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Multiple Deprivation and Health Inequalities in Belgium

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In memory of Rozália Žiačiková

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Chapter 1 General introduction

1.1 Introduction

Socioeconomic health inequalities are systematic, avoidable, and unfair differences in health outcomes that can be observed between social groups within the same population or as a gradient across a population ranked by social position (McCartney et al., 2019). These disparities have long been recognized, with historical evidence pointing to the influence of socioeconomic and lifestyle factors on health outcomes. The earliest reported observation of a possible link between socioeconomic risk factors and health outcomes occurred in Italy over three centuries ago when an unusually high incidence of breast cancer among Catholic nuns was observed (Wilson et al., 2002). By the mid-19th century, Edwin Chadwick suggested that the mortality inequalities between different social classes in the English city of Liverpool were due to poverty and lifestyle factors common to the poorer working classes (S. Macintyre, 1997). At the same time, German physician Rudolph Virchow introduced the idea that diseases among the population are rooted in societal flaws, arguing that the focus of medicine should shift from treating individuals to transforming society itself (Gibbons, 2005). French physician Louis Villerme advocated for improving the educational system and working conditions as a part of social interventions that would possibly reduce class-based disparities in mortality (Amick, 1995).

Throughout the 20^{th} century, researchers across Europe continued to investigate the association between social class and health outcomes. In Britain, epidemiologists particularly started to analyze national mortality patterns using data from the decennial census (S. Macintyre, 1997). In 1942, existing data on mortality inequalities, the Great Depression, and World War II encouraged the British government to institute the welfare state (Acheson, 1998).

After the Second World War, the development of welfare states fostered the belief that inequalities in health would gradually disappear. By the mid-1970s, roughly 30 years later, evidence suggested that the health of British citizens was lagging compared to other industrialized countries (Acheson, 1998). In response, the British government established the Research Working Group on Inequalities in Health in 1977 (Acheson, 1998). By 1980, the group published the Black Report, which highlighted significant health disparities in mortality and morbidity (Chandola et al., 2003; S. Macintyre, 1997; Marmot et al., 1991). These findings sparked widespread interest in health inequality research across various disciplines.

Over the past three decades, substantial evidence from many European countries has shown that health inequalities have not only persisted but also widened. Consequently, investigating health disparities has become one of the most important research topics in public health and related fields (Mackenbach et al., 2015; Marmot & Bell, 2012; Scholz, 2020), and reducing these disparities remains one of the greatest challenges for global health, even in highly developed welfare states (Commission on Social Determinants of Health, 2008).

Socioeconomic inequalities in health are observed at almost every stage in the life course – from conception (in utero exposures), to birth (neonatal or infant mortality) through middle age (e.g., cardiovascular disease, accidents) to old age (functional disability). Many studies have shown that socioeconomic inequalities in health do not just represent a threshold effect of poverty but that health follows a social gradient: people with lower educational attainment, a lower occupational class, or a lower level of income tend to have worse health. This gradient has been observed across all health indicators, i.e. lower socioeconomic status (SES) is associated with shorter life expectancy (Brønnum-Hansen & Baadsgaard, 2007, 2012; Deboosere et al., 2008;

Martikainen et al., 2001; Steingrímsdóttir et al., 2012), more years spent in ill-health (Dalstra et al., 2005; Huisman et al., 2003), higher mortality rates for cardiovascular diseases (Lang & Ducimetière, 1995; Mackenbach et al., 2003; Mackenbach et al., 2000; Scholes et al., 2012; Scholes et al., 2013) and cancer (Lewer et al., 2020; Mackenbach, 2006; Mackenbach et al., 2004; Vaccarella et al., 2023). Socioeconomic inequality in many morbidity indicators has also been documented, e.g. an incidence and prevalence of many chronic conditions (Glover et al., 2004; Hoebel et al., 2018; Mira et al., 2022; Ni et al., 2023); the prevalence of most mental health problems (Corell et al., 2024; Dougall et al., 2023; Hazell et al., 2022; Macintyre et al., 2018); and prevalence of functional limitations and disabilities (Klokgieters et al., 2021; Perez-Hernandez et al., 2019; Ramsay et al., 2008).

