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Spatial variation in cause-specific premature mortality and its association with socioeconomic deprivation in Belgium from 2000 to 2019

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Abstract

Background Premature mortality risks vary in space and time among subpopulations and are influenced by numerous factors, including levels of socioeconomic deprivation. In Belgium, socioeconomic deprivation has recently been quantified using the Belgian Indices of Multiple Deprivation; however, its contribution to the spatial patterns of premature mortality has not yet been assessed. This study aims to investigate the variation in premature mortality risks and their association with socioeconomic deprivation.

Methods The Belgian Index of Multiple Deprivation 2011 and its deprivation domains, including employment, income, education, housing, and crime, are used to measure overall and domain-specific deprivation in all 589 municipalities in Belgium between 2000 and 2019. We estimate the all-cause and cause-specific relative risks of dying prematurely using Bayesian hierarchical models.

Results The spatial patterns of relative risks varied by cause of death. The most common pattern observed was a North-South gradient, with higher risks in Wallonia and lower risks in Flanders. Subnational variation increased over time for all causes of death, differing by cause. Higher deprivation levels were linked to greater premature mortality risks, particularly associated with employment and housing deprivation. In both sexes, the strongest associations with deprivation were observed for deaths due to alcohol consumption, COPD, and diabetes mellitus.

Conclusion This study highlights the significant associations between socioeconomic deprivation and the risk of premature death in Belgium, revealing notable spatial disparities. The North-South gradient underscores the persistent regional inequalities, with Wallonia bearing the highest burden of premature mortality risks. These results emphasize the importance of addressing the complex interplay of socioeconomic factors in shaping health outcomes and the need for targeted public health interventions to reduce premature mortality and promote health equity across Belgium.

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Keywords Relative risk of premature death, Health inequality, Deprivation, Belgian index of multiple deprivation, Belgium

Text box 1. Contributions to the literature

- This study examines the subnational variation in cause-specific relative risks of premature death across municipalities in Belgium from 2000 to 2019.
- Over time, subnational variation in the relative risk of premature death has increased; however, the extent of this increase varies depending on the specific cause of death.
- The strength of the relationship between premature death risks and overall or domain-specific deprivation varied by cause of death. In most cases, the association was positive, except for deaths resulting from road accidents, which showed a negative relationship.

Introduction

Population-level risks of premature mortality vary in space and time between subpopulations and are influenced by many factors, including levels of socioeconomic deprivation. It is a well-known fact that mortality risks are often driven by poverty, with the poor experiencing greater risks than more affluent populations [1–3]. However, poverty is just one aspect of deprivation, which is a far more complex construct. Deprivation is also defined by factors such as unemployment, low education, inadequate housing, adverse environmental conditions, and poor health. Thus, addressing the spatio-temporal variation in premature mortality risks associated with socioeconomic deprivation, rather than focusing solely on poverty, is an important task for researchers and policymakers. It enables them to assess the direction of inequalities in premature mortality trends over time and identify the high-risk areas that require intervention.

In Belgium, socioeconomic inequalities in mortality have mostly been studied at the country level [4, 5]. In 2017, Renard et al. used education attainment as a proxy for socioeconomic status and confirmed a reduction in premature mortality in men and women in the period of 1991–2001, as well as an increase in relative inequalities in both sexes [6]. In 2018, Eggerickx et al. studied the evolution of social disparities in Belgian mortality between 1991 and 2016 and found a significant increase in mortality inequalities since the 1990s [7]. The increase in socioeconomic health inequalities is even more evident at the sub-national level, with higher premature mortality risks in Wallonia compared to Flanders, as concluded by Renard et al. (2014), who investigated the burden of premature mortality for men and women between 1993 and 2009 [8]. According to Van Oyen et al. (2002), compared to the Flemish region, people living in the Walloon region also live shorter and tend to have poorer health while doing so: they live more years in poor perceived health, more years with functional limitations, and

more years in poor mental well-being [9]. Renard et al. (2015) also reported large between-district disparities in cardiovascular, cerebrovascular, diabetes, alcohol-related, mental- and neurological diseases, and non-transport accidents premature mortality [10]. A more recent study by Otavova et al. (2024) confirmed large disparities in premature mortality, suggesting that men and women living in the most deprived areas of Belgium were 1.96 and 1.78 times more likely to die prematurely, respectively, compared to those living in the least deprived areas over the study period (1998–2019) [11].

Various explanations have been offered for regional differences in mortality patterns, including individual as well as area-level characteristics. As for individual socioeconomic characteristics, multiple studies from Belgium and abroad have found a strong socioeconomic gradient in mortality with increased risk among individuals with a lower socioeconomic status [12–15]. Moreover, on an individual level, differences in lifestyle—particularly smoking—and occupational exposure are potential pathways through which personal characteristics may influence premature mortality. The socioeconomic characteristics of the neighborhood and living environment have been shown to significantly influence health outcomes [16] and mortality [17]. Other explanations of regional differences include diverse environmental factors such as air pollution, presence of industrial hotspots, proximity of roads, and lack of green space [18]; the effects of different health policies and amenities, and behavioral and cultural factors to the extent that they are unrelated to the individual socio-economic position [19].

In this study, we investigate the spatial variation in cause-specific premature mortality and its association with socioeconomic deprivation within Belgium between 2000 and 2019. In addition to extending the existing body of literature on spatial variation in socioeconomic health inequalities in the Belgian context, our study brings several innovations. First, we use a composite measure of socioeconomic deprivation, the average deprivation score, based on the Belgian Indices of Multiple Deprivation 2011 (BIMD2011) [20], to measure deprivation across Belgian municipalities. Besides the overall deprivation, we investigate the effect of domain-specific deprivation (i.e. income, education, employment, housing, and crime) on premature mortality. Second, using spatio-temporal modeling we estimate the relative risk of all-cause and cause-specific premature mortality and answer the following research questions:

- 1) In which geographical areas is the risk of premature death the highest?
- 2) Is the subnational variation in cause-specific risk of premature death decreasing or increasing?
- 3) To what extent does overall or domain-specific socioeconomic deprivation contribute to subnational variation in cause-specific premature mortality?

Methods

Belgian index of multiple deprivation 2011 (BIMD2011) and the average deprivation score measure

The BIMD2011 is a time- and spatial-specific tool for measuring multiple deprivation at the level of the smallest geographical unit in Belgium, the statistical sector [20]. The BIMD2011 encompasses six domains of deprivation: income, education, employment, housing, health, and crime. These domains are combined to obtain a single BIMD2011 score for each geographical area. To avoid a correlation between the indices with the health domain and the health outcomes analyzed here, we rebuilt the BIMD2011 without the health domain for this study.

Due to concerns related to privacy and the unreliability of small population estimates, we excluded from our analysis all statistical sectors with 10 or fewer inhabitants in the year 2011, equaling 1,018 (5.2%) statistical sectors, out of which 36.5% had zero inhabitants and corresponded to forest, parks, rivers, etc... The total number of statistical sectors was therefore 18,764.

In this study, the BIMD2011 scores were then used for the computation of the average deprivation score measure that summarizes the average level of deprivation across the next higher-level area, the municipality. The municipal level was used to avoid statistical problems with small numbers associated with the use of the statistical sectors. The average deprivation score measure is population-weighted, as each statistical sector's BIMD score is multiplied by its population size. These values are then summed within a municipality before being divided by the municipality's total population to create the average deprivation score for the given municipality. The values of average deprivation scores span from 3.80 to 57.32, with a median of 15.15 and a mean of 18.06, and a standard deviation of 10.05. With an increase in the average deprivation score, deprivation increases. Figure 1 shows the distribution of the deprivation deciles, based on the average deprivation scores, at the municipal level. More details on the distribution of the overall and domain-specific average deprivation scores can be found in Figure S1 and Table S1 in Supplementary materials.

Geographical and administrative division of Belgium

Reporting subnational results requires a brief introduction to the country's geographical division between the years 2000 and 2019. Belgium is divided into 3 regions:

Flanders, Wallonia, and Brussels-Capital Region. The first two regions are each subdivided into five provinces: Flanders splits into West and East Flanders, Antwerp, Flemish Brabant, and Limburg; Wallonia splits into Hainaut, Walloon Brabant, Liège, Namur, and Luxembourg. The provinces and Brussels are subdivided into 43 administrative districts and further into 589 municipalities. Although we model at the level of municipality, we often report our findings at the level of the district or the province if our results show clustering of high or low relative risks of premature mortality in the area.

Data

We used pseudonymized individual-level all-cause and cause-specific mortality data extracted from the Civil Registry in Belgium relative to deaths occurring between January 1, 2000, and December 31, 2019, in people aged 1 to 74 years [21]. Infant deaths were excluded from the present study for two reasons. First, an infant's death is captured in our dataset from the National Register only when an infant lives through January 1st following his or her birth. It is therefore not possible to estimate infant mortality from the data used. Second, infant mortality represents a small share of deaths in Belgium. For instance, in 2022, it accounted for less than 0.3% of all deaths.

Data included age, sex, the underlying cause of death according to the International Classification of Diseases (10th Revision), and the place of residence of the deceased, as defined by the municipality. Mid-year population estimates by municipality, sex, and single-year age from 2000 to 2019 were calculated from the National Register data, which includes all legal residents of Belgium and excludes irregular migrants and asylum seekers.

Premature mortality

Premature mortality was defined as mortality occurring before the age of 75. The threshold of 75 years was chosen for two main reasons. First, the officially reported causes of death after the age of 75 are less reliable because of the higher incidence of competing causes of death in older people [22]. Second, such an upper limit is consistent with the recent definition of avoidable mortality [23]. Premature mortality represents a small fraction of all deaths – between 2000 and 2019, 34.7% of all deaths occurred between the ages of 1 and 75.

