar]],
                               pool[get(id_name) %in% current_ids &
                                      get(time_name) == t-i][[id_name]],
                               FUN=min), 0),
                  1)]
  })
}


########## Set baseline covariates ##########
basecovs.all <- c("X1", "X2", "X3", "X4", "X10",
                  "X12", "X11", "X13", "X5", "X8", "X6",
                  "X9", "X7", paste0("p_AG_", 0:9))
```

```
########## Run gformula model ##########
gf <- gformula_survival(
  obs_data = dt,
  id = "person_id",
  time_points = time_points,
  time_name = "time",
  covnames = covnames,
  outcome_name = "Y",
  ymodel = outcome_model,
  covtypes = covtypes,
  covparams = tv_cov_models,
  intvars = intvars,
  ref_int = 0,
  interventions = interventions,
  int_descript = int_descript,
  histories = c(lagged, lag1_round, lag2_round, lag3_round),
  histvars = list(covnames,
                  c("L1", "L2", "L3",
                    "L4", "L5",
                    "L6", "L7", "L8"),
                  c("L1", "L2", "L3",
                    "L4", "L5",
                    "L6", "L7", "L8"),
                  c("L1", "L2", "L3",
                    "L4", "L5",
                    "L6", "L7", "L8")),
  basecovs = basecovs.all,
  sim_data_b = TRUE,
  nsimul = 10000,
  seed = 1234)
```

Table S1. Illustration of hypothetical intervention strategies that reduce source contributions to ambient $PM_{2.5}$ in Canada over the period of 2007 to 2016, by years and intervention strategies

Intervention strategies	**Annual reduction in observed source contributions to $PM_{2.5}$ from a source ***									
	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
25% phased	25%	25%	25%	50%	50%	50%	75%	75%	75%	100%
50% phased	50%	50%	50%	50%	50%	100%	100%	100%	100%	100%
10% incremental	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
25% incremental	25%	50%	75%	100%	100%	100%	100%	100%	100%	100%
50% incremental	50%	100%	100%	100%	100%	100%	100%	100%	100%	100%
zero out	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

* Relative to the natural course of observed source contributions from a specified emission source

Table S2. Summary of covariates in the analysis of emission mitigation and mortality with the 2006 CanCHEC and *g*-formula

Variables	Years assessed	Type of variable when used as predictor	Type of variable when used as dependent variable
Age	2006	1-year category *	Not predicted
Sex	2006	Indicator	Not predicted
Race/ethnicity	2006	Indicator	Not predicted
Indigenous identity	2006	Indicator	Not predicted
Landed immigrant	2006	An indicator for immigrant (y/n) and a continuous variable for years since immigration to Canada	Not predicted
Marital status	2006	6 categories	Not predicted
Education	2006	4 categories	Not predicted
Employment	2006	3 categories	Not predicted
Occupation	2006	6 categories	Not predicted
Time (years since baseline)	All	A linear term and a quadratic term	Not predicted
Annual household income	All	10 categories †	Continuous (bounded normal)
Urban form characteristics	All	5 categories †	Continuous (bounded normal)
Community size	All	6 categories †	Continuous (bounded normal)
Airshed	All	6 categories †	Continuous (bounded normal)
Neighborhood material deprivation	All	5 categories †	Continuous (bounded normal)
Neighborhood dependency	All	5 categories †	Continuous (bounded normal)
Neighborhood residential instability	All	5 categories †	Continuous (bounded normal)
Neighborhood ethnic concentration	All	5 categories †	Continuous (bounded normal)
Annual $PM_{2.5}$ (natural logarithm transformed)	All	Continuous (normal)	Continuous (normal)
Nonaccidental death (outcome)	All	-	Time to event (pooled logistic)

* Restricted cubic spline function with 5 knots in all analyses, with the exception of analyses stratified by age in which it used 3 knots.

† Fitted as a categorical variable in the outcome model, whereas fitted as a continuous variable in the covariate models.

Table S3. Shape Constrained Health Impact Function outputs from 20 potential shapes of $PM_{2.5}$-mortality association examined

Location	**mu**	**Coeffect**	**Standard error**	**tau**	**AIC**	**Model form**
0	3.33E-07	0.013758586	0.001610607	0.1	2098016.314	z*logit
25	5.066667	0.009400996	0.001242146	0.1	2098031.985	z*logit
50	6.719052	0.007373060	0.001170288	0.1	2098049.578	z*logit
75	8.366667	0.005984167	0.001224286	0.1	2098065.372	z*logit
0	3.33E-07	0.156753366	0.016322073	0.1	2097996.869	log(z)*logit
25	5.066667	0.089558889	0.010705904	0.1	2098019.218	log(z)*logit
50	6.719052	0.068149780	0.009877653	0.1	2098041.647	log(z)*logit
75	8.366667	0.054302063	0.010275815	0.1	2098061.335	log(z)*logit
0	3.33E-07	0.012744721	0.001560701	0.2	2098022.619	z*logit
25	5.066667	0.010767467	0.001494651	0.2	2098037.422	z*logit
50	6.719052	0.010337010	0.001547356	0.2	2098044.696	z*logit
75	8.366667	0.010331821	0.001682928	0.2	2098051.639	z*logit
0	3.33E-07	0.139854219	0.015296147	0.2	2098005.589	log(z)*logit
25	5.066667	0.108444057	0.013546337	0.2	2098025.189	log(z)*logit
50	6.719052	0.101785116	0.013777825	0.2	2098034.724	log(z)*logit
75	8.366667	0.099889509	0.014803401	0.2	2098043.785	log(z)*logit
5	3.143111	0.120384691	0.012754868	0.1	2098000.025	log(z)*logit
-5	-3.14311	0.166020730	0.017572047	0.1	2097999.873	log(z)*logit
- *	-	0.014085478	0.001678212	-	2098018.857	log-linear
- *	-	0.108517703	0.010948828	-	**2097990.713**	log-log

* Two parameters, mu and tau, are not required for outcome regression under the assumption of log-log or log-linear shape for $PM_{2.5}$-mortality relationship

Table S4. Selected advantages and disadvantages of the g-formula approach compared with the traditional Cox model approach

Selected differences	**Cox model**	**g-formula**
Evaluate any interventions (*e.g.*, sustained and dynamic)	No	Yes
Scale of effect measure	Multiplicative	Additive and multiplicate
Conditional or marginal effect measure	Conditional	Marginal
Identifiability assumptions	Less explicit	More explicit
Overcome exposure-confounder feedback *	No	Yes
Subject to built-in selection bias **	Yes	No
Subject to non-collapsibility issue	Yes	No
Transportability ***	More transportable	Less transportable
Easy to implement	Yes	No
Computational constraint	Low to moderate	High

* A confounder affects exposure and the exposure affects the confounder
** A bias arising from conditioning on being free of the outcome during the follow-up. Because being free of outcome can be a common effect of the exposure of interest and frailty (a common but unobserved cause of future outcome), this opens an associational path between the exposure and future outcome, introducing a bias in the effect measure (*e.g.*, hazard ratio).
*** Transportability of causal effects with air pollution relies on a mix of causal effect modifiers such as age and SES among populations. The estimated effect measures using the g-formula from Canada may be more transportable to other high-income countries than low- and mid-income countries.