When studying socioeconomic health inequalities, choosing the appropriate measure of one's position within society is crucial. Although poverty or deprivation are considered multidimensional constructs, most studies have typically measured socioeconomic status by one of the three dimensions, often considered in isolation: income, occupation, and education. In more recent years, researchers have begun to recognize the need to create a measure of SES encompassing more than one dimension. As a result, there has been an expanding literature assessing inequalities in health by composite measures (Angus et al., 2020; Carstairs & Morris, 1989a; Chen et al., 2015; Datta et al., 2010; Zeki Al Hazzouri et al., 2011).

These new measures, called indices, intend to capture the multidimensionality of deprivation and the poverty it signifies either on an individual or aggregated level (Boarini & Mira d'Ercole, 2006; Carstairs, 1995; Eggerickx et al., 2019; Jarman et al., 1991; Noble et al., 2006). While individual-level measures of deprivation offer a detailed perspective by capturing variations between individuals within the same community and potentially uncovering disparities overlooked by area-based indices (Chandola et al., 2003), they face significant challenges related to data accessibility and availability. On the contrary, area-based indices often rely on readily available census or administrative data, thus, they can be more cost-effective and easier to implement. They capture the deprivation of an entire geographical unit, reflecting the impact of the collective environment, and providing a direct way of identifying areas with the highest deprivation levels, enabling direct targeting of the financial resources or medical interventions to the inequality hotspots (Noble et al., 2006).

The work introduced in this dissertation fills the gap in research on the multidimensionality of socioeconomic health inequalities in

Belgium. Given the lack of a modern multidimensional measure of SES in Belgium, my first step was to develop such a tool, later named the Belgian Indices of Multiple Deprivation 2001 and 2011 (BIMD2001 and BIMD2011). The Indices measure socioeconomic deprivation at the level of the smallest geographical unit, the statistical sector, and due to their multidimensionality, they take into account different dimensions, such as income, education, employment, housing, health, and crime. The BIMD2001 and BIMD2011 and their respective domains were further used in my research to shed light on the association between deprivation and various types of mortality, i.e. premature mortality, all-age mortality, and old-age mortality.

1.2 Theoretical considerations

Possible underlying mechanisms of SE health inequalities

The long-standing debate on fundamental mechanisms behind socioeconomic inequalities in health centers on whether the association between socioeconomic status and health is due to the impact of socioeconomic status on health (social causation) or to the impact of health on socioeconomic status (health selection) (Chandola et al., 2003; Galama & van Kippersluis, 2019; Hoffmann et al., 2019; Mackenbach, 2006). A third mechanism suggests that background factors, such as genetic and acquired individual factors, family background, or lifestyle preferences influence both, socioeconomic status and health (Goldman, 2001). This mechanism is difficult to test empirically and thus the debate mostly focuses on the relative importance of causation versus selection.

The relevance of the causation or selection hypotheses is often linked to the studied research field. While most health sociologists and social epidemiologists believe that health selection is not very important (Goldman, 2001; Manor et al., 2003; Marmot et al., 1997), many economists argue that the influence of health on material status is much stronger than causality in the relationship between SES and health (Galama & van Kippersluis, 2019). In reality, multiple pathways between SES and health and vice versa exist. These complex relationships can be illustrated through examples involving education and financial measures of SES. Numerous studies have found that education causally affects health by enabling individuals to better understand healthy lifestyles and risk factors, manage diseases, and more efficiently benefit from new knowledge and technology (Glied & Lleras-Muney, 2008). Education also helps individuals appreciate the importance of preventive and curative care (Lleras-Muney, 2005; Oreopoulos, 2006; Smith, 2007). Conversely, the effect of health on education has been demonstrated, such as the association between low birth weight and worse schooling outcomes (Behrman & Rosenzweig, 2004; Black et al., 2007; Case et al., 2005). The impact of SES, measured by financial indicators like income or wealth, on health outcomes remains uncertain. While some studies suggest that income or wealth may have little to no effect on health (Cutler et al., 2008; Michaud & van Soest, 2008; Smith, 2007), others argue that prolonged exposure to economic hardship can lead to poorer health outcomes (Herd et al., 2008; Lynch, Kaplan, & Shema, 1997). In countries such as the USA, where healthcare systems are predominantly driven by private markets, higher income levels can facilitate access to superior medical care and potentially contribute to better health maintenance (Galama & van Kippersluis, 2019). In the other direction of causality, poor health in adulthood is commonly cited as significantly impacting one's ability to work, generate income, or accumulate wealth (Herd et al., 2008; Smith, 2007).