Causes of death

In addition to data on all-cause premature mortality, we analyzed 13 specific avoidable causes of death: (1) lung cancer; (2) lip, oral cavity, pharynx, larynx, and esophageal cancer (referred to as mouth cancer throughout the article); (3) colorectal cancer; (4) diabetes mellitus; (5)

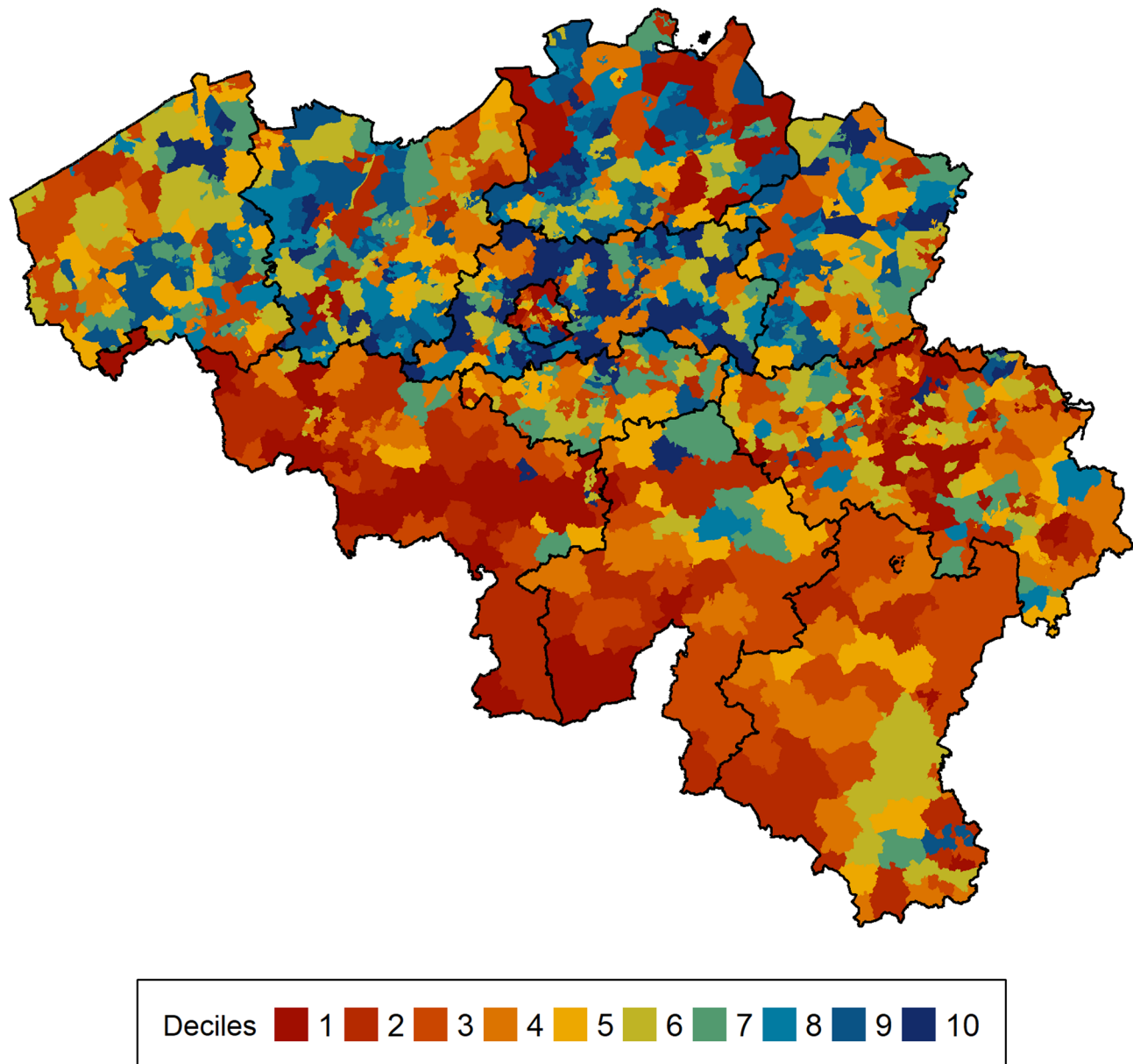


Fig. 1 Distribution of average deprivation scores assigned to deciles from 1 (most deprived) to 10 (least deprived) across Belgian municipalities in 2011

cerebrovascular diseases; (6) cardiovascular diseases; (7) alcohol-related deaths; (8) chronic obstructive pulmonary diseases (COPD); (9) mental and neurological diseases excluding alcohol-related deaths; (10) breast cancer; (11) suicides; (12) non-transport accidents; and (13) road accidents (Table 1). The selected causes of death represent relevant public health problems because of the large number of corresponding deaths, possibly avoidable through effective prevention or treatment [24, 25].

Standardized mortality ratios (SMR)

For each municipality m , $m = 1, \dots, 589$, we calculated the SMR as the ratio of the observed (D) to the expected (E) number of deaths. The expected number represents the

total number of deaths that would be expected if the population of the specific municipality, m , had experienced the national (Nat) age-specific mortality rates in the given period p , $p = 1, \dots, 4$, referring to 2000–2004, 2005–2009, 2010–2014, and 2015–2019. It can be expressed as follows:

$$SMR_{smp} = \theta_{smp} = \frac{D_{smp}}{\sum_x M_{sp}^{Nat} N_{smpx}} = \frac{D_{smp}}{E_{smp}}$$

Where θ_{smp} is the SMR that we estimate for a sex s , municipality m , and a period p , and x refers to 5-year age groups (except in the first age group made of children aged 1–4). An estimated SMR higher than 1 means that

Table 1 Overview of the selected causes of death and number of deaths in the period 2000–2019 in the age range 1–74 in Belgium

Cause of death	ICD-10 codes	Men	Women
ALL CAUSES		449,606	261,411
Cardiovascular diseases	I01-I09, I20-I52, I70-I99	81,846	35,959
Cerebrovascular diseases & HTA	I10-I15, I60-I69	19,181	14,339
Lung cancer	C34	55,919	20,408
Lip, oral cavity, pharynx, larynx and esophageal cancer	C00-C14, C15, C32	15,963	3,955
Colorectal cancer	C18-C20	14,120	9,451
Breast cancer	C50		24,930
Diabetes mellitus	E10-E14	5,644	3,416
Mental and neurological diseases excluding alcohol-related deaths	F and G, except F10, G312, G621	16,621	13,041
COPD	J40-J44	19,128	9,552
Alcohol-related deaths	F10, G312, G621, I426, K292, K860, K852, K70, K73, K74 (exc. K74.3 K74.4 K74.5), X45	13,674	6,415
Road accidents	V00-V89 (except V81, V82)	13,118	3,930
Non-transport accidents	W00-X59	14,414	7,017
Suicide	X60-X84	24,704	9,515

we observe more death counts in the municipality than expected if inhabitants in the municipality had been exposed to the age-specific mortality rates of the Belgian population in a given period p .

From SMRs to naïve regression and spatio-temporal modeling

Although SMRs can provide insight into the spatial variability of mortality, extremely high or low values may appear in areas with small populations due to stochasticity. Modeling techniques are useful to obtain relative risks (RR) because they enable the incorporation of covariates and borrowing information from neighboring areas to improve local estimates, resulting in the smoothing or shrinking of extreme values based on population size [26]. A common approach is to model the observed counts $Y_i, i = 1, \dots, n$, using a Poisson distribution with mean $E_i \times \theta_i$, where E_i is the expected counts and θ_i is the relative risk in area i .

First, the mortality risk was modeled by a simple log-linear Poisson model with the average deprivation score and a period as explanatory variables. The following Poisson model was fitted separately for men and women, each selected cause of death, and deprivation domain:

$$Y_{smp} \sim (E_{smp} \theta_{smp})$$

$$\ln(\theta_{smp}) = \alpha + \beta_1 x_{smp} + \beta_2 PERIOD_m$$

We assume a Poisson distribution for the number of deaths, Y_{smp} , for sex s , municipality m , period p , and θ_{smp} is the mortality risk for sex s , in municipality m , during period p relative to the expected deaths E_{smp} . This model was fitted using maximum likelihood estimation using the *glm()* function from the *stats R* package [27], with as independent variables, the

average deprivation score (numerical) and the period (categorical).

Moran's I statistic was used to check the presence of spatial autocorrelation, [28]. It is given by:

$$I = \frac{K \sum_{m=1}^{589} \sum_{n=1}^{589} w_{mn} (r_m - \bar{r}) (r_n - \bar{r})}{\left(\sum_{m=1}^{589} \sum_{n=1}^{589} w_{mn} \right) \left(\sum_{m=1}^{589} r_m - \bar{r} \right)^2}$$

where r_m denotes the residual for the m^{th} municipality. In addition, w_{mn} denotes whether the pair of municipalities m and n are close to each other. We assume that $w_{mn} = 1$ if municipalities (m, n) share a common border, and $w_{mn} = 0$ otherwise. The value of Moran's I statistic is close to zero in the case of spatial independence while larger values denote positive spatial autocorrelation. The results showed a strong residual autocorrelation for all models, with a p -value much less than 0.001. We did not assess the presence of residual temporal autocorrelations as with $N=4$ time periods the results would not be reliable.