Table S5. Baseline characteristics of study population (count, percent, or mean ± SD, total N = 2,663,645)

Baseline Characteristics	Cohort	
	N=2,663,645 *	**%**
Demographic characteristics		
Person years, y	25,730,790	100
Age, y	50.9±12.8	-
Sex		
Male	1,293,890	48.6
Female	1,369,755	51.4
Race/ethnicity		
White or Indigenous	2,383,790	89.5
Visible minority	279,855	10.5
Indigenous identity		
Not Indigenous	2,540,545	95.4
Aboriginal	123,100	4.6
Landed immigrant		
Lived in Canada for 6-10 years	80,935	3.0
Lived in Canada for 11-20 years	136,980	5.1
Lived in Canada for >20 years	335,465	12.6
Marital status		
Single	308,865	11.6
Common-law	298,740	11.2
Married	1,662,825	62.4
Separated	80,770	3.0
Divorced	190,815	7.2
Widowed	121,630	4.6
Education		
Less than high school	542,060	20.4
High school	964,700	36.2
Post-secondary non-university	638,165	24.0
University	518,720	19.5
Employment		
Employed	1,744,340	65.5
Unemployed	90,440	3.4
Not in labor force	828,865	31.1
Occupation		
Management	225,175	8.5

Baseline Characteristics	Cohort	
	N=2,663,645 *	%
Professional	355,255	13.3
Skilled	602,075	22.6
Semi-skilled	571,250	21.5
Unskilled	187,320	7.0
Not applicable	722,570	27.1
Household income adequacy †		
1st decile - lowest	234,020	8.8
2nd decile	250,245	9.4
3rd decile	260,760	9.8
4th decile	268,645	10.1
5th decile	273,045	10.3
6th decile	275,025	10.3
7th decile	274,415	10.3
8th decile	274,000	10.3
9th decile	272,925	10.2
10th decile - highest	280,565	10.5
Environmental characteristics		
Urban form characteristics		
Active urban core	203,110	7.6
Transit-reliant suburb	180,310	6.8
Car-reliant suburb	1,136,480	42.7
Exurban	154,455	5.8
Non-CMA/CA ‡	989,290	37.1
CMA/CA size		
Pop: $\geq$1,500,000 §	806,390	30.3
Pop: 500,000–1,499,999	415,150	15.6
Pop: 100,000–499,999	498,795	18.7
Pop: 30,000–99,999	264,745	9.95
Pop: 10,000–29,000	100,240	3.8
Non-CMA/CA	578,325	21.7
Airshed		
Western	331,160	12.4
Prairie	354,705	13.3
Western Central	151,315	5.7
East Central	1,557,790	58.5
South Atlantic	245,770	9.2
Northern	22,905	0.9
Social-economic characteristics ‖		

Baseline Characteristics	Cohort	
	N=2,663,645 *	%
Dependency		
1st quintile - lowest	477,010	17.9
2nd quintile	443,710	16.7
3rd quintile	429,755	16.1
4th quintile	537,020	20.2
5th quintile - highest	776,150	29.1
Material deprivation		
1st quintile - lowest	549,700	20.6
2nd quintile	513,105	19.3
3rd quintile	531,545	20.0
4th quintile	454,770	17.1
5th quintile - highest	614,525	23.1
Residential instability		
1st quintile - lowest	624,005	23.4
2nd quintile	709,620	26.6
3rd quintile	535,990	20.1
4th quintile	462,855	17.4
5th quintile - highest	331,175	12.4
Ethnic concentration		
1st quintile - lowest	841,290	31.6
2nd quintile	662,200	24.9
3rd quintile	467,215	17.5
4th quintile	361,700	13.6
5th quintile - highest	331,240	12.4

* All counts were rounded up to the nearest five in compliance with privacy requirements by Statistics Canada.

† Household income adequacy is an index used by Statistics Canada that accounts for total household income and household size.

‡ CMA/CA: census metropolitan area/census agglomeration area.

§ Pop: population.

‖ From Canadian Census, at the census dissemination area level, the smallest standard geographic area for which all census data are disseminated in Canada.