The design of studies included in this thesis does not allow for making any conclusions on the underlying mechanisms of SE health inequalities. We, however, investigate an association between deprivation and health, showing a scenario of what would happen if the whole of Belgium had deprivation levels in the least deprived areas (*Chapter 3* and *Chapter 4*), indirectly suggesting the social causation framework.

From simple measures of socioeconomic status to deprivation indices

Socioeconomic status refers to the social and economic factors that influence what positions individuals or groups hold within the structure of a society (Galobardes et al., 2006). Many factors are at play when it comes to the individual's socioeconomic position: level of education, employment status, housing conditions, and income (Hummer et al., 1998; Kunst & Mackenbach, 1994). Although the social science and social epidemiology literature treat SES as a multidimensional construct consisting of various socioeconomic factors (Atkinson, 2003; Carstairs, 1981; Hummer et al., 1998; McLennan, 2019; Noble et al., 2010; Noble et al., 2006), most studies only focus on one of these measures of SES due to the complications involved in combining the various dimensions.

The danger in measuring SES with only one indicator lies in an incomplete and potentially misleading understanding of an individual's or group's true socioeconomic position. Among potential negative implications is the oversimplification of the deprivation complexity that fails to capture the full range of socioeconomic deprivation (Bradley & Corwyn, 2002). In addition, different SES dimensions influence health in various pathways. For instance, income and education can impact the etiology of many health outcomes, partially through pathways involving material resources. Education, additionally, can reflect noneconomic social characteristics, such as health-related knowledge, problem-solving skills, or influence over others or one's life (Ross & Mirowsky, 1999; Winch, 2002). Another disadvantage of measuring SES by a single indicator is the potential introduction of specific bias (Braveman et al., 2005). Income, a concrete measure of SES that is relatively easy to obtain, can be biased if it is not processed properly. If only individual income is available, bias can occur because some household members may have no income, living from their partner's income (Bassuk et al., 2002). Adjusting by household size is necessary but even then we cannot be sure that income is equally distributed between household members (Hoffmann et al., 2019). Some also argue that income is not an appropriate measure of SES in old age (Huisman et al., 2003) and it is challenging to compare the role of this indicator for the elderly across different countries (von dem Knesebeck et al., 2003). Occupation or occupational status is an important measure of SES, especially in health studies, as it may indicate a direct connection to environmental exposure. It also has several disadvantages, i.e. its use in the elderly may be inappropriate if they no longer work (Huisman et al., 2003); large diversity in occupation or frequent job changes may cause complicated or less reliable measuring (Daly et al., 2002; Hummer et al., 1998); and it may be problematic to measure for some people, e.g. women in older cohorts (Ross & Wu, 1996).

Education, another commonly used indicator of SES, comes in the life course before occupation and income. Even if these three indicators are correlated, education measures a very different dimension of socioeconomic status – a formal level of education that might have been obtained several years or decades ago. Compared to income and occupation, education is a very stable variable, resilient to the ups and downs of professional life (Hertzman et al., 2017; Smith et al., 1998). The strengths of this measure also represent its limitations. Education measured in early years cannot reflect gained knowledge in late adulthood and the elderly. For cohorts born in the first half of the 20th century, education may not be the best measure of SES as fewer people had higher education (Huisman et al., 2003).

Finally, the relevance and impact of a single measure of SES can vary not only by a study context but also across different countries and cultures (Lynch & Kaplan, 2000). Occupation is frequently used as a measure of SES in Europe (Kunst et al., 1998), while income or education is more commonly used in the United States. Studies including SES measures need to include a justification for why a given indicator was selected over others, discuss its meaning for the given analysis, and explain how unmeasured socioeconomic differences may affect the findings (Braveman et al., 2005).

Socioeconomic status and deprivation are intrinsically connected, as individuals with lower SES often experience constraints in financial resources, educational attainment, or employment opportunities. These limitations lead to material deprivation, where basic needs such as adequate housing, a nutritious diet, and access to healthcare are frequently unmet. Social deprivation, characterized by inadequate access to social, cultural, and recreational opportunities necessary for a fulfilling life, is another negative outcome linked to lower educational attainment or limited access to well-paying jobs.