Due to the presence of spatio-temporal correlation, the popular Besag-York-Mollié (BYM2) model with a spatial structure and a spatio-temporal model proposed by Bernardinelli et al. (1995) was fitted. The selection of the final model was based on the deviance information criterion DIC [29].

The final model is specified as follows and is fitted for every cause of death and sex separately:

$$\log(\theta_{smp}) = \alpha + \beta_1 x_{mp} + \beta_2 period + \sqrt{\frac{1-\phi}{\tau}} v_m + \sqrt{\frac{\phi}{\tau}} \mu_m + \gamma_m$$

here smp designate sex s , municipality m , and period p ; $\sqrt{\frac{1-\phi}{\tau}}v_m + \sqrt{\frac{\phi}{\tau}}\mu_m$ represent BYM2 spatial effect; $v_m \sim (0, \sigma_v^2)$ is unstructured random effect (non-spatial heterogeneity); μ_m is scaled spatial structured effect; ϕ determines the proportion of spatial (structured) variation; and γ_m is the overall precision (inverse of total variance of the spatial component). The spatially structured random effect μ_m is assigned a Conditional Autoregressive (CAR) distribution, smoothing the data according to a neighborhood structure. We used the Gamma prior for the precision of the random effect μ_m . The Gamma prior is defined as:

$$\frac{1}{\sigma^2} \sim \text{Gamma}(1, 5 \times 10^{-5})$$

The Variance Partition Coefficient (VPC) was extracted from the BYM2 model to estimate the proportion of spatial variation attributable to contextual (geographic) factors. The BYM2 formulation decomposes the spatial random effect into a structured component and an unstructured component. A high VPC indicates that the residual spatial variation is primarily structured - i.e., it follows geographical patterns - whereas a low VPC suggests that most variation is random across space. This measure allows us to quantify the practical relevance of geography in explaining subnational differences in the relative risk of cause-specific premature mortality [30].

Implementation in R - INLA package

We fitted the spatio-temporal model within the Integrated Nested Laplace Approximation (INLA). INLA is a computational less-intensive alternative to MCMC and it is designed to perform approximate Bayesian inference in latent Gaussian models [31]. INLA uses a combination of analytical approximation and numerical integration to obtain approximated posterior distributions of the parameters which can then be post-processed to compute quantities of interest such as posterior expectations and quantiles. The INLA approach is implemented in the R-INLA package, available at www.r-inla.org.

All analyses were done in R version 4.1.1 [32].

Results

In which geographical areas is the risk of premature death the highest?

Figure 2 displays the relative risk of premature mortality across Belgian municipalities for the first (2000–2004) and last (2015–2019) study periods, with estimates disaggregated by sex. The figure highlights both temporal and spatial variations in relative risks of premature death, revealing a pronounced North-South gradient: municipalities in Wallonia consistently exhibit higher risks than those in Flanders. Notably, Brussels also showed

above-average relative risks. Areas with elevated relative risks are spatially concentrated, forming a contiguous belt stretching from the French border, through municipalities in the districts of Tournai and Mons, continuing through Thuin, Charleroi, Namur, Huy, and Liège, and reaching the German border in the district of Verviers.

In both the first and final study periods, the highest relative risks were found in the districts of Mons, Charleroi, Liège, and Thuin. In contrast, municipalities with the lowest relative risks of all-cause premature mortality were located in the districts of Leuven, Ghent, Tongeren, and Antwerp.

The spatial distribution of cause-specific relative risks exhibited diverse patterns, including North-South, Northwest-Southeast, and West-East gradients, as well as more complex mixed patterns. Several causes of premature death - such as cardiovascular diseases (Figure S2), cerebrovascular diseases (Figure S3), alcohol consumption (Figure S4), COPD (Figure S5), diabetes mellitus (Figure S6), mental and neurological diseases (Figure S7), non-transport accidents (Figure S8), and lung cancer (Figure S9) showed a spatial pattern similar to the one of the overall premature mortality risk, characterized by a clear North-South gradient. In these cases, higher relative risks were predominantly concentrated in Walloon municipalities, whereas Flemish municipalities more often had relative risks below 1.

In contrast, the relative risks of premature mortality due to cancer of the lip, oral cavity, pharynx, larynx, and esophageal cancer (Fig. 3), as well as suicide (Figure S10), displayed a Northwest-Southeast gradient. Figure 3 also illustrates notable sex differences in the geographical distribution of relative risks. Among men, the highest relative risks were concentrated in the provinces of Hainaut, East Flanders, and West Flanders; among women, they were most pronounced in Hainaut, Liège, and Namur. Conversely, both sexes shared similar patterns for the lowest relative risks, which were primarily observed in Limburg, Antwerp, and Liège.

A distinct West-East gradient was evident in the distribution of relative risks for breast cancer (Fig. 4). Higher relative risks for premature death due to breast cancer were concentrated in the provinces of West Flanders, East Flanders, and Hainaut, while lower relative risks were observed in the provinces of Liège and Luxembourg.

A mixed pattern was observed in the distribution of relative risks for premature death due to colorectal cancer (Figure S11) and road accidents (Fig. 5). A greater concentration of a high relative risk of premature death due to colorectal cancer was observed in municipalities located in the provinces of East Flanders and Hainaut, whereas the lowest risks were in the provinces of Liège and Limburg. The highest relative risks of premature death due to road accidents extended across both

Premature mortality

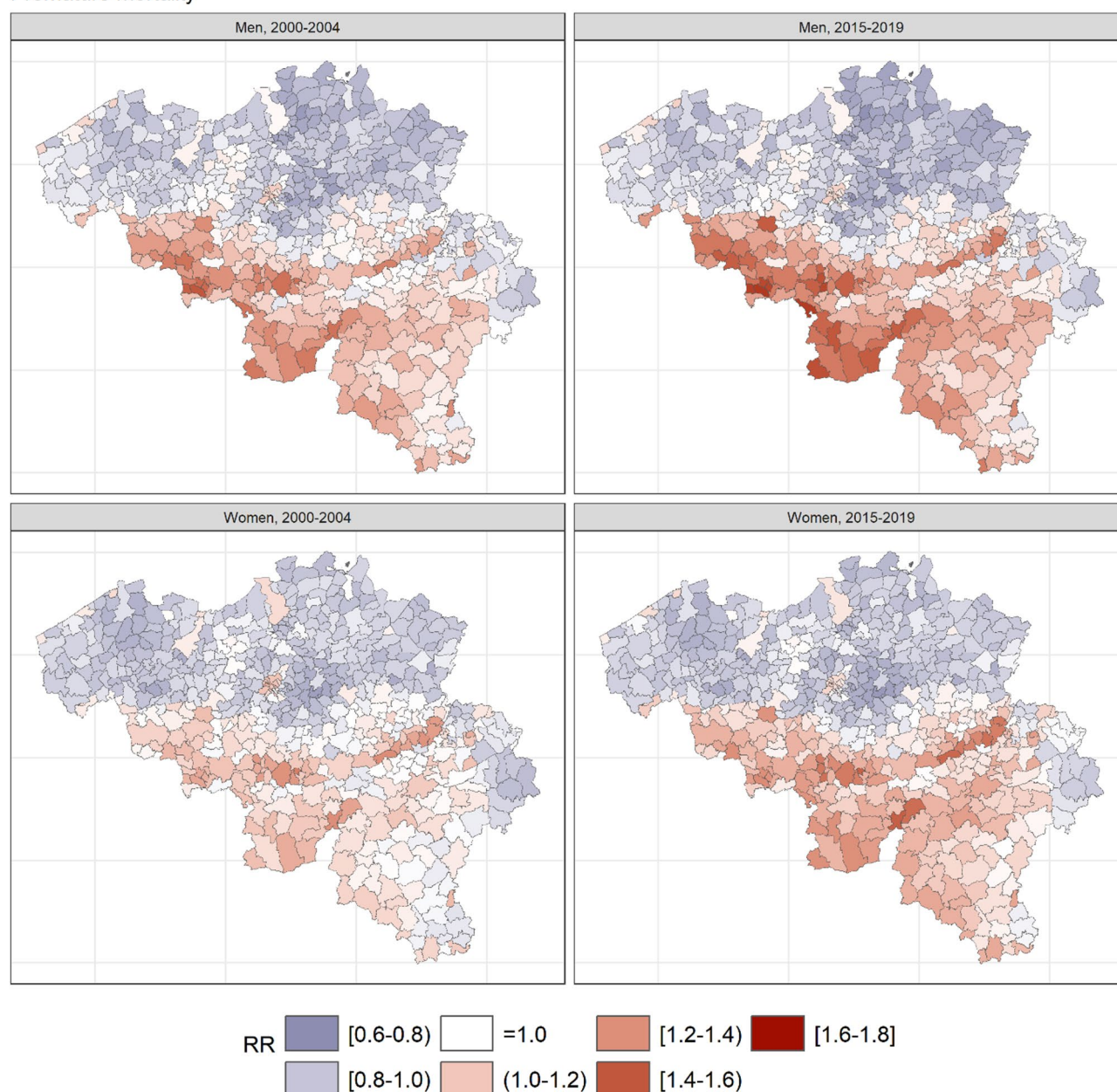


Fig. 2 Spatial and temporal patterns of relative risk of premature mortality in Belgium during the first (2000–2004) and last (2015–2019) study periods, by sex

Walloon and Flemish municipalities, including areas in the provinces of West Flanders and Limburg (Fig. 5). In contrast, the lowest relative risks were recorded in the municipalities of Saint-Gilles, Ixelles, and Etterbeek, all located within the Brussels-Capital Region.