Table S6. Absolute change in mortality risk (per million population) and 95% confidence interval (95% CI) for the associations of $PM_{2.5}$ reduction with premature mortality in Canada over the period 2007-2016, by years, emission sources, and intervention strategies relative to the natural course of observed $PM_{2.5}$ exposures ('no intervention' scenario)

Sources	**Interventions**					
Agriculture	Zero out	50% incremental	25% incremental	10% incremental	50% phased	25% phased
2007	0	0	0	0	0	0
2008	-26.0 (-31.3, -20.8)	-12.9 (-15.5, -10.3)	-6.4 (-7.7, -5.1)	-2.6 (-3.1, -2)	-12.9 (-15.5, -10.3)	-6.4 (-7.7, -5.1)
2009	-73.9 (-87.3, -60.5)	-51.0 (-60.2, -41.9)	-25.3 (-29.9, -20.7)	-10.2 (-12, -8.3)	-36.4 (-43.0, -29.8)	-18.0 (-21.4, -14.6)
2010	-134.2 (-157.5, -110.9)	-102.6 (-120.2, -85.0)	-57.1 (-67.1, -47.1)	-22.9 (-26.9, -18.9)	-65.3 (-76.9, -53.8)	-31.8 (-37.5, -26.0)
2011	-171.8 (-202.0, -141.5)	-145.4 (-172.0, -118.9)	-94.2 (-111.9, -76.4)	-37.5 (-44.6, -30.5)	-83.8 (-98.7, -69.0)	-47.5 (-56.1, -38.8)
2012	-204.3 (-242.1, -166.4)	-178.9 (-213.3, -144.6)	-132.1 (-158.4, -105.7)	-55.5 (-66.8, -44.2)	-99.6 (-118.1, -81.1)	-64.6 (-77.4, -51.8)
2013	-227.7 (-272.0, -183.5)	-203.4 (-244.2, -162.6)	-161.0 (-195.0, -126.9)	-70.8 (-86.1, -55.5)	-120.7 (-145.1, -96.3)	-78.9 (-95.3, -62.4)
2014	-243.6 (-293.5, -193.8)	-221.6 (-267.4, -175.8)	-182.2 (-221.7, -142.6)	-89.0 (-109.2, -68.8)	-143.2 (-173.8, -112.7)	-95.8 (-116.6, -75.0)
2015	-252.8 (-306.0, -199.6)	-232.0 (-281.0, -182.9)	-195.7 (-241.7, -149.7)	-103.9 (-130.7, -77.2)	-163.2 (-203.4, -122.9)	-108.7 (-135.9, -81.5)
2016	-255.4 (-312.7, -198.1)	-235.3 (-290.6, -180.0)	-202.8 (-254.3, -151.4)	-114.8 (-148.9, -80.7)	-173.9 (-220.5, -127.2)	-118.1 (-151.8, -84.3)
Industry	Zero out	50% incremental	25% incremental	10% incremental	50% phased	25% phased
2007	0	0	0	0	0	0
2008	-36.9 (-44.4, -29.3)	-18.3 (-22, -14.5)	-9.1 (-10.9, -7.2)	-3.6 (-4.4, -2.9)	-18.3 (-22, -14.5)	-9.1 (-10.9, -7.2)
2009	-106.2 (-125.1, -87.2)	-73.3 (-86.4, -60.1)	-36.2 (-42.6, -29.8)	-14.5 (-17.1, -11.9)	-52.2 (-61.6, -42.8)	-25.7 (-30.2, -21.1)
2010	-193.8 (-227.0, -160.5)	-147.8 (-172.8, -122.8)	-82.7 (-96.8, -68.6)	-32.6 (-38.4, -26.9)	-94.4 (-110.5, -78.3)	-46.0 (-54.2, -37.7)
2011	-247.8 (-292.1, -203.6)	-208.7 (-246.8, -170.6)	-135.8 (-161.8, -109.9)	-53.8 (-64.0, -43.6)	-120.7 (-141.9, -99.5)	-68.5 (-81.1, -55.9)
2012	-294.7 (-349.1, -240.2)	-257.0 (-305.4, -208.6)	-189.5 (-227.4, -151.5)	-79.4 (-95.6, -63.2)	-143.1 (-169.9, -116.3)	-92.8 (-111.4, -74.2)
2013	-327.9 (-390.3, -265.5)	-292.2 (-350.0, -234.3)	-232.1 (-281.2, -183.0)	-102.3 (-124.4, -80.1)	-174.3 (-208.8, -139.9)	-114.1 (-137.9, -90.2)
2014	-353.2 (-425.1, -281.2)	-319.1 (-384.0, -254.1)	-264.3 (-320.3, -208.2)	-126.4 (-154.7, -98.1)	-208.1 (-251.8, -164.5)	-137.0 (-166.7, -107.3)
2015	-366.2 (-442.3, -290.2)	-333.8 (-403.9, -263.7)	-282.8 (-349.0, -216.7)	-149.0 (-187.6, -110.4)	-236.8 (-294.1, -179.5)	-156.1 (-195.3, -117.0)
2016	-369.3 (-452.3, -286.4)	-339.0 (-418.3, -259.6)	-291.6 (-365.2, -218.0)	-164.7 (-213.4, -116.0)	-250.2 (-316.2, -184.2)	-170.0 (-216.9, -123.1)