To conclude, it has become evident that lower SES can systematically worsen deprivation, and individuals may experience multiple forms of deprivation at different points in their life course, which can have a cumulative effect. Therefore, selecting just one indicator is not ideal. A solution was found in constructing a composite index of socioeconomic status that would account for material and social deprivation.

Multidimensional measure of socioeconomic deprivation

Socioeconomic status and deprivation are related but distinct concepts, both of which are used in inequality research. Whereas socioeconomic status reflects an individual's or group's social and economic position within a society (Hoffmann et al., 2019), deprivation focuses on what individuals or communities lack (Townsend, 1987). Investigating deprivation helps to identify and address disparities in access to essential resources, such as education, housing, or healthcare.

The idea of creating a multidimensional measure of socioeconomic deprivation is not recent. Already in the late 1980s, Townsend (1987) defined deprivation as 'a state of observable and demonstrable disadvantage relative to the local community or the wider society or nation to which an individual, family, or group belongs' and established the foundations upon which the existing research on area deprivation is based. It was also Townsend who argued that deprivation consists of material and social aspects, in which material deprivation is represented by the goods, services, resources, amenities, or physical and living environment, while social deprivation refers to the roles, relationships, functions, customs, rights, and responsibilities of membership of society and its subgroups (Townsend, 1987).

The first index, the Jarman Index, was based on the 1981 census in the United Kingdom. Its goal was to identify areas with greater needs for healthcare resources based on socioeconomic factors (Jarman et al., 1991). The Jarman Index set the stage for the development of other indices, such as the Townsend and Carstairs indices, and greatly contributed to the broader understanding of how socioeconomic factors impact health and healthcare needs (Jarman, 1983; Morris & Carstairs, 1991).

The first and most well-known indices, the Townsend Deprivation Index (Townsend, 1987) and Carstairs Deprivation Index (Carstairs & Morris, 1990) were developed in the late 1980s and early 1990s for the UK and Scotland. Both indices were similar in that they measured area-level deprivation, and both used standardized multiple variables, obtained from census data, to create a composite score (Morris & Carstairs, 1991). Compared to the Jarman Index, the Townsend and Carstairs indices were based on fewer variables, focusing strictly on socioeconomic status, and used slightly different variables, reflecting various aspects of deprivation.

The Townsend Deprivation consisted of a non-weighted sum of four socioeconomic indicators, i.e. unemployment (proportion of economically active residents who are unemployed), household overcrowding (proportion of households with more residents than rooms), non-home ownership (proportion of households not owning their home), and non-car ownership (proportion of households without access to a car) – with a higher score indicating higher levels of deprivation (Townsend, 1987). The Carstairs Deprivation Index, initially developed for use in Scotland but later applied more broadly, included variables such as low social class (proportion of male residents in semi-skilled and unskilled manual workers), lack of car ownership, overcrowding, and male unemployment (proportion of economically active males who are unemployed) (Carstairs & Morris, 1990). Both indices were extensively used in public health research for a) investigating the association between deprivation and health outcomes, such as mortality and morbidity (Carstairs & Morris, 1989a), and b) identifying deprived areas that might benefit from targeted interventions and funding allocation.

The first modern indices were created primarily in the United Kingdom with the first Index of Multiple Deprivation introduced in 2000 in England (Communities and Local Government, 2000). The English indices have been providing a detailed picture of deprivation at small-area levels, combining multiple domains such as income, employment, education, crime, housing, and living environment – and they have been typically updated every few years, currently existing versions 2000, 2004, 2007, 2010, 2015, and 2019 (McLennan, 2019). Similar indices were created in Scotland (Allik et al., 2016), Wales (Llywodraeth Cymru Welsh Government, 2014), and Northern Ireland (Northern Ireland Statistics and Research Agency, 2017), each adapted to a specific context and data availability in these regions. In the last two decades, indices have been developed in several other European countries (Launoy et al., 2018), such as in France (Havard et al., 2008), Czechia (Slachtova et al., 2009), Slovenia (Zadnik et al., 2018), Italy (Caranci et al., 2010), and Germany (Kuznetsov et al., 2012), and non-European countries, such as New Zealand (Exeter et al., 2017), Canada (Minister responsible for Statistics Canada, 2019), and United States (Zelenina et al., 2022).