Is the subnational variation in cause-specific risk of premature death decreasing or increasing?

The heterogeneity in relative risk values across periods can be assessed by comparing the standard deviation estimates and their 95% confidence intervals (95% CI).

An increase in the period-specific standard deviation of the relative risk reflects an increase in the subnational variation.

The results introduced in Fig. 6 reveal a clear rightward shift, indicating higher heterogeneity in municipal premature mortality levels during the most recent period compared to earlier ones. Among men, a significant increase in variability was observed between the first (2000–2004) and last (2015–2019) periods for cardiovascular diseases, cerebrovascular diseases, colorectal cancer, lung cancer, mental-neurological diseases,

Lip, oral cavity, pharynx, larynx, and oesophageal cancer

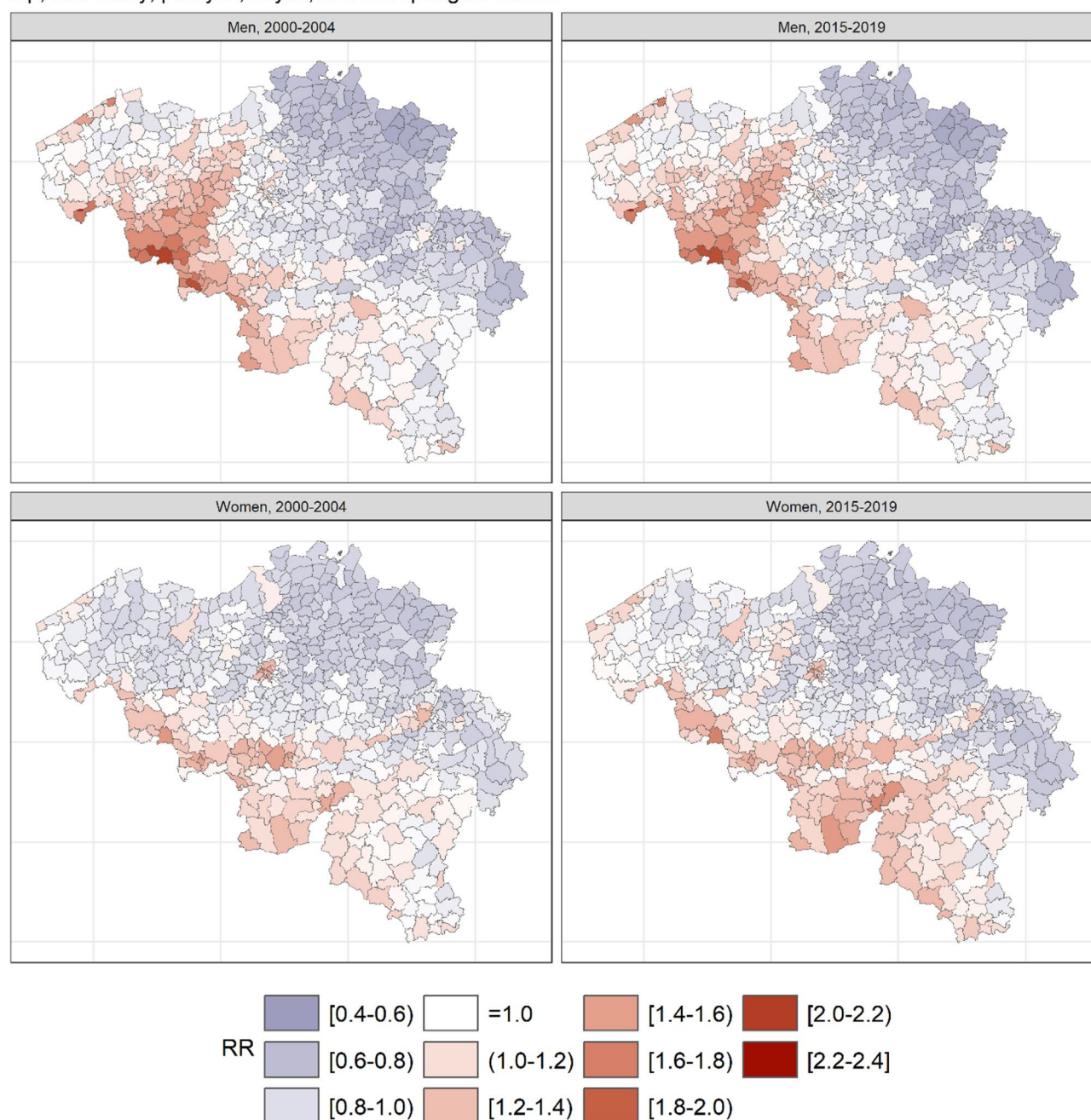


Fig. 3 Spatial and temporal patterns of relative risk of premature mortality due to cancer of the lip, oral cavity, pharynx, larynx, and esophagus in Belgium during the first (2000–2004) and last (2015–2019) study periods, by sex

and suicide. For women, there was a significant increase in the standard deviation of relative risk for premature mortality between the same periods, particularly for cardiovascular diseases, lung cancer, mental-neurological diseases, road accidents, and suicides. Additionally, significant period-to-period differences were found for breast cancer, cerebrovascular diseases, colorectal cancer, and mouth cancer.

Overall, heterogeneity in relative risk among women has exceeded that of men across all causes since the first period studied, with the exception of cancer of the lip, oral cavity, pharynx, larynx, and esophagus, and colorectal cancer. Notably, the standard deviation of colorectal cancer in women reached parity with that of men in the third period (2010–2014), while for cancer of the lip, oral cavity, pharynx, larynx, and esophagus, this parity was achieved only in the last period (2015–2019). A detailed

Breast cancer

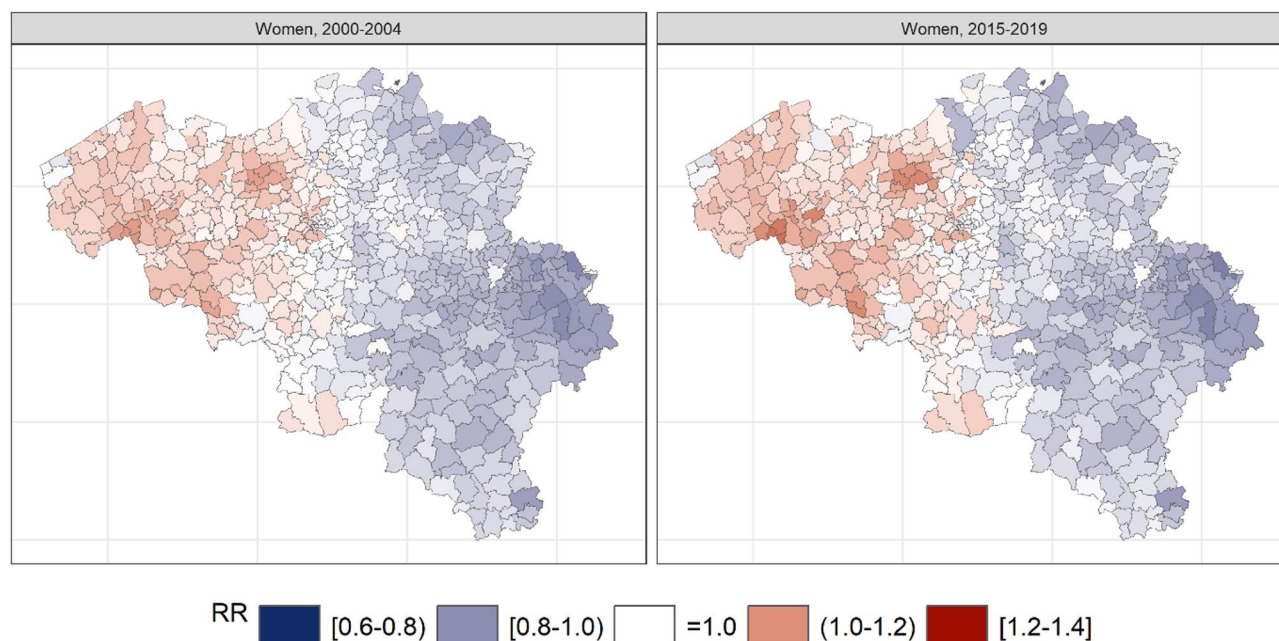


Fig. 4 Spatial and temporal patterns of relative risk of premature mortality due to breast cancer in Belgium during the first (2000–2004) and last (2015–2019) study periods, among women

overview of standard deviations by cause of death and sex are provided in Table S2 and Table S3 in Supplementary Materials.

The Variance Partition Coefficient analysis revealed important differences in the spatial structure of the relative risk of premature mortality by sex and cause. Among men, most causes exhibited high VPC values, indicating a large proportion of spatial variation was attributable to structured geographic patterns. For instance, VPCs exceeded 90% for road accidents (97.8%), mental and neurological diseases (97.5%), lung cancer (97.5%), cardiovascular diseases (97.4%), and colorectal cancer (97.4%). In contrast, conditions such as COPD (27%), non-transport accidents (20.3%), and diabetes mellitus (10.8%) showed much lower VPCs, suggesting a larger share of unstructured or random spatial variation. Among women, spatial structure was also prominent for several causes, with VPCs above 95% for lung cancer (98.3%), road accidents (98.5%), cardiovascular diseases (98.2%), and cancer of the lip, oral cavity, pharynx, larynx, and esophagus (96.8%). However, greater variability in VPCs was observed across conditions. Breast cancer, diabetes mellitus, and alcohol-related deaths had minimal structured spatial variation despite relatively high total spatial variance in some cases, most notably breast cancer with a total variance of 62%. This suggests that for some causes in women, geographic differences are either largely unstructured or driven by isolated high-risk areas rather than broader spatial trends. The VPC values are shown in Table 2.