Power generation	Zero out	50% incremental	25% incremental	10% incremental	50% phased	25% phased
2007	0	0	0	0	0	0
2008	-20.2 (-24.4, -16.0)	-10 (-12.1, -8.0)	-5.0 (-6.0, -4.0)	-2.0 (-2.4, -1.6)	-10.0 (-12.1, -8.0)	-5.0 (-6.0, -4.0)
2009	-58.5 (-69.1, -47.9)	-40.5 (-47.7, -33.4)	-20.1 (-23.7, -16.4)	-8.0 (-9.5, -6.5)	-28.8 (-34.0, -23.6)	-14.2 (-16.9, -11.5)
2010	-106.1 (-124.4, -87.7)	-81.4 (-95.4, -67.4)	-45.4 (-53.4, -37.3)	-18.2 (-21.4, -14.9)	-51.7 (-60.7, -42.7)	-25.3 (-29.9, -20.7)
2011	-135.0 (-159.4, -110.6)	-115.3 (-136.8, -93.8)	-74.7 (-89.0, -60.4)	-29.6 (-35.3, -23.9)	-66.3 (-78.3, -54.3)	-37.7 (-44.7, -30.7)
2012	-159.4 (-189.5, -129.4)	-140.9 (-168.6, -113.2)	-104.9 (-126.0, -83.7)	-43.9 (-52.8, -34.9)	-78.7 (-93.8, -63.5)	-51.6 (-61.9, -41.3)

2013	-178.4 (-213.1, -143.7)	-160.5 (-192.5, -128.5)	-128.1 (-155.2, -101.0)	-55.9 (-68.3, -43.5)	-95.1 (-114.6, -75.6)	-62.4 (-75.9, -48.9)
2014	-191.1 (-230.2, -151.9)	-174.8 (-210.3, -139.3)	-144.4 (-175.1, -113.7)	-69.3 (-85.1, -53.4)	-112.1 (-136.0, -88.2)	-74.7 (-91.1, -58.3)
2015	-198.1 (-239.7, -156.6)	-183.1 (-222.3, -143.9)	-155.3 (-191.3, -119.3)	-81.8 (-103.1, -60.5)	-129.6 (-160.7, -98.5)	-85.8 (-107.1, -64.4)
2016	-201.4 (-247.1, -155.6)	-185.9 (-229.9, -141.8)	-160.7 (-201.7, -119.7)	-90.3 (-117.4, -63.3)	-136.8 (-173.4, -100.0)	-92.9 (-119.4, -66.4)

Residential combustion	Zero out	50% Incremental	25% Incremental	10% Incremental	50% Phased	25% Phased
2007	0	0	0	0	0	0
2008	-35.7 (-43, -28.4)	-17.7 (-21.3, -14.0)	-8.8 (-10.6, -7.0)	-3.5 (-4.2, -2.8)	-17.7 (-21.3, -14.0)	-8.8 (-10.6, -7.0)
2009	-104.7 (-123.2, -86.2)	-72.8 (-85.6, -59.9)	-36.1 (-42.5, -29.8)	-14.2 (-16.7, -11.7)	-51.7 (-61.0, -42.4)	-25.6 (-30.1, -21.0)
2010	-195.3 (-228.7, -161.9)	-148.3 (-173.4, -123.2)	-83.0 (-97.2, -68.9)	-32.8 (-38.6, -26.9)	-94.2 (-110.4, -77.9)	-46.1 (-54.2, -37.9)
2011	-251.3 (-296.0, -206.6)	-209.3 (-248.2, -170.4)	-135.8 (-161.8, -109.9)	-53.9 (-64.2, -43.6)	-120.8 (-142.2, -99.4)	-68.5 (-81.0, -56.0)
2012	-300.0 (-355.3, -244.8)	-258.0 (-307.3, -208.7)	-189.7 (-227.2, -152.2)	-78.8 (-94.7, -62.9)	-143.0 (-169.6, -116.5)	-92.6 (-110.0, -74.0)
2013	-335.9 (-399.2, -272.6)	-294.9 (-353.1, -236.7)	-231.4 (-280.5, -182.3)	-103 (-125.3, -80.7)	-174.3 (-208.8, -139.8)	-114.8 (-139.0, -90.6)
2014	-362.2 (-433.7, -290.6)	-322.9 (-387.9, -257.9)	-264.6 (-321.0, -208.2)	-127.8 (-156.9, -98.7)	-207.7 (-251.2, -164.1)	-138.3 (-168.1, -108.5)
2015	-377.6 (-455.5, -299.7)	-339.1 (-410.5, -267.6)	-285.0 (-350.5, -219.5)	-149.9 (-187.8, -112.0)	-238.6 (-295.2, -182.1)	-157.1 (-195.6, -118.6)
2016	-384.5 (-470.5, -298.6)	-346.0 (-426.2, -265.7)	-295.5 (-369.1, -221.8)	-164.9 (-214.1, -115.7)	-253.3 (-319.4, -187.3)	-169.3 (-216.7, -121.8)

Transport	Zero out	50% Incremental	25% Incremental	10% Incremental	50% Phased	25% Phased
2007	0	0	0	0	0	0
2008	-38.9 (-46.8, -30.9)	-19.2 (-23.1, -15.3)	-9.6 (-11.5, -7.6)	-3.8 (-4.6, -3.0)	-19.2 (-23.1, -15.3)	-9.6 (-11.5, -7.6)
2009	-112.0 (-132.0, -92.1)	-77.4 (-91.3, -63.5)	-38.3 (-45.1, -31.6)	-15.2 (-18.0, -12.5)	-55.1 (-65.1, -45.1)	-27.2 (-32.1, -22.3)
2010	-206.2 (-241.7, -170.6)	-156.2 (-182.6, -129.8)	-87.6 (-102.6, -72.7)	-34.8 (-41.0, -28.5)	-100.2 (-117.5, -82.9)	-48.9 (-57.6, -40.2)