Efforts have also been made to develop transnational European indices. In 2012, Pornet et al. proposed a method for constructing a European deprivation index initially developed for France, with the intent of making it replicable across multiple European countries. This index would integrate individual and aggregate indicators from the European Union's Statistics on Income and Living Conditions (EU-SILC) survey (Pornet et al., 2012). However, it remains unclear whether this index has since been implemented in countries beyond France.

The first ecological deprivation indices (Jarman, Townsend, and Carstairs indices) have been developed pragmatically from census data, which provide a large number of variables suitable for measuring SES (Pornet et al., 2012), while the modern indices started incorporating administrative data as they are more routinely collected and allow for inclusion of more variables. Availability and access to a greater number of variables allowed researchers to create indices that encompass not only deprivation domains related to the most commonly used indicators such as employment, income, and education, but also domains covering deprivation related to housing, health, crime, or environment. Introducing more ecological variables from one domain increased methodological complexity, forcing researchers to use more reliable statistical methods. These often include principal component analysis for combining indicators into domains, or factor analysis for obtaining weights later assigned to indicators. The inclusion of more variables from the same deprivation dimension led to the creation of deprivation domains, enabling researchers to specify the prevalent type of deprivation in a geographical area.

Most existing indices are ecological rather than individual measures, assessing socioeconomic deprivation at the level of small geographical areas. Smaller areas can better illustrate various aspects of the local population, including demography, social circumstances, mortality, and morbidity. Additionally, the small areas offer an acceptable level of heterogeneity, which is relevant for identifying the needs of the local population.

1.3 Research on socioeconomic health inequalities in Belgium

In Belgium, studies on socioeconomic health disparities have been published since the 1980s, primarily focusing on inequality in mortality (Blum et al., 1989; Damiens, 2020; Drieskens et al., 1994; Eggerickx et al., 2018, 2020; Lagasse et al., 1990; Lorant, 2000; Masuy-Stroobant, 1983; Renard, Devleesschauwer, et al., 2017; Van Wanseele, 1986).

However, due to poor data availability and the lack of a usable socio-professional categorization on death certificates, Belgian research on mortality inequality was relatively weak until the early 2000s. Studies from that period relied on small-scaled registers and were often conducted at aggregated levels (Kittel et al., 2003).

The situation improved significantly in the early 2000s with the availability of the health interview surveys conducted in 1997 (Van Oyen et al., 2005; Van Oyen et al., 2002) and the national mortality database, which linked population censuses with mortality data from both the National Registry and the death certificate database (Bossuyt et al., 2004; Deboosere & Gadeyne, 1999). These developments paved the way for the first comprehensive studies on inequality in all-cause mortality (Gadeyne & Deboosere, 2000) and systematic analysis of the cause-specific mortality inequalities (Gadeyne, 2006). This was followed by analyses of changes in life and health expectancies between 1991 and 2001 (Deboosere et al., 2008; Van Oyen et al., 2011), by studies on all-age and premature mortality to disparities in years of life lost (Chen-Xu et al., 2024; Otavova et al., 2024), morbidity (Mertens et al., 2024; Mertens et al., 2021), detailed cause-specific studies (De Grande et al., 2015b; Van Oyen et al., 2008; Vanthomme, Vandenheede, et al., 2017), cancer mortality (Hagedoorn, Vandenheede, Vanthomme, et al., 2016; Hagedoorn, Vandenheede, Willaert, et al., 2016; Vanthomme, Van den Borre, et al., 2017; Vanthomme, Vandenheede, et al., 2017), and most recently by studies focused on social inequalities in COVID-19 related health outcomes (De Pauw et al., 2023; Hubin et al., 2024). The trends in health disparities have been closely monitored by regional governments and public health institutes (Sciensano, 2022; Service public fédéral de programmation Développement durable, 2013; Vlaamse overheid, 2017).