To what extent does overall or domain-specific socioeconomic deprivation contribute to subnational variation in cause-specific premature mortality?

To address this question, we used exponentialized fixed-effect estimates, i.e., the posterior means and 95% CI of the overall deprivation score or domain-specific deprivation scores derived from each fitted model. The effect of deprivation on all-cause and cause-specific mortality risks is quantified as a relative risk associated with a fixed increase, ξ , in the covariate value. We defined ξ as the standard deviation of the average deprivation score ($SD = 10.04$), representing a realistic increase in deprivation. Given the similarity in the distribution of the average scores across domains, this same unit increase was applied to domain-specific results to maintain consistency across the outcomes.

Figure 7 shows a positive relationship between socioeconomic deprivation and the risk of all-cause premature mortality and most cause-specific premature mortality at the municipal level. An increase in the deprivation score by one standard deviation unit, i.e. 10.04 units, increased the risks of dying prematurely by 13.28% (95%CI, 12.78–13.78) and 12.51% (95%CI, 12.01–13.01) among men and women at the municipal level, respectively. For both sexes, the strongest association between deprivation and relative risk on the municipal level was observed for alcohol-related deaths, COPD, and diabetes mellitus, suggesting that if deprivation increased by 10.04 units, the risk of dying prematurely increased by 22.20% (95%CI, 21.80–22.60), 22.89% (95%CI, 20.70–25.08), and 23.08%

Road accidents

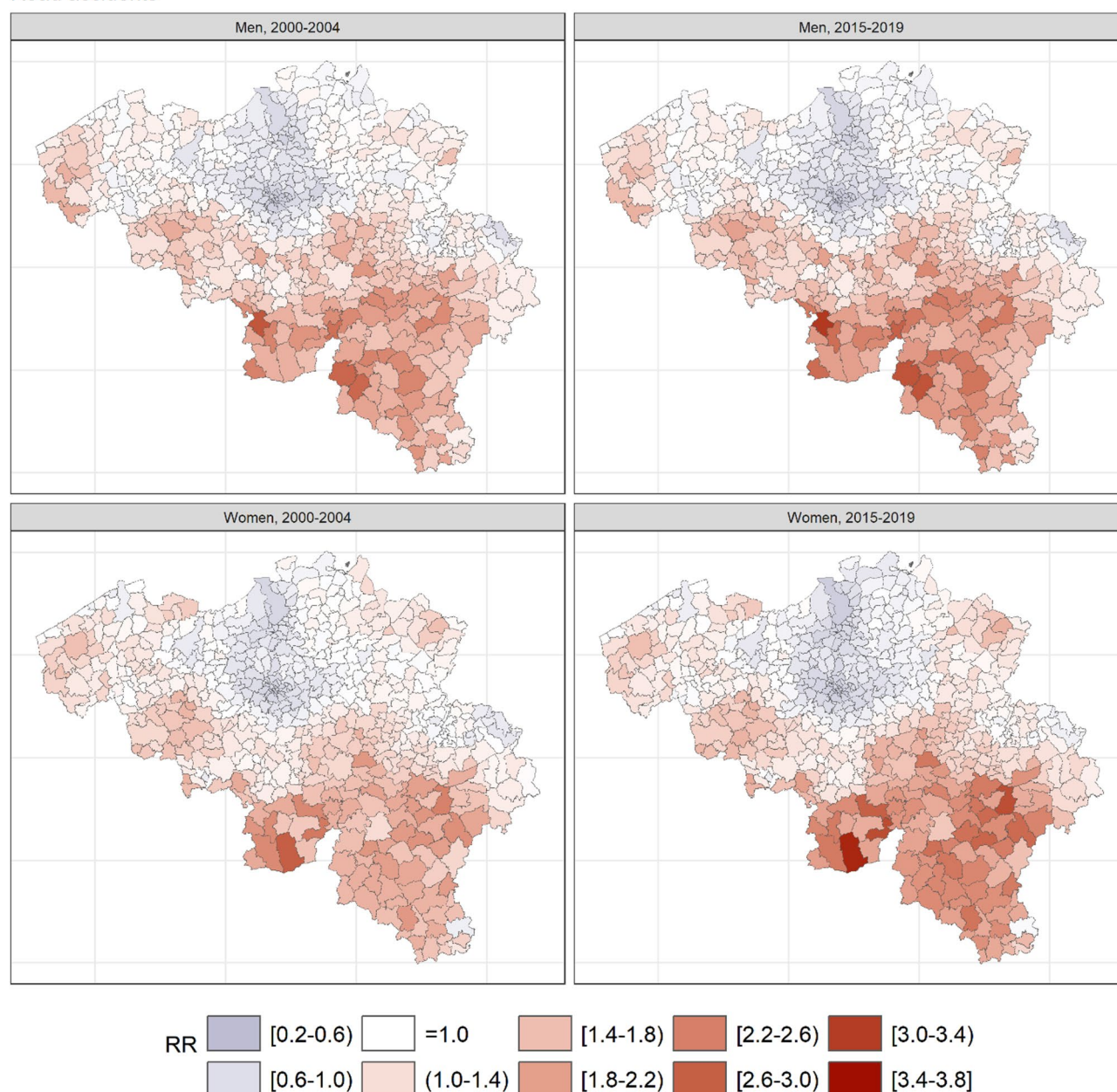


Fig. 5 Spatial and temporal patterns of relative risk for premature mortality due to road accidents in Belgium during the first (2000–2004) and last (2015–2019) study periods, by sex

(95%CI, 20.21–25.95) in men, and 23.61% (95%CI, 23.10–24.12), 27.71% (95%CI, 25.00–30.42), and 24.92% (95%CI, 22.70–27.14) in women. While the overall increase in all-cause premature mortality risk was slightly higher for men, deprivation had a stronger effect on several specific causes of death in women – particularly for lung cancer (6% higher relative risk), mouth cancer (4% higher relative risk), and colorectal cancer and suicide (2% higher relative risk).

Interestingly, an inverse relationship was observed for road traffic accidents. Higher levels of deprivation were

associated with a reduced municipal-level risk of premature death by 2.77% (95%CI, 2.11–3.20) in men and by 3.50% (95%CI, 3.10–3.90) in women, respectively.

For men and women, the trend of the effects associated with an increase in domain-specific deprivation scores at the municipal level was similar across all-cause and most cause-specific premature mortality risks (Figs. 8 and 9), but the magnitude varied. The strongest associations with premature mortality risks were observed for the employment and housing domains, followed by the education and income domains. In contrast, the crime