2011	-262.9 (-309.7, -216.1)	-221.7 (-262.8, -180.7)	-144.0 (-171.3, -116.6)	-57.3 (-68.1, -46.4)	-128.5 (-150.8, -106.0)	-72.6 (-85.8, -59.4)
2012	-313.7 (-371.5, -255.9)	-272.5 (-324.4, -220.6)	-200.8 (-240.6, -161.0)	-84.1 (-101.3, -66.8)	-152.0 (-180.5, -123.5)	-98.9 (-118.6, -79.1)
2013	-351.4 (-418.4, -284.4)	-311.0 (-371.9, -250.1)	-246.3 (-298.3, -194.0)	-109.0 (-132.5, -85.5)	-185.0 (-221.7, -148.3)	-121.9 (-147.5, -96.2)
2014	-377.4 (-452.6, -302.1)	-338.7 (-407.5, -270.0)	-280.0 (-339.8, -220.2)	-134.5 (-165.1, -103.0)	-220.0 (-266.7, -173.2)	-145.6 (-177.1, -114.1)
2015	-391.2 (-471.8, -310.7)	-353.4 (-428.6, -278.2)	-300.0 (-370.6, -229.4)	-157.8 (-198.4, -117.0)	-252.1 (-313.3, -190.9)	-166.2 (-207.5, -125.0)
2016	-395.9 (-484.1, -307.6)	-360.3 (-444.2, -276.4)	-310.5 (-388.6, -232.4)	-174.7 (-226.1, -123.0)	-266.4 (-336.3, -196.4)	-180.1 (-230.9, -129.4)

Table S7. Mean percentage change in mortality risk and 95% confidence interval (95% CI) for the associations of $PM_{2.5}$ reduction with premature mortality in Canada over the period 2007-2016, by years, emission sources, and intervention strategies relative to the natural course of observed $PM_{2.5}$ exposures ('no intervention' scenario)

Sources	**Interventions**					
Agriculture	Zero out	50% Incremental	25% Incremental	10% Incremental	50% Phased	25% Phased
2007	1	1	1	1	1	1
2008	-0.2% (-0.3%, -0.2%)	-0.1% (-0.1%, -0.1%)	-0.1% (-0.1%, 0%)	0% (0%, 0%)	-0.1% (-0.1%, -0.1%)	-0.1% (-0.1%, 0%)
2009	-0.4% (-0.5%, -0.3%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.2%, -0.1%)	-0.1% (-0.1%, 0%)	-0.2% (-0.2%, -0.2%)	-0.1% (-0.1%, -0.1%)
2010	-0.5% (-0.6%, -0.4%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.3%, -0.2%)	-0.1% (-0.1%, -0.1%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.1%, -0.1%)
2011	-0.5% (-0.6%, -0.4%)	-0.4% (-0.5%, -0.4%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.1%, -0.1%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.2%, -0.1%)
2012	-0.5% (-0.6%, -0.4%)	-0.5% (-0.5%, -0.4%)	-0.3% (-0.4%, -0.3%)	-0.1% (-0.2%, -0.1%)	-0.3% (-0.3%, -0.2%)	-0.2% (-0.2%, -0.1%)
2013	-0.5% (-0.6%, -0.4%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.4%, -0.3%)	-0.2% (-0.2%, -0.1%)	-0.3% (-0.3%, -0.2%)	-0.2% (-0.2%, -0.1%)
2014	-0.4% (-0.5%, -0.4%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.4%, -0.3%)	-0.2% (-0.2%, -0.1%)	-0.3% (-0.3%, -0.2%)	-0.2% (-0.2%, -0.1%)
2015	-0.4% (-0.5%, -0.3%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.4%, -0.2%)	-0.2% (-0.2%, -0.1%)	-0.3% (-0.3%, -0.2%)	-0.2% (-0.2%, -0.1%)
2016	-0.4% (-0.5%, -0.3%)	-0.3% (-0.4%, -0.3%)	-0.3% (-0.4%, -0.2%)	-0.2% (-0.2%, -0.1%)	-0.3% (-0.3%, -0.2%)	-0.2% (-0.2%, -0.1%)
Industry	Zero out	50% Incremental	25% Incremental	10% Incremental	50% Phased	25% Phased
2007	1	1	1	1	1	1
2008	-0.3% (-0.4%, -0.2%)	-0.2% (-0.2%, -0.1%)	-0.1% (-0.1%, -0.1%)	0% (0%, 0%)	-0.2% (-0.2%, -0.1%)	-0.1% (-0.1%, -0.1%)
2009	-0.6% (-0.7%, -0.5%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.2%, -0.2%)	-0.1% (-0.1%, -0.1%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.2%, -0.1%)
2010	-0.8% (-0.9%, -0.6%)	-0.6% (-0.7%, -0.5%)	-0.3% (-0.4%, -0.3%)	-0.1% (-0.2%, -0.1%)	-0.4% (-0.4%, -0.3%)	-0.2% (-0.2%, -0.1%)