In Belgium, most studies investigating health inequalities have used educational attainment as a marker of socioeconomic position (De Grande et al., 2013; De Grande et al., 2015a, 2015b; De Grande et al., 2014; Deboosere et al., 2008; Drieskens et al., 1994; Gadeyne et al., 2012; Gadeyne et al., 2017; Hoffmann et al., 2015; Kulhanova et al., 2014; Mertens et al., 2024; Mertens et al., 2021; Renard, Devleesschauwer, et al., 2017; Renard et al., 2019; van Hedel et al., 2015; Van Oyen et al., 2005; Vandenheede et al., 2015; Vandenheede et al., 2013), with only fewer using income (Decoster et al., 2021) or unemployment as a proxy of socioeconomic status (Kangas et al., 2023; Louis et al., 2024). Even fewer studies considered two or more indicators of socioeconomic status (Bauwelinck et al., 2021; Cavillot et al., 2023). Although not commonly used, a multidimensional measure of socioeconomic deprivation was first used in a Belgian study in the early 1990s, which consisted of several consumption events capturing different aspects of life experience (Delhausse et al., 1993). They included car ownership, quality of housing, and home equipment, but also specific goods being consumed for supper or a type of leisure. However, this index only covered 6,000 households and did not represent the entire country of Belgium. In 2018, Eggerickx et al. developed an individual-level multidimensional indicator that made it possible to divide the whole population of Belgium into eight social groups. Although this multidimensional measure was based on census data on education, socio-professional category, and housing characteristics, it did not allow for exploring the contribution of each indicator to the overall deprivation separately. In addition, the work of Eggerickx et al. has some methodological limitations that might result in biased estimates. For instance, dependent children living with their parents are given the score of the parent with the greatest score; or the indicator scores are combined by summation without prior standardization or without any use of extrinsic weights preventing any of the indicators from having a greater impact on the final score.

1.4 Research questions addressed in this thesis

The main goal of this dissertation is to provide a complete, coherent, more in-depth picture of socioeconomic health inequalities in Belgium. To achieve this goal, this dissertation addresses several research questions across five empirical chapters.

Chapter 2 includes a detailed overview of the development of the Belgian Indices of Multiple Deprivation 2001 and 2011 (BIMD2001 and BIMD2011). It describes the motivation behind the creation of the BIMDs at the level of the smallest geographical unit, the statistical sector, explains the methodology behind the BIMDs, and demonstrates the use of BIMDs by classifying each of the studied, geographical areas into deprivation deciles according to their level of deprivation. The following research questions are answered:

- What is the geographical variation of the most and least deprived statistical sectors by individual deprivation domains and overall BIMDs?
- Where are the hotspots of deprivation located?

In Chapter 3, the 2001 and 2011 Housing Domains (from the BIMD2001 and BIMD2011) with the 1991 Housing Domain (developed additionally) are utilized, to investigate an association between housing inequality and mortality. In doing so, housing conditions are used as concrete manifestations of socioeconomic deprivation, and the association between housing and increased mortality in Belgium is investigated. The following research questions are addressed:

- Is the housing inequality associated with increased mortality?
- How many deaths could be prevented if the entire population of Belgium faced the mortality rates of the least deprived areas in terms of housing?

In Chapter 4, research on socioeconomic health inequalities continues by studying disparities in all-cause and detailed, cause-specific premature mortality across statistical sectors, grouped by their deprivation deciles. In this chapter, the overall socioeconomic deprivation is measured by the BIMD2001 and BIMD211 at the level of a statistical sector. The health metrics, such as premature mortality rates, population attributable fractions, and potential years of life lost are computed, and the following research questions are investigated:

- What are the levels and trends in premature mortality rates in the most and least deprived areas?
- What is the proportion of premature deaths that could be attributed to socioeconomic inequality?
- What is the proportion of potential years of life lost due to socioeconomic inequality?

In Chapter 5, health inequality research is expanded by investigating spatio-temporal variation of cause-specific relative risk of premature death across all 589 Belgian municipalities. The following research questions are answered:

- Which geographical areas exhibit the highest risk of dying prematurely?
- Is the subnational variation in cause-specific risk of premature death decreasing or increasing?
- What effects do overall socioeconomic deprivation or domain-specific deprivation have on subnational variation in the cause-specific risk of premature death?

In Chapter 6, the research interest is given to socioeconomic inequality in lifespan indicators, such as life expectancy at birth and modal age at death, as well as their dispersion measures. All sets of indicators are estimated by year, sex, and deprivation deciles, computed at the level of the statistical sector. In addition, cause-specific analysis is conducted and the following research questions are answered:

- What are the trends and levels of cause-specific modal age at death in the most and least deprived deciles from 2000 to 2019?
- Are there similarities with the time trends of life expectancy at birth in the most and least deprived deciles?
- What is the degree of variability in the age at death among elderly individuals in each deprivation decile during the study period?