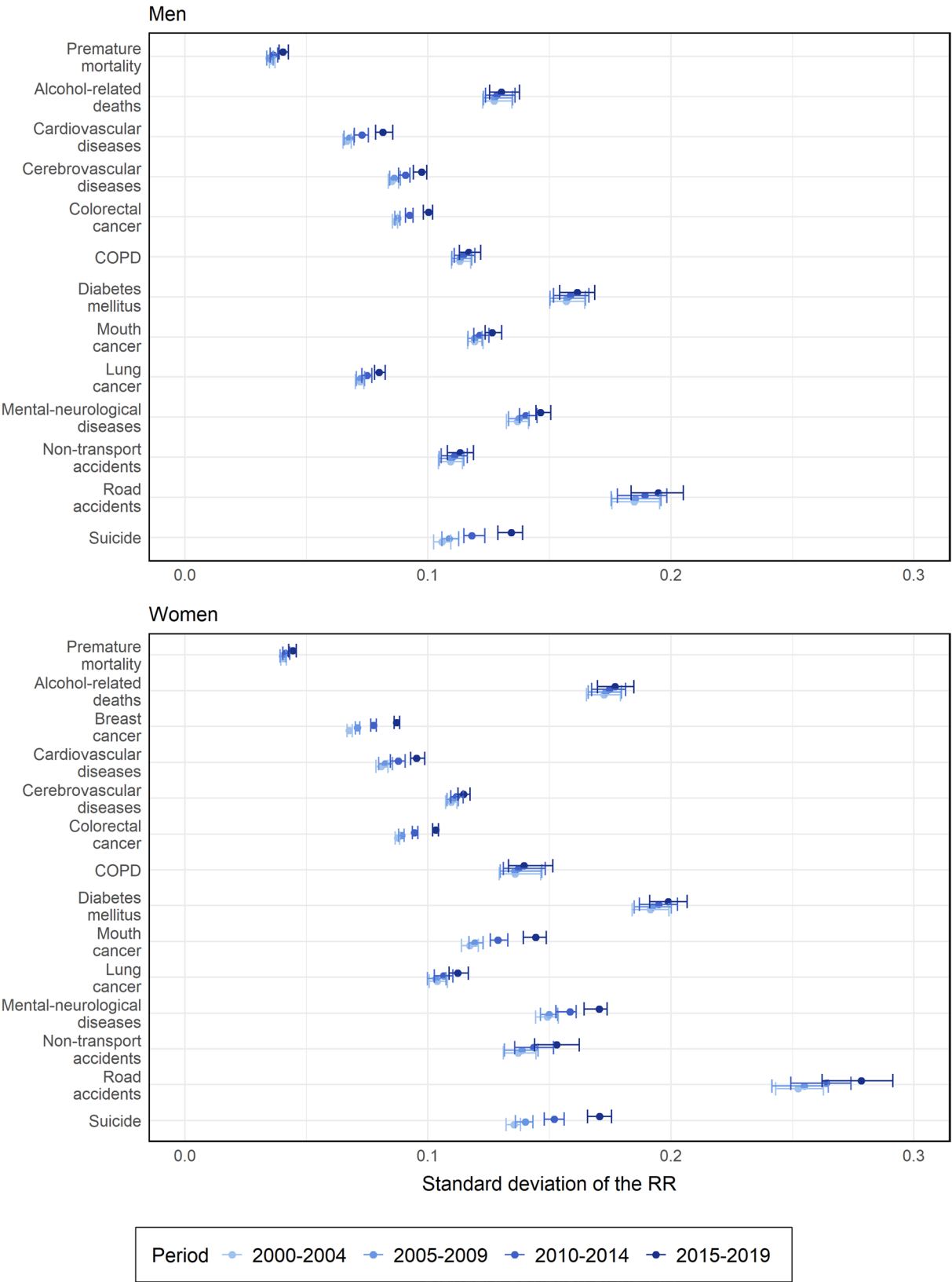


Fig. 6 Standard deviation of cause-specific relative risk estimates, by sex

Table 2 Overview of the variance partition coefficient by cause of death and sex

RR of premature mortality due to:	Men		Women	
	VPC structured proportion (%)	Total spatial variance (%)	VPC structured proportion (%)	Total spatial variance (%)
All-cause	90.50	0.03	98.19	0.04
Cardiovascular diseases	97.39	0.26	98.23	0.22
Cerebrovascular diseases	94.04	0.02	6.94	0.01
Lung cancer	97.47	0.06	98.28	0.12
Lip, oral cavity, pharynx, larynx, and esophageal cancer	93.29	0.02	96.82	0.10
Colorectal cancer	97.40	0.05	91.91	0.02
Breast cancer			0.01	62.00
Diabetes mellitus	10.78	0.00	0.17	0.01
Mental and neurological diseases	97.48	0.09	95.18	0.16
COPD	26.98	0.00	23.56	0.01
Alcohol-related deaths	81.17	0.01	14.84	0.00
Road accidents	97.77	0.04	98.51	0.15
Non-transport accidents	20.35	20.35	95.51	0.07
Suicide	91.71	0.14	80.75	0.12

domain had the smallest association with the relative risk of dying prematurely for most causes of death. Among men, the largest municipal relative risk associated with an increase in the employment average deprivation score by 10.04 units was observed for alcohol-related deaths by 17.79% (95%CI, 17.49–18.08), for deaths due to COPD by 17.89% (95%CI, 17.64–18.13), and due to diabetes mellitus by 16.62% (95%CI, 16.25–16.99). Among women, a 10.04 unit increase in the housing average deprivation score raised the relative risk of premature death due to diabetes mellitus by 23.88% (95%CI, 23.26–24.51). Similarly, a comparable increase in employment average deprivation increased the relative risk of dying due to COPD by 21.73% (95%CI, 21.40–22.06) and the relative risk of alcohol-related deaths by 18.22% (95%CI, 17.82–18.62). An inverse association was observed between deprivation and the relative risk of death due to road accidents. A 10.04-unit increase in the income average deprivation score was associated with about 5.50% reduction in risk for both sexes. A decrease in relative risk was also observed with increased education and crime average deprivation scores for both men and women and with employment average deprivation scores for women. Additional results are available in Tables S4, S5, S6, and S7 in Supplementary Materials.

Discussion

In this study, we found a large within-country spatial and temporal variation in all-cause and cause-specific risk of premature mortality, an increase in heterogeneity of relative risks over time, and a positive association between overall and most domain-specific deprivation and premature mortality in Belgium.

While the geographical patterns of high and low relative risks of premature mortality varied by cause, most spatial patterns included the distribution of the highest relative risks in a narrow band, referred to as the ‘Walloon axis’ [33]. The Walloon axis traces the course of the Meuse river from Liège to Namur, and continues to the West along the river of Sambre to Charleroi, extending into the Haine Valley and the Mons-Borinage region. This area is characterized by a high population concentration - nearly half of the Walloon population resided there in 2010 - and high levels of deprivation. According to the Belgian Index of Multiple Deprivation (BIMD2011), the majority of the statistical sectors in this area were classified among the most deprived in Belgium [20].

A different pattern, the West-East gradient, was observed in the relative risk of premature mortality due to breast cancer, indicating a higher relative risk among individuals living in less deprived areas of Belgium. This finding contrasts with the expected direction seen for most other causes of death. Similar results were previously reported in a study by Renard et al. [10], but without a satisfactory explanation. Evidence from other countries suggests that the narrowing socioeconomic disparities in breast cancer mortality may be influenced by a range of factors [34, 35]. For instance, period effects associated with the introduction of breast cancer screening programs may disproportionately benefit women with higher levels of education [36]. Additionally, shifts in reproductive behavior, such as the trend among women in higher socioeconomic groups to delay motherhood, may also play a role. It is important to note that breast cancer etiology varies with age, and risk factors differ before and after menopause. This age-dependent

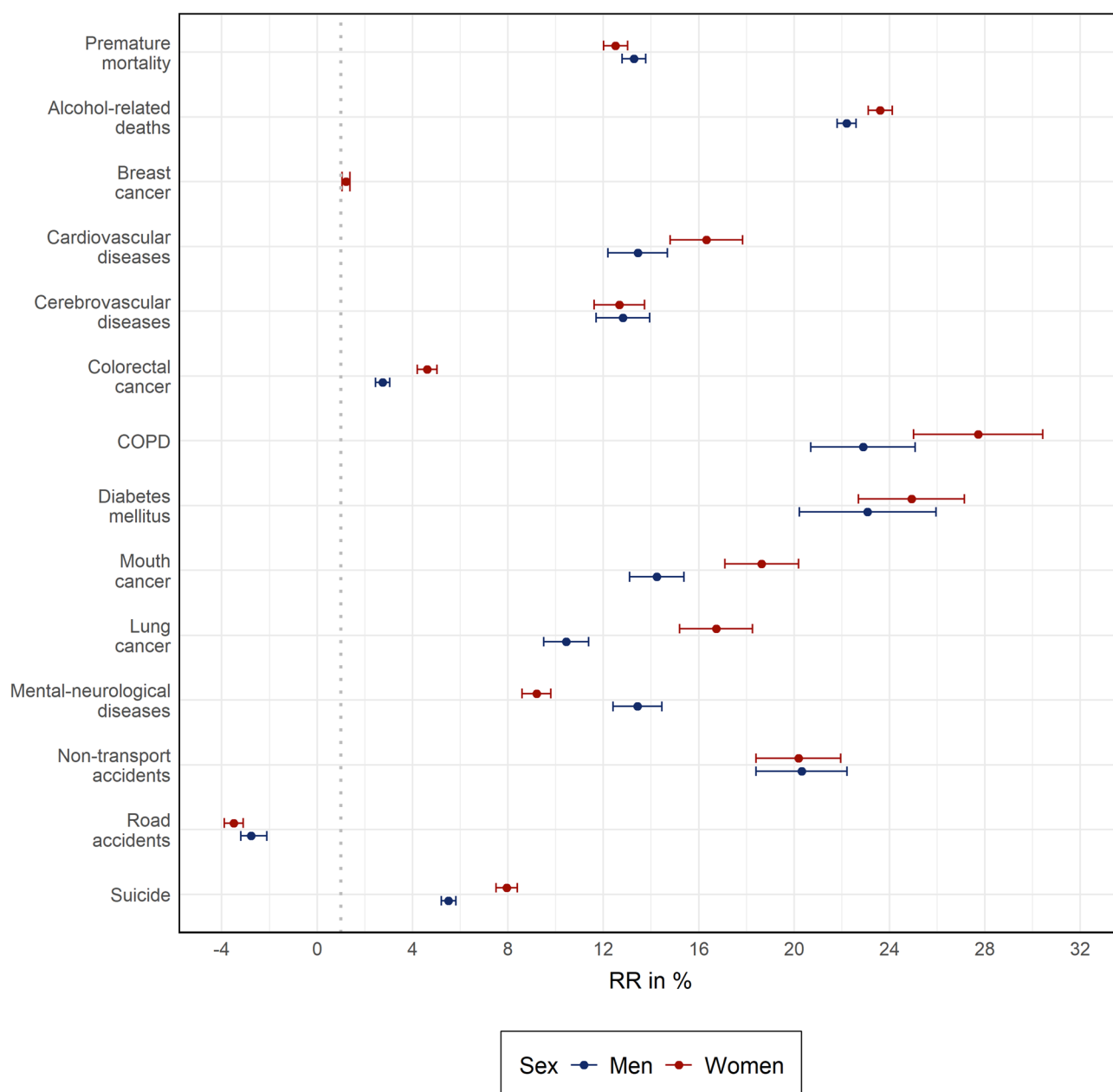


Fig. 7 Estimated mean point estimates of relative risks and their 95% confidence intervals for all-cause and cause-specific premature mortality associated with a unit increase (i.e. 10.04) in the overall average deprivation score, by sex

variation may explain why socioeconomic differences in mortality appear to favor less-educated women only at older ages [37].

Our findings stand in contrast to a recent study by Gotink et al. (2024), which reported higher breast cancer mortality rates among lower-educated, premenopausal women in Belgium [38]. Nonetheless, investigating the underlying causes of this reversed gradient in the relative risk of premature death due to breast cancer falls beyond the scope of this study.