2011	-0.8% (-0.9%, -0.6%)	-0.6% (-0.8%, -0.5%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.2%, -0.1%)	-0.4% (-0.4%, -0.3%)	-0.2% (-0.2%, -0.2%)
2012	-0.7% (-0.9%, -0.6%)	-0.6% (-0.8%, -0.5%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.2%, -0.2%)	-0.4% (-0.4%, -0.3%)	-0.2% (-0.3%, -0.2%)
2013	-0.7% (-0.8%, -0.6%)	-0.6% (-0.7%, -0.5%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.4%, -0.3%)	-0.2% (-0.3%, -0.2%)
2014	-0.7% (-0.8%, -0.5%)	-0.6% (-0.7%, -0.5%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.3%, -0.2%)
2015	-0.6% (-0.7%, -0.5%)	-0.5% (-0.7%, -0.4%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.3%, -0.2%)
2016	-0.5% (-0.7%, -0.4%)	-0.5% (-0.6%, -0.4%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.3%, -0.2%)
Power generation	Zero out	50% Incremental	25% Incremental	10% Incremental	50% Phased	25% Phased
2007	1	1	1	1	1	1
2008	-0.2% (-0.2%, -0.1%)	-0.1% (-0.1%, -0.1%)	0% (-0.1%, 0%)	0% (0%, 0%)	-0.1% (-0.1%, -0.1%)	0% (-0.1%, 0%)
2009	-0.3% (-0.4%, -0.3%)	-0.2% (-0.3%, -0.2%)	-0.1% (-0.1%, -0.1%)	0% (-0.1%, 0%)	-0.2% (-0.2%, -0.1%)	-0.1% (-0.1%, -0.1%)
2010	-0.4% (-0.5%, -0.3%)	-0.3% (-0.4%, -0.3%)	-0.2% (-0.2%, -0.1%)	-0.1% (-0.1%, -0.1%)	-0.2% (-0.2%, -0.2%)	-0.1% (-0.1%, -0.1%)
2011	-0.4% (-0.5%, -0.3%)	-0.4% (-0.4%, -0.3%)	-0.2% (-0.3%, -0.2%)	-0.1% (-0.1%, -0.1%)	-0.2% (-0.2%, -0.2%)	-0.1% (-0.1%, -0.1%)
2012	-0.4% (-0.5%, -0.3%)	-0.4% (-0.4%, -0.3%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.1%, -0.1%)	-0.2% (-0.2%, -0.2%)	-0.1% (-0.2%, -0.1%)

2013	-0.4% (-0.5%, -0.3%)	-0.3% (-0.4%, -0.3%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.1%, -0.1%)	-0.2% (-0.2%, -0.2%)	-0.1% (-0.2%, -0.1%)
2014	-0.4% (-0.4%, -0.3%)	-0.3% (-0.4%, -0.3%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.2%, -0.1%)	-0.2% (-0.3%, -0.2%)	-0.1% (-0.2%, -0.1%)
2015	-0.3% (-0.4%, -0.3%)	-0.3% (-0.4%, -0.2%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.2%, -0.1%)	-0.2% (-0.3%, -0.2%)	-0.1% (-0.2%, -0.1%)
2016	-0.3% (-0.4%, -0.2%)	-0.3% (-0.3%, -0.2%)	-0.2% (-0.3%, -0.2%)	-0.1% (-0.2%, -0.1%)	-0.2% (-0.3%, -0.1%)	-0.1% (-0.2%, -0.1%)

Residential combustion	Zero out	50% Incremental	25% Incremental	10% Incremental	50% Phased	25% Phased
2007	1	1	1	1	1	1
2008	-0.3% (-0.4%, -0.2%)	-0.1% (-0.2%, -0.1%)	-0.1% (-0.1%, -0.1%)	0% (0%, 0%)	-0.1% (-0.2%, -0.1%)	-0.1% (-0.1%, -0.1%)
2009	-0.6% (-0.7%, -0.5%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.2%, -0.2%)	-0.1% (-0.1%, -0.1%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.2%, -0.1%)
2010	-0.8% (-0.9%, -0.6%)	-0.6% (-0.7%, -0.5%)	-0.3% (-0.4%, -0.3%)	-0.1% (-0.2%, -0.1%)	-0.4% (-0.4%, -0.3%)	-0.2% (-0.2%, -0.1%)
2011	-0.8% (-0.9%, -0.6%)	-0.6% (-0.8%, -0.5%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.2%, -0.1%)	-0.4% (-0.4%, -0.3%)	-0.2% (-0.2%, -0.2%)
2012	-0.8% (-0.9%, -0.6%)	-0.7% (-0.8%, -0.5%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.2%, -0.2%)	-0.4% (-0.4%, -0.3%)	-0.2% (-0.3%, -0.2%)
2013	-0.7% (-0.9%, -0.6%)	-0.6% (-0.8%, -0.5%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.4%, -0.3%)	-0.2% (-0.3%, -0.2%)
2014	-0.7% (-0.8%, -0.5%)	-0.6% (-0.7%, -0.5%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.3%, -0.2%)