1.5 Data

The dataset used in the present research is part of the DEMOBEL project led by Statbel (Statistics Belgium, 2017a). The DEMOBEL database includes register-based information with 1991, 2001, and 2011 National Belgium censuses and civil registry certificates. To ensure the respondent's privacy, all databases were pseudonymized by assigning a multi-digit code specific to the project. This pseudonymization prevents linkages of the data with other administrative databases located in the DEMO center or in other research centers. The database covers all persons officially registered in Belgium on January 1st in a given year (Eggerickx et al., 2019; Statistics Belgium).

Death certificates

In Belgium, each death is recorded in the civil registry. The death certificate includes details such as the location, date, and cause of death, certified by a medical doctor or nurse, as well as demographic and socioeconomic information about the deceased, completed by the civil registrars (Cohen et al., 2006; Houttekier et al., 2011). The high quality of the death certificates is ensured by several checks, including those conducted by the regional health administration (Renard et al., 2014). Each certificate lists an immediate cause of death, categorized by the 10th International Classification of Diseases (ICD10). If the death is a consequence of another pathology or cause, an underlying cause of death is also recorded. Additionally, the death certificate provides information on associated and intermediate causes of death if there are interfering pathologies or causes.

Census 1991, 2001, and 2011

The 1991 and 2001 Belgian population and housing censuses were conducted in March 1991 and October-November 2001 through self-administrated questionnaires sent by postal mail to all persons officially registered in Belgium (Deboosere & Gadeyne, 2005). The 2011 census was a snapshot of the Belgian population on January 1st, 2011, and it was the first register-based census in Belgium – the register was the only information source. This database relied on good-quality registers, such as the national register, the social security register, the employment register, the educational register and university register, or land register, and cadasters (Statbel, 2022).

In this dissertation, the information obtained by the 1991, 2001, and 2011 censuses was used for building the 1991 Housing Domain introduced in *Chapter 3*, and for building several domains included in the 2001 and 2011 Belgian Indices of Multiple Deprivation described in *Chapter 2*.

National Register

The National Register provides information about the sociodemographic characteristics of the officially registered Belgian population but excludes asylum seekers, illegal migrants, the homeless population, European civil servants, and diplomatic staff from the embassies (Poulain & Herm, 2013). The National Register gives information on date of birth, sex, household composition, marital status, nationality, and place of residence on January 1st in a given year. Access to this database allowed me to calculate a population under exposure or mid-year population at the level of the statistical sector or municipality between the years 1998 and 2020.

1.6 An overview of the five empirical chapters

The five empirical contributions in this dissertation were written as standalone journal articles, with their introduction, methodology, results, discussion, and conclusion. For this reason, they can be read independently. *Chapters 2, Chapter 3,* and *Chapter 4* have already been published in Spatial and Spatio-temporal Epidemiology (*Chapter 2*) and BMC Public Health (*Chapter 3* and *Chapter 4*). The article in *Chapter 5* is being prepared for submission and *Chapter 6* contains a short version of a future manuscript.

Chapter 2 Measuring small-area level deprivation in Belgium: the Belgian Index of Multiple Deprivation[1]

2.1 Introduction

The creation and use of composite indices for capturing the multidimensionality of deprivation have become extremely popular among researchers and policymakers worldwide (Allik et al., 2020). These complex measures have been an important tool for identifying the most disadvantaged areas at the national, regional, or small-area levels (Exeter et al., 2017; McLennan et al., 2019; Noble et al., 2010; Noble et al., 2006; Scottish Government, 2020). In Belgium, simple measures of deprivation, such as income or education, have been traditionally used and the creation of a multidimensional deprivation index has been long due. This paper presents a theoretical and

[1] This chapter is published in: Otavova M, Masquelier B, Faes C, Van den Borre L, Bouland C, De Clercq E,Vandeninden B, De Bleser A, Devleesschauwer B. (2023). *Measuring small-area level deprivation in Belgium: The Belgian Index of Multiple Deprivation*. Spatial and Spatio-temporal Epidemiology. Volume 45. https://doi.org/10.1016/j.sste.2023.100587 .It is reproduced here as in the published version.

methodological shift from simple to complex or multidimensional measures of area deprivation in Belgium and describes the development of the Belgian Indices of Multiple Deprivation for the years 2001 and 2011 (BIMD2001 and BIMD2011).