An increase in heterogeneity in the relative risk of cause-specific premature death indicates that variability in risk estimates across the municipal populations has widened. Among men and women, alcohol-related deaths, deaths from diabetes mellitus, deaths by road accidents, and deaths associated with mental-neurological diseases were those with some of the greatest heterogeneity in relative risks at the municipal level. However, for some causes, the observed heterogeneity across municipalities followed clear and systematic geographic patterns, suggesting that spatial context itself plays a

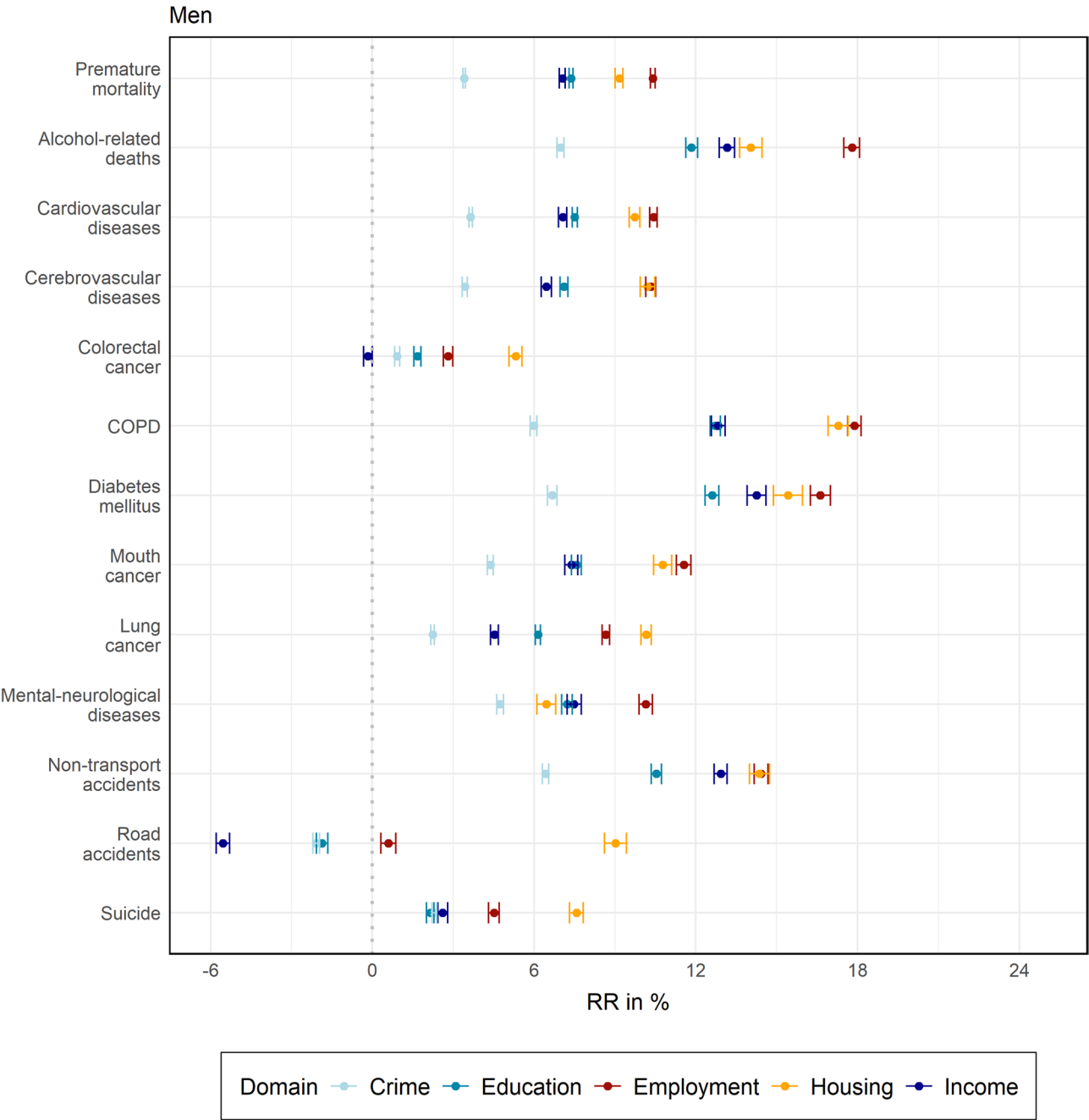


Fig. 8 Estimated mean point estimates of relative risks and their 95% confidence intervals for all-cause and cause-specific premature mortality associated with a unit increase (i.e. 10.04) in the domain-specific average deprivation score, among men

meaningful role in shaping health outcomes. This was the case for cardiovascular diseases, lung cancer, road accidents, and mental and neurological disorders, where spatial differences in risk were not random but showed a high degree of structured clustering across both men and women. In these instances, municipalities represent more than just analytical units, as they appear to capture important contextual influences on premature mortality, potentially related to environmental exposures,

healthcare accessibility, or broader social determinants. In such cases, geographically targeted interventions may not only be appropriate but also cost-effective, as they allow public health efforts to be concentrated in areas where contextual factors consistently elevate risk. By focusing on municipalities with persistently higher relative risks, resources can be deployed more efficiently to address local conditions that contribute to premature mortality.

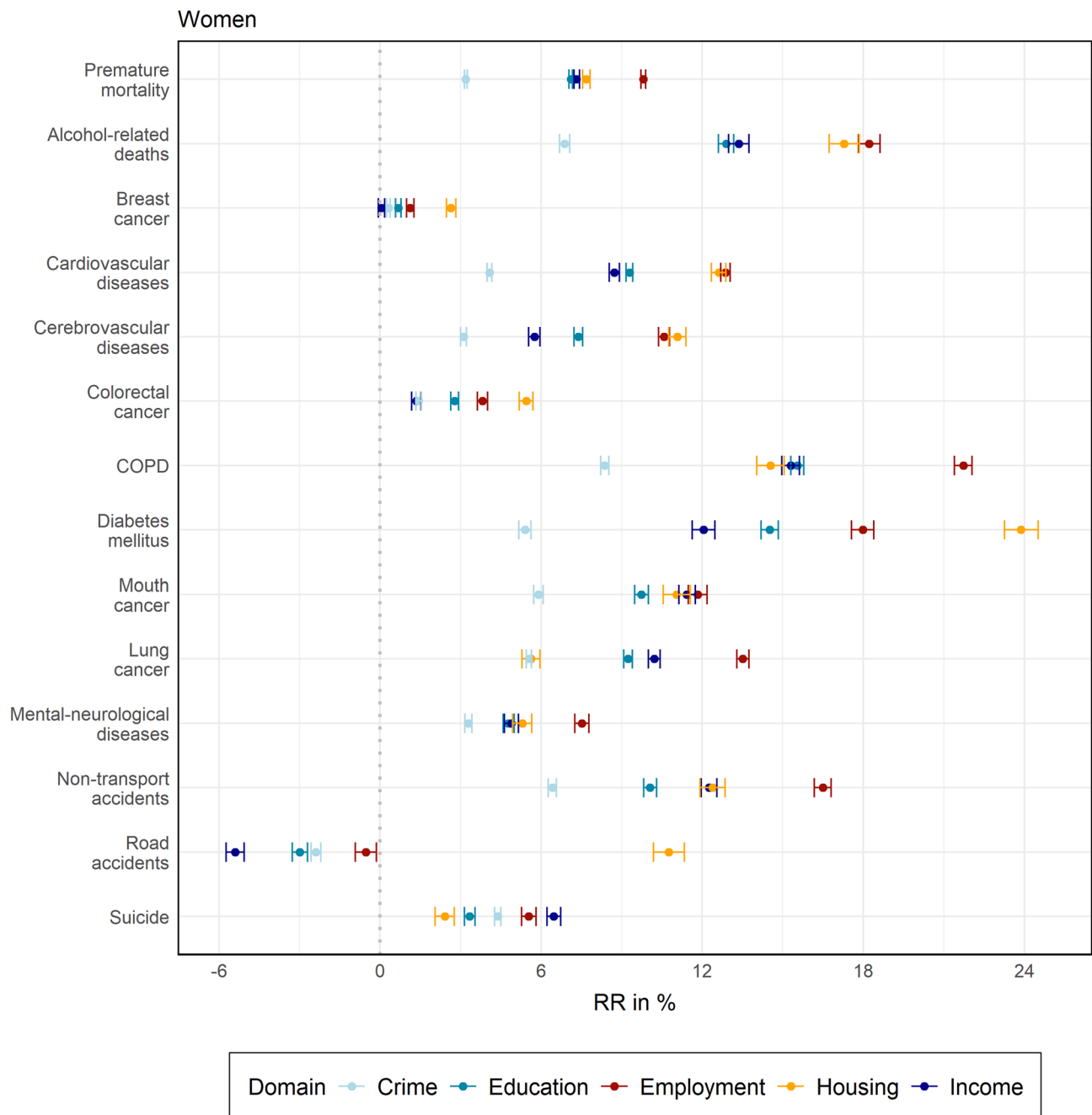


Fig. 9 Estimated mean point estimates of relative risks and their 95% confidence intervals for all-cause and cause-specific premature mortality associated with a unit increase (i.e. 10.04) in the domain-specific average deprivation score, among women

In contrast, for causes such as alcohol-related deaths, diabetes mellitus, and COPD, spatial variation appeared more diffuse or irregular, particularly among women. This suggests that contextual effects may be weaker or more inconsistently distributed, and that individual-level characteristics or unmeasured factors may play a more prominent role. In such cases, geographically targeted interventions risk overlooking high-risk individuals who do not reside in consistently high-risk areas.

For these outcomes, population-wide or mixed strategies—combining geographic targeting with individual-level approaches—may be better suited to ensure fair and effective prevention.