2015	-0.6% (-0.7%, -0.5%)	-0.5% (-0.7%, -0.4%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.3%, -0.2%)
2016	-0.6% (-0.7%, -0.4%)	-0.5% (-0.6%, -0.4%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.3%, -0.2%)

Transportation	Zero out	50% Incremental	25% Incremental	10% Incremental	50% Phased	25% Phased
2007	1	1	1	1	1	1
2008	-0.3% (-0.4%, -0.3%)	-0.2% (-0.2%, -0.1%)	-0.1% (-0.1%, -0.1%)	0% (0%, 0%)	-0.2% (-0.2%, -0.1%)	-0.1% (-0.1%, -0.1%)
2009	-0.6% (-0.7%, -0.5%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.2%, -0.2%)	-0.1% (-0.1%, -0.1%)	-0.3% (-0.3%, -0.2%)	-0.1% (-0.2%, -0.1%)
2010	-0.8% (-0.9%, -0.7%)	-0.6% (-0.7%, -0.5%)	-0.3% (-0.4%, -0.3%)	-0.1% (-0.2%, -0.1%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.2%, -0.2%)
2011	-0.8% (-1.0%, -0.7%)	-0.7% (-0.8%, -0.6%)	-0.4% (-0.5%, -0.4%)	-0.2% (-0.2%, -0.1%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.3%, -0.2%)
2012	-0.8% (-0.9%, -0.6%)	-0.7% (-0.8%, -0.6%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.2% (-0.3%, -0.2%)
2013	-0.8% (-0.9%, -0.6%)	-0.7% (-0.8%, -0.5%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.3%, -0.2%)
2014	-0.7% (-0.8%, -0.6%)	-0.6% (-0.8%, -0.5%)	-0.5% (-0.6%, -0.4%)	-0.2% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.3%, -0.2%)
2015	-0.6% (-0.8%, -0.5%)	-0.6% (-0.7%, -0.5%)	-0.5% (-0.6%, -0.4%)	-0.3% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.3%, -0.2%)
2016	-0.6% (-0.7%, -0.4%)	-0.5% (-0.6%, -0.4%)	-0.4% (-0.6%, -0.3%)	-0.3% (-0.3%, -0.2%)	-0.4% (-0.5%, -0.3%)	-0.3% (-0.3%, -0.2%)

Figure Legends

Figure S1. Causal diagram for the association between ambient $PM_{2.5}$ and mortality

Figure S2. Flow chart of cohort creation

Figure S3. Annual mean exposure to ambient $PM_{2.5}$ in the 2006 CanCHEC cohort (2.7M adults, aged 30-79 years), by year

Figure S4. Changes in mean annual exposure of ambient $PM_{2.5}$ in the 2006 CanCHEC cohort (2.7M adults, aged 30-79 years) if source contributions to $PM_{2.5}$ exposure had been reduced in Canada over the period 2007-2016, by selected major emission sources and intervention strategies relative to the natural course of observed $PM_{2.5}$ exposures (‘no intervention’ scenario)

Figure S5. Sensitivity analyses of $PM_{2.5}$ reduction with mortality in the CanCHEC cohort, 2007-2016 (expressed as absolute difference in mortality risks, per million), by emission sources and strategies

Figure S6. Sensitivity analyses of $PM_{2.5}$ reduction with mortality in the CanCHEC cohort, 2007-2016 (expressed as percentage change in mortality risk, in %), by emission sources and strategies

Figure S7. Comparison of observed and predicted survival probability, $PM_{2.5}$ exposure, and time-varying covariates for each year during the period 2007-2016

Figure S8. Absolute change in mortality risk and 95% confidence interval (95% CI) per million persons for the associations of reductions in source contributions to $PM_{2.5}$ with premature mortality in the 2006 CanCHEC cohort over the period 2007-2016, by two selected emission sources, intervention strategies, and personal-level characteristics at baseline

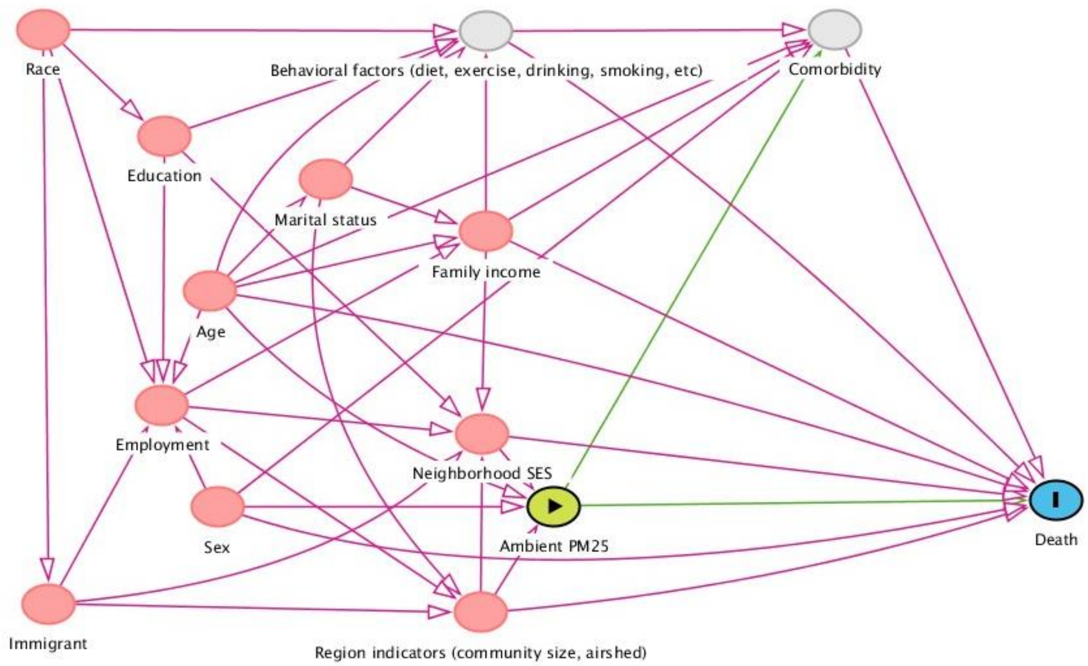

Figure S1. Causal diagram for the association between ambient $PM_{2.5}$ and mortality (note that grey nodes indicate unmeasured factors whereas red nodes denote measured factors)

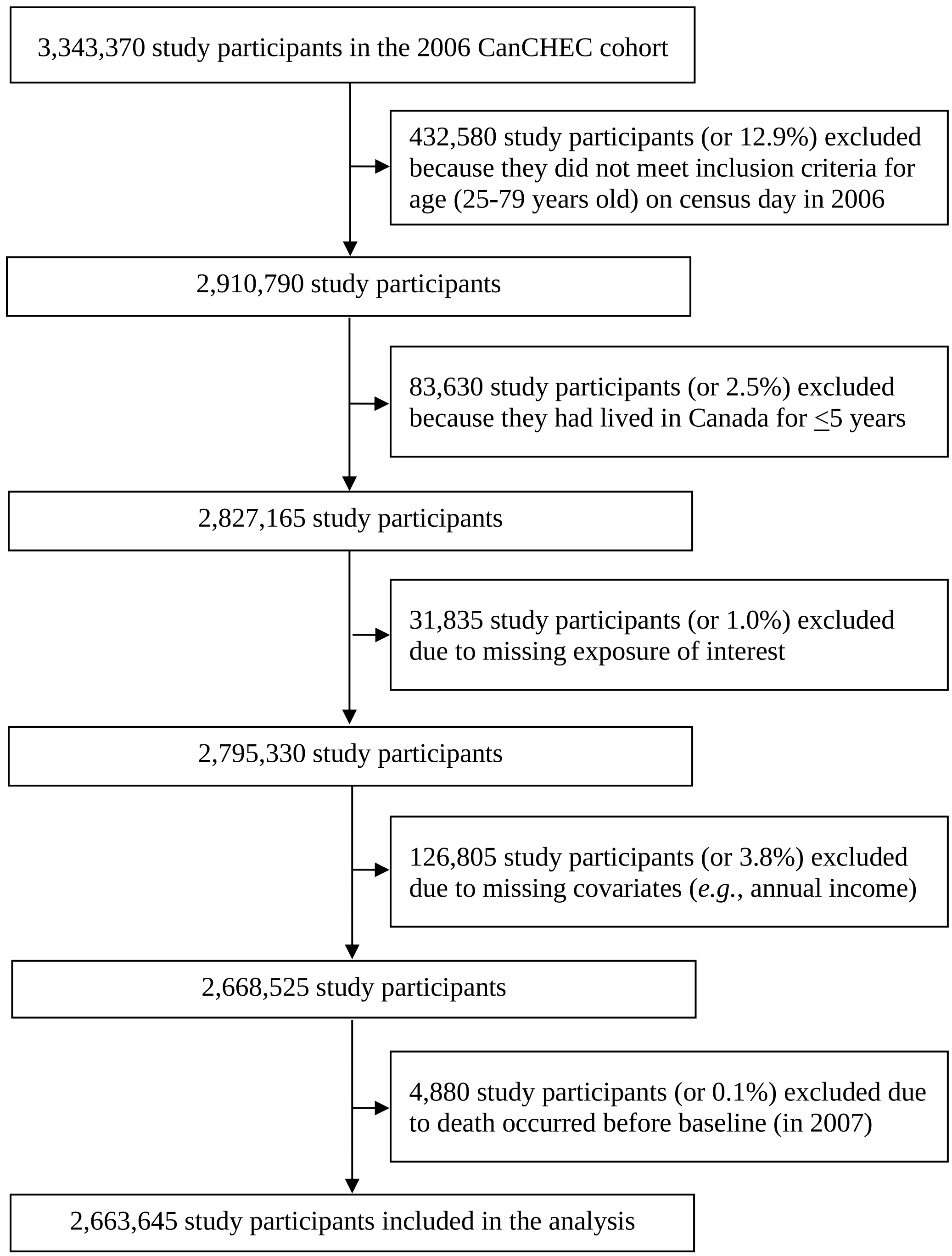

Figure S2. Flow chart of cohort creation

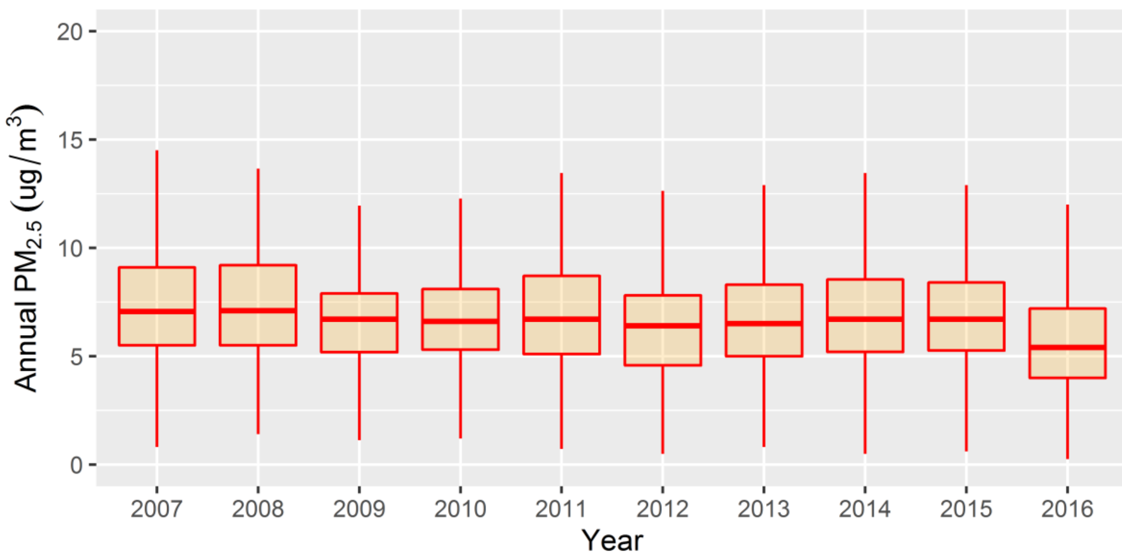

Figure S3. Annual mean exposure to ambient $PM_{2.5}$ in the 2006 CanCHEC cohort (2.7M adults, aged 30-79 years), by year

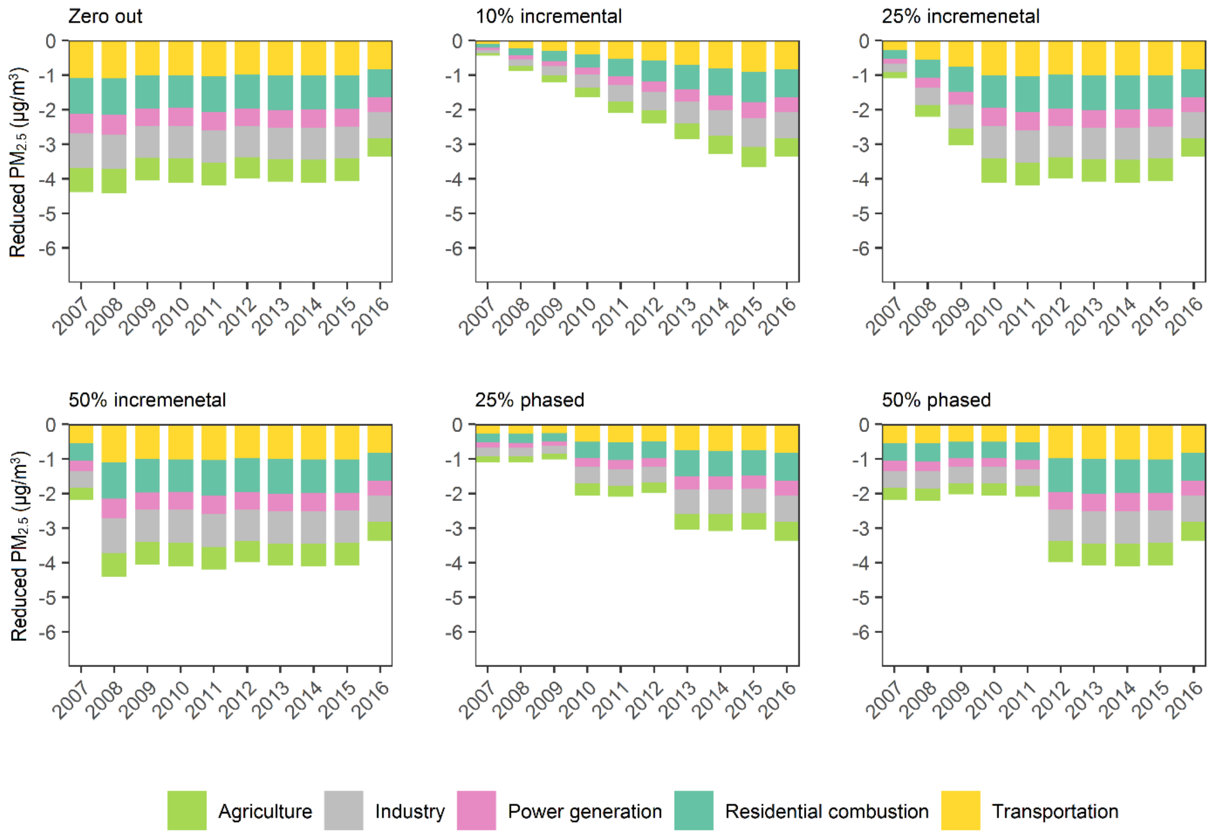

Figure S4. Changes in mean annual exposure of ambient $PM_{2.5}$ in the 2006 CanCHEC cohort (2.7M adults, aged 30-79 years) if source contributions to $PM_{2.5}$ exposure had been reduced in Canada over the period 2007-2016, by selected major emission sources and intervention strategies relative to the natural course of observed $PM_{2.5}$ exposures ('no intervention' scenario)

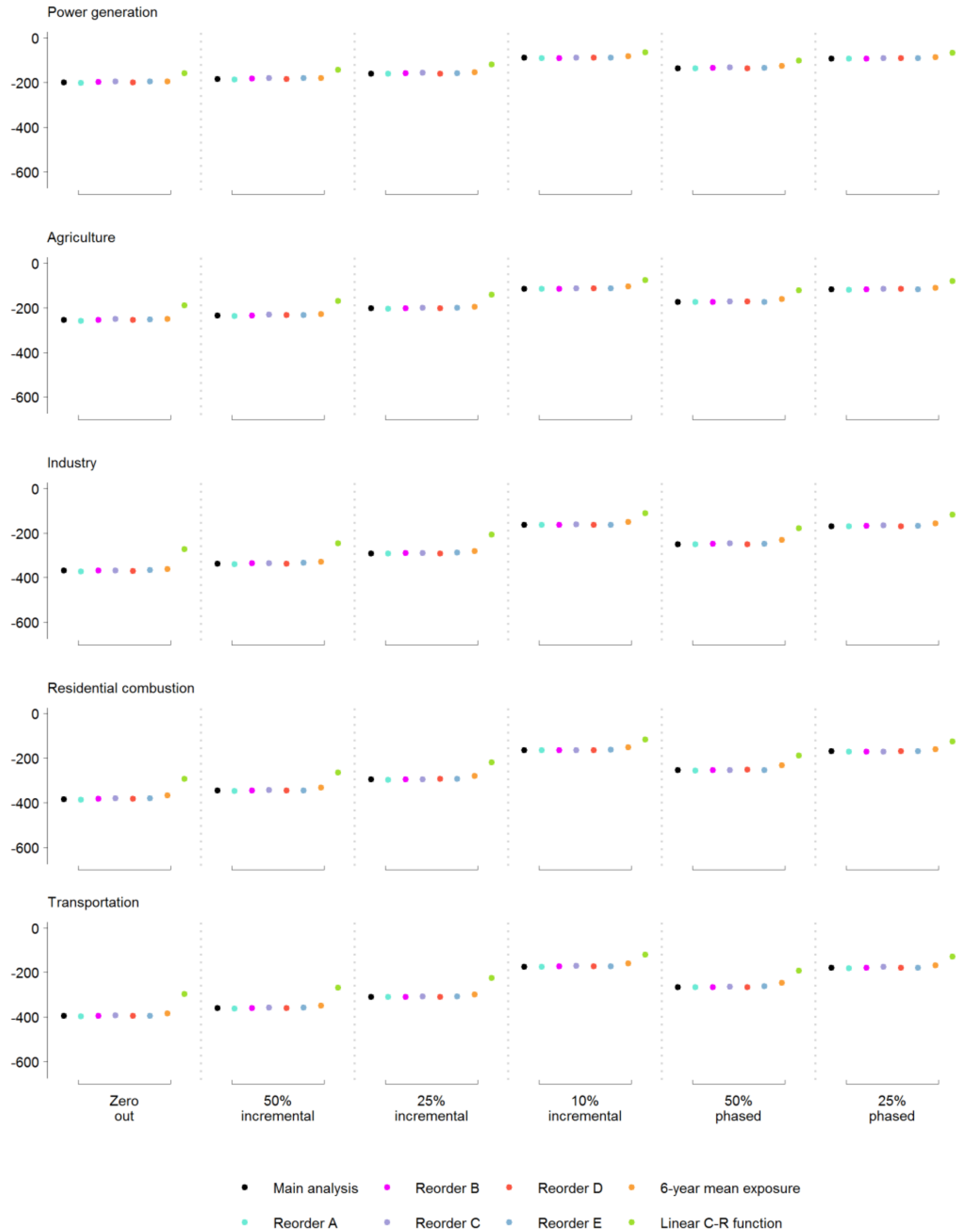

Figure S5. Sensitivity analyses of $PM_{2.5}$ reduction with mortality in the CanCHEC cohort, 2007-2016 (expressed as absolute difference in mortality risks, per million), by emission sources and strategies ([1] Reorder B assumed a causal ordering of time-varying covariates: airshed → community size → urban form → area-level deprivation → income → $PM_{2.5}$; [2] Reorder C: income → airshed → community size → urban form → area-level deprivation → $PM_{2.5}$; [3] Reorder D: airshed → community size → urban form → $PM_{2.5}$ → income → area-level deprivation; [4] Reorder E: $PM_{2.5}$ → airshed → community size → urban form → income → area-level deprivation; [5] 6-year mean exposure denotes 6-year moving average of $PM_{2.5}$ with 1-yr lag; [6] linear C-R function assumes a log-linear shape of $PM_{2.5}$-mortality association)

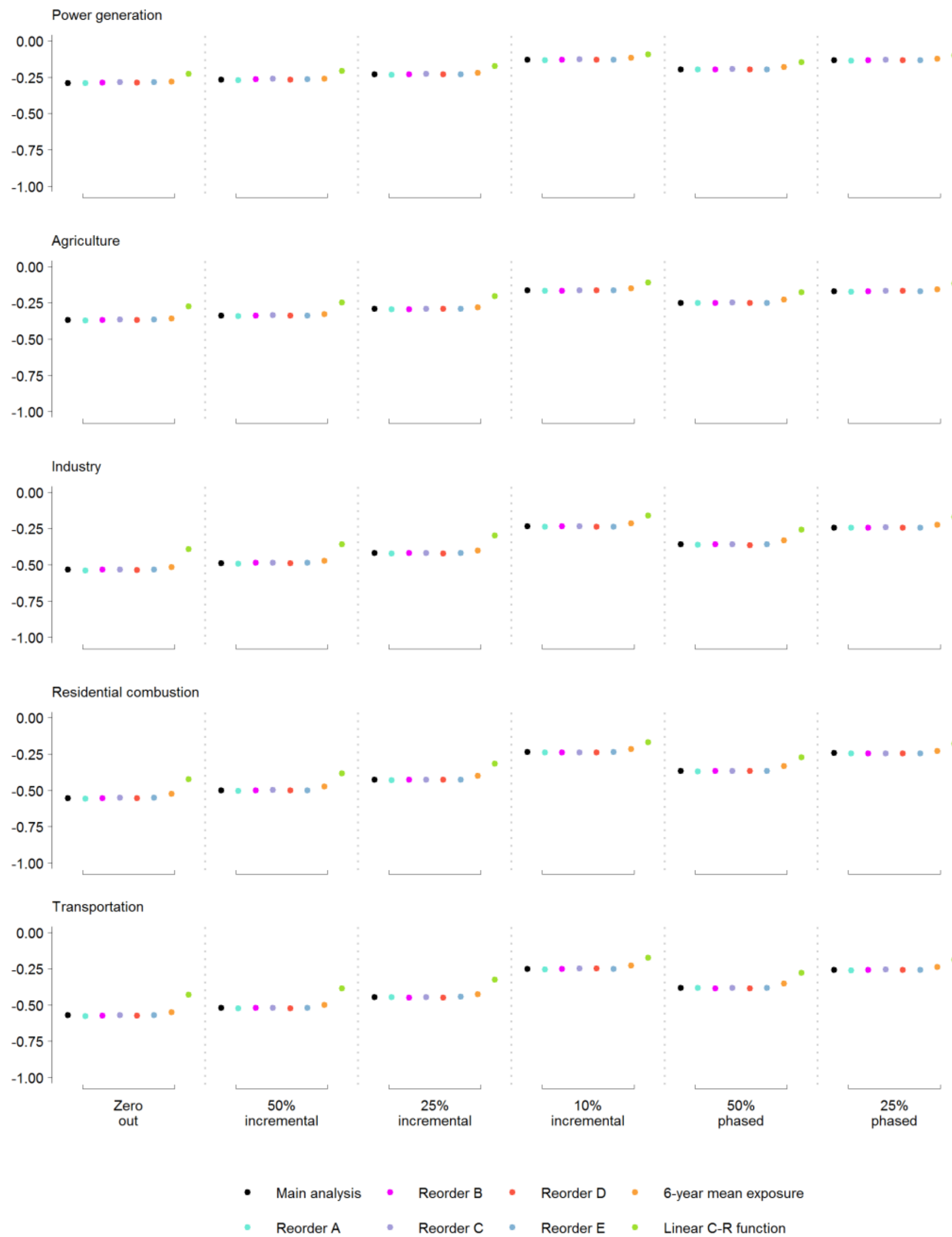

Figure S6. Sensitivity analyses of $PM_{2.5}$ reduction with mortality in the CanCHEC cohort, 2007-2016 (expressed as percentage change in mortality risk, in %), by emission sources and strategies ([1] Reorder B assumed a causal ordering of time-varying covariates: airshed → community size → urban form → area-level deprivation → income → $PM_{2.5}$; [2] Reorder C: income → airshed → community size → urban form → area-level deprivation → $PM_{2.5}$; [3] Reorder D: airshed → community size → urban form → $PM_{2.5}$ → income → area-level deprivation; [4] Reorder E: $PM_{2.5}$ → airshed → community size → urban form → income → area-level deprivation; [5] 6-year mean exposure denotes 6-year moving average of $PM_{2.5}$ with 1-year lag; [6] linear C-R function assumes a log-linear shape of $PM_{2.5}$-mortality association)

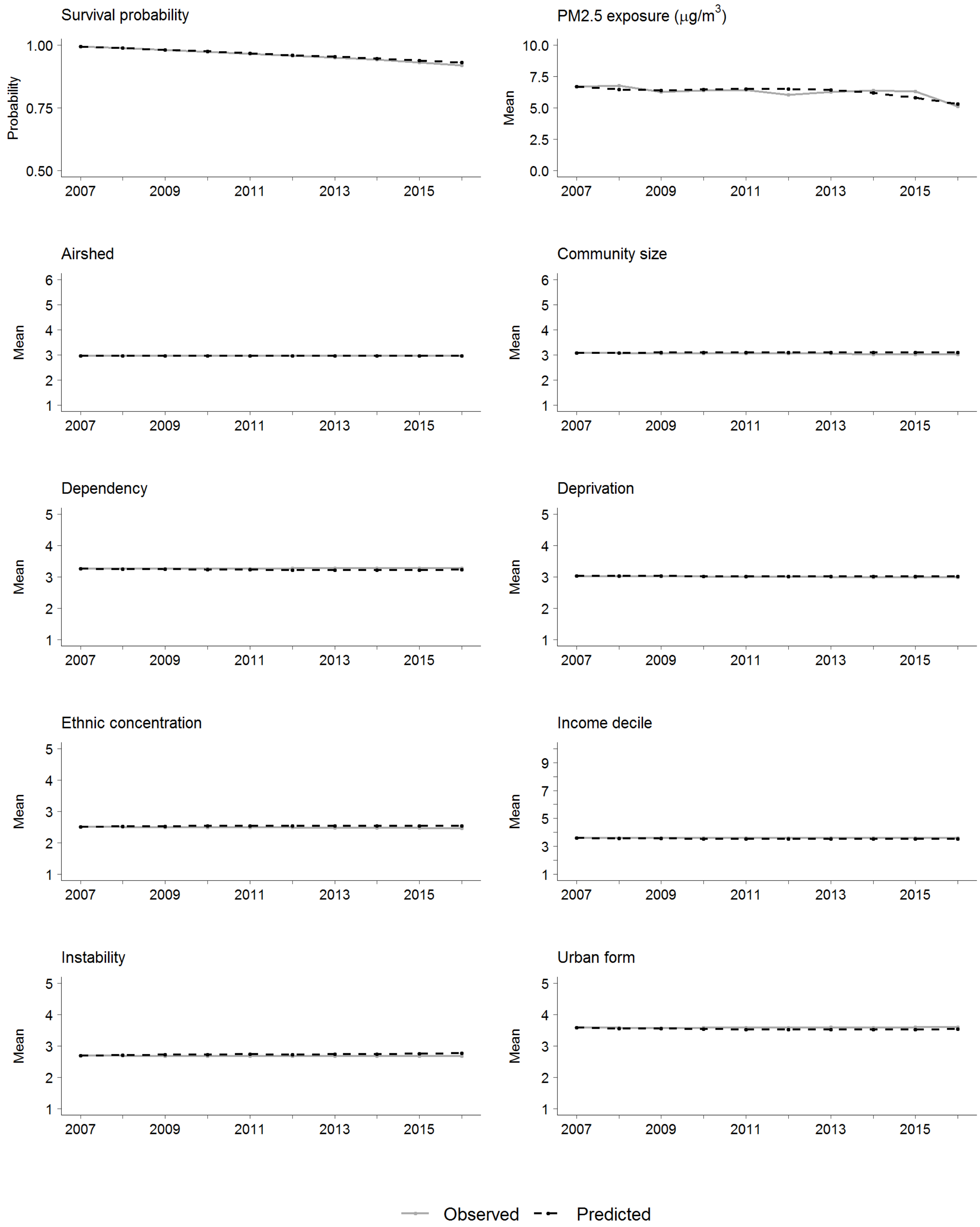

Figure S7. Comparison of observed and predicted survival probability, $PM_{2.5}$ exposure, and time-varying covariates for each year during the period 2007-2016

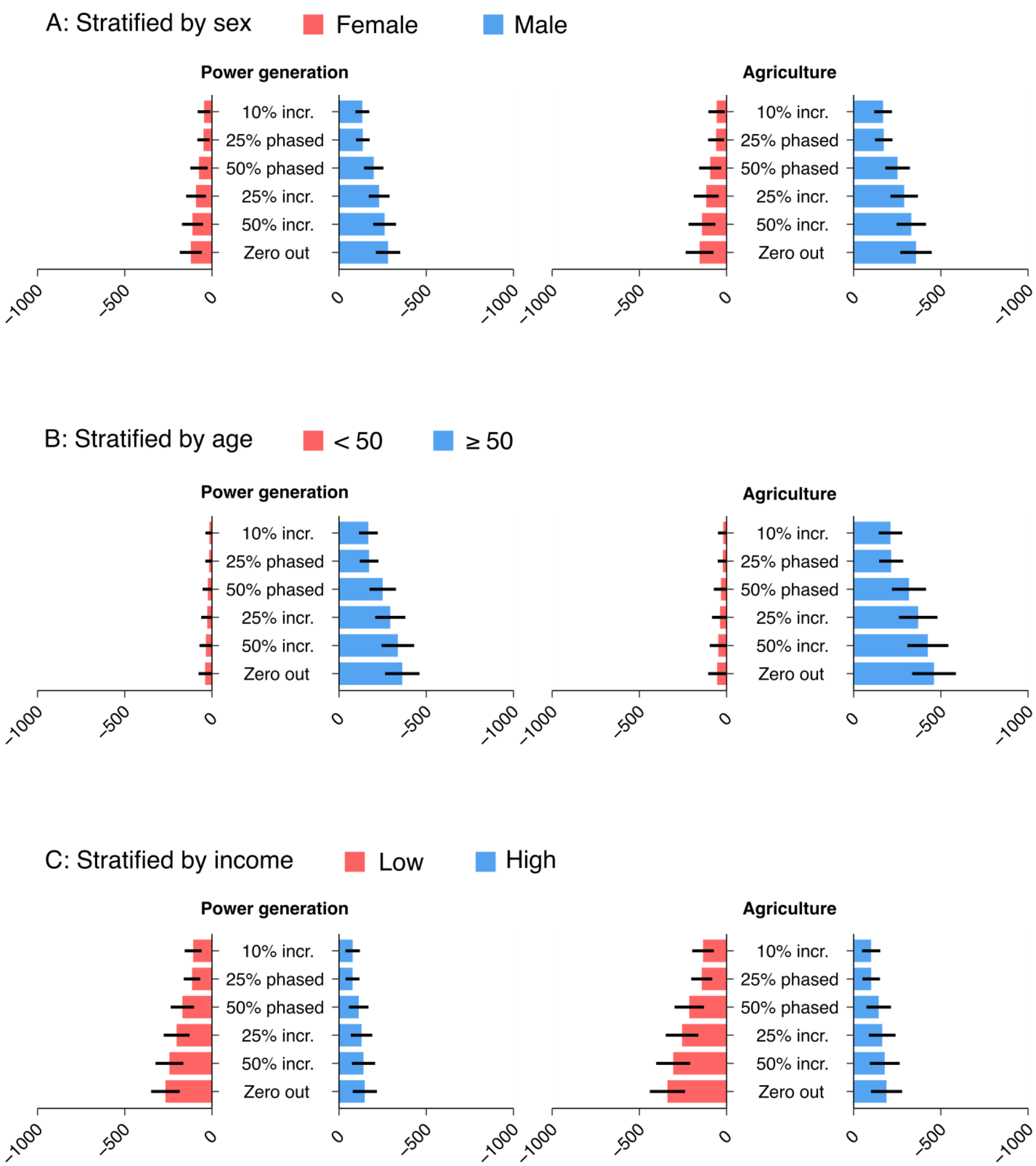

Figure S8. Absolute change in mortality risk and 95% confidence interval (95% CI) per million persons for the associations of reductions in source contributions to $PM_{2.5}$ with premature mortality in the 2006 CanCHEC cohort over the period 2007-2016, by two selected emission sources, intervention strategies, and personal-level characteristics at baseline

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