The common risk factors for causes of death with the greatest heterogeneity are unhealthy lifestyle behaviors, including alcohol consumption, tobacco use, or poor diet. While these behavioral risk factors are commonly referred to as proximate determinants, their distribution

across socioeconomic groups is shaped by deeper structural factors, such as limited access to behavior change resources and broader material deprivation [39, 40]. Consequently, reducing the heterogeneity in cause-specific relative risks will require comprehensive interventions – not only at the individual (e.g., health education) but also at the population level, through policies aimed at removing systemic barriers to healthy living. These causes of death have also been identified as those driving the increase in inequalities in Belgium [11] and other countries [41–43]. As such, they represent high-impact targets for interventions: addressing the inequalities in their risk factors could lead to significant reductions in overall premature mortality in Belgium.

Our findings also revealed a positive correlation between the average deprivation scores (overall and domain-specific) and all-cause and most cause-specific relative risk of premature mortality. The strongest associations were found for COPD, alcohol-related causes, and diabetes mellitus. A rare negative association was observed between deprivation and the relative risk of premature deaths due to road accidents. This inverse relationship is likely explained by mobility-related factors. Road traffic mortality is often linked to longer distances traveled and higher speeds – two elements we see in Belgian municipalities with a higher proportion of rural areas. Urban areas with higher average deprivation have better access to public transportation, reducing car use and limiting exposure to high-speed travel [10]. Moreover, data on car ownership per household indicate a lower car ownership among those living in more deprived areas, further reducing their risk exposure [44].

Strengths and limitations

Our study has three key strengths. First, it utilizes both overall and domain-specific average deprivation scores. Second, it models relative risks using the spatio-temporal framework. Third, it provides a detailed analysis of cause-specific relative risks at the municipal level, disaggregated by sex.

The average deprivation score is a population-weighted measure computed for all 589 Belgian municipalities. It is derived from the global BIMD2011 scores or the deprivation domains included in the BIMD2011. The BIMD2011 combines data on income, education, employment, housing, and crime, providing comprehensive insight into inequalities related to upstream socioeconomic circumstances. The main advantage of using the overall- or domain-specific average deprivation scores is the wider range of deprivations covered. Deprivation can impact health and health behaviors simultaneously, and the diversity of the Belgian population means that the interaction between different forms of deprivation needs to be taken into account.

Moreover, the BIMD2011 and the average deprivation score are replicable and can be easily updated with the most recent data. This makes them valuable tools for future research, enabling follow-up studies to monitor changes in the relative risks of premature mortality in Belgium from 2019 onward [20].

Another strength of our study is the use of spatio-temporal modeling, which allows for more reliable and robust estimation of specific relative risks, even in municipalities with small populations [45]. This approach accounts for spatial correlation by recognizing that observations in neighboring areas may be more similar than those in distant areas. By incorporating covariates and borrowing information from neighboring regions, the model improves local estimates and smooths out extreme relative risk values [46] – a common limitation of SMRs in small populations.

A major methodological advantage of our study is our modeling of cause-specific relative risks at the municipal level, stratified by sex. Through a detailed spatio-temporal analysis of cause-specific relative risks, we can identify which type of cause-specific premature mortality contributes to higher relative risks of all-cause premature mortality in Belgian municipalities and identify geographical areas in need of interventions that would reduce the cause-specific relative risks.

In choosing a suitable geographical area, we preferred municipalities, one of the smallest administrative units in Belgium. This choice was guided by several considerations. First, municipal boundaries remained stable between 2000 and 2019, ensuring temporal consistency. Second, municipalities are sufficiently large to provide statistically robust estimates while still small enough to maintain relative population homogeneity, reducing the risk of ecological fallacy. Finally, the use of aggregate municipal-level data provided a practical solution to address privacy, security, and confidentiality concerns associated with administrative data [47]. Nonetheless, future research could consider whether larger-scale classifications, such as provinces, might help explain residual spatial structure not fully captured at the municipal level. Integrating such classifications could improve the interpretability and policy relevance of spatial risk patterns.

The current study has several limitations that should be considered when interpreting the results. As we focus on examining the effect of deprivation on the relative risk of premature death at an aggregate (municipal) level, conclusions cannot be extrapolated to individuals. An ecological fallacy would be committed [48] by incorrectly assuming that all individuals living in municipalities with high average deprivation score, i.e. areas classified as more deprived, must themselves be highly deprived and have higher relative risks, and alternatively, that those living in municipalities with low average deprivation score

must themselves be less deprived and have lower relative risks.

Another potential limitation of this study is the presence of measurement errors in the explanatory variables, the overall or domain-specific deprivation scores, which may not fully capture the variability of deprivation across municipalities. Additionally, there is a possibility of misclassification related to exposure history, as not all individuals who died in a given municipality necessarily lived there for an extended period and their actual exposure to deprivation may differ from that of long-term residents. The misclassification could lead to attenuation bias, an underestimation of the true association between deprivation and mortality. Furthermore, if the misclassification varied systematically across deprivation groups – it could introduce an obscure pattern. As a result, our findings should be interpreted with caution, as the true relationship between deprivation and mortality may be stronger and more complex than our estimates suggest.

Bias may also arise due to spatial dependence and heterogeneity, as deprivation and health outcomes are not randomly distributed but influenced by geographic and socioeconomic patterns. If municipal differences in deprivation and health determinants are not properly accounted for, the estimated associations may be biased, either attenuating or inflating the true effects. Additionally, similarities among neighboring municipalities could lead to spatial correlation, further affecting the reliability of the results. To mitigate these potential biases, we employed the BYM2 model with a spatio-temporal structure proposed by Bernardinelli et al. (1995), which accounts for both structured and unstructured spatial effects, incorporating spatial dependencies and temporal trends into the analysis. While this approach helps to adjust for spatial biases, some residual spatial heterogeneity may persist due to unmeasured confounders. Future work could benefit from integrative modeling strategies that combine spatial smoothing with multilevel variance decomposition of Generalized Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (G-MAIHDA). These approaches offer a more comprehensive framework for disentangling the contributions of individual- and area-level determinants of health [49].

In the current study, besides measuring spatial variation of cause-specific relative risk, we measure the association between socioeconomic deprivation and relative risk. We, however, do not aim to capture a causal effect of deprivation on the relative risk of premature death. The design of our cross-sectional study does not allow us to assess the causal relationship between deprivation and relative risk and is not suitable for showing that any of the deprivation domains have caused premature death or that their improvement would result in a decrease in the relative risk of premature death.

A key limitation of our study lies in the inherent trade-off between using composite deprivation indices and analyzing individual deprivation domains. While the Belgian Index of Multiple Deprivation effectively summarizes multiple correlated socioeconomic factors, it also introduces a degree of honest ambiguity by obscuring the relative contribution of its individual components [50]. To address this, we examine specific deprivation domains (income, education, employment, housing, and crime) and their associations with the spatial variation in relative risk of premature mortality. However, analyzing individual domains separately presents a potential risk of “dishonest specificity”, where an effect might be misattributed to a single domain without considering its interdependencies with other factors. To mitigate this, we carefully contextualize our findings, ensuring that our interpretations do not overstate the impact of any single domain. For instance, we explicitly avoid framing any one specific domain as the sole determinant of premature mortality risk.

Conclusion

We investigated the spatial distribution of the relative risks of all-cause and cause-specific premature mortality and their associations with socioeconomic deprivation in Belgium between 2000 and 2019. The results of our study show that the low and high relative risks were spatially distributed in several different patterns, with the most common pattern showing a North-South gradient. The magnitude of socioeconomic inequalities in the risk of cause-specific premature death increased over the periods studied, with the largest increase observed for causes of death related to unhealthy lifestyles. Our study also shows a positive association between overall and domain-specific socioeconomic deprivation and the relative risk of cause-specific premature death, but its magnitude varied by cause and sex.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s13690-025-01694-1>.

Supplementary Material 1

Acknowledgements

This work was produced using data from Statbel (Directorate-general Statistics – Statistics Belgium) – Demobel (adaptation of the National Register), Census 1991, 2001, 2011, and IPCAL. Computational resources have been provided by the supercomputing facilities of the Université catholique de Louvain (CISM/UCL) and the Consortium des Équipements de Calcul Intensif en Fédération Wallonie Bruxelles (CÉCI) funded by the Fond de la Recherche Scientifique de Belgique (F.R.S.-FNRS) under convention 2.5020.11 and by the Walloon Region. The authors want to thank Statbel and particularly Patrick Lusyne and Cloë Ost for preparing and making pseudonymized data available for research, the Centre for Demographic Research (DEMO) of UCLouvain for allowing us to access the data, the CISM team for managing the statistical servers, and the

Federal Police Belgium – DRI – Business Police Accounting for providing us with data on crime.

Author contributions

MO contributed to data preparation, data analysis, interpretation of results, and manuscript writing. BM was involved in interpreting the results and writing the manuscript. CF participated in the study design and contributed to result interpretation. CB, EMD, BV, and BD assisted in interpreting the results and contributed to manuscript writing. BSS was responsible for model selection, coordinated the study, and contributed to result interpretation.

Funding

This study was conducted as part of the ELLIS project (Monitoring and Mitigating Environmental Health Inequalities), funded by the Belgian Federal Science Policy (B2/191/P3/ELLIS).

Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

One of the co-authors, Brecht Devleeschauwer, is serving as Editor in Chief for Archives of Public Health.

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Received: 9 December 2024 / Accepted: 29 July 2025

Published online: 23 October 2025

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