The idea of an area-based composite measure of deprivation stems from the work of Peter Townsend, a British sociologist. In the 1980s, Townsend defined deprivation as being multidimensional, composed of material and social deprivation. Material deprivation relates to inadequacies in, for example, goods, services, resources, and physical and living environments. Social deprivation includes inadequacies in relationships, functions, customs, rights, and responsibilities resulting from being a member of society or its subgroup (Townsend, 1987). Individuals might experience multiple forms of deprivation that might have a cumulative effect. Townsend developed the first multidimensional deprivation index using census-based indicators of deprivation – i.e., unemployment, household overcrowding, non-home ownership, and non-car ownership (Townsend, 1987; Townsend et al., 1992).

The first modern Indices of Multiple Deprivation were developed in England in the 2000s, followed by comparable indices for Northern Ireland, Wales, and Scotland, and have since become common in many other countries (Allik et al., 2016; Exeter et al., 2017; Noble et al., 2010; Scottish Government, 2020). Although based on Townsend's ideas, the modern indices have moved away from a census-based approach by incorporating all routinely collected administrative data. The possibility of using various data sources allowed the indices to include more relevant indicators and to be more frequently updated.

In recent years, these indices have become an important tool for understanding the association between area-based deprivation, health, and social outcomes (Butler et al., 2013; Carstairs & Morris, 1989b; Exeter et al., 2011; Exeter et al., 2017; Kleinschmidt et al., 1995; Norman et al., 2011). Besides being used in academic research, indices are key for identifying the most disadvantaged areas and for ensuring that these areas would be directly targeted by the community or government policies. In many countries, e.g. in the UK, national and local organizations use indices to distribute funding or target resources to areas. On a local scale, indices can be used as evidence in the development strategies, interventions or funding applications (Department for Communities and Local Government).

In Belgium, only a handful of studies used a multidimensional measure of socio-economic deprivation. In 1993, Delhausse et al. used an aggregate index of deprivation proposed by Desay and Shah (1988) that consisted of a number of consumption events, capturing different aspects of life experience. For instance, a car ownership, quality of housing and home equipment, but also specific goods being consumed for supper or the type of leisure (Delhausse et al., 1993; Desay & Shah, 1988). The disadvantage of the index was its limited coverage as it was computed for 6,000 households only, not covering the whole of Belgium.

More recently, Eggerickx et al. (2018) developed a multidimensional indicator for Belgium at the individual level, based on three aspects of social inequalities provided by the national censuses: the level of education, the socio-professional category, and the characteristics of housing This indicator made it possible to divide the whole population of Belgium into eight social groups, but it did not allow exploring the contribution of individual aspects to the overall deprivation, nor their separate use.

In this paper, we present the framework of the first spatial- and time-specific Belgian index of deprivation, the methods that were employed in its development, and describe the domains and indicators that make up the BIMD2001 and BIMD2011. Our main aim is to construct a reliable, multidimensional tool that would enable the measuring of geographical variations in social and economic circumstances in Belgium, either independently or in conjunction with other data, and/or pinpoint areas that would benefit from additional funding or attention through special programs and initiatives. We encourage and support the use of the BIMD2001 and the BIMD2011 by making them, as well as our findings, publicly available, for all to explore. We hope that these indices will be broadly used by policymakers in communities and local governments, as well as by local authorities and academia.

2.2 Methods

Overall approach

The construction of indices of multiple deprivation required multiple steps (Figure 2.1). First, we determined the appropriate geographical level and time scale. Second, in sync with a literature review of currently existing indices and in collaboration with Belgian stakeholders and experts, we identified six domains and their related indicators that measure different but equally relevant aspects of deprivation. Our first aim was to combine indicators into domains and then domains into overall indices, so we would obtain a single summary measure for each domain and overall indices across statistical sectors.

The former required standardizing the indicators by ranking, scaling them, and adding the scaled scores together using equal weights, or, if possible, weights generated by maximum likelihood factor analysis. The latter involved an exponential transformation of domain scores and combining these scores with explicit weights into overall BIMD scores. For better interpretability, the domain and BIMDs scores were ranked and assigned to deciles from the most (1) to the least deprived (10). The indices were created using the R version 4.1.1 (*R version 4.1.1*). In what follows, each of these steps will be described in detail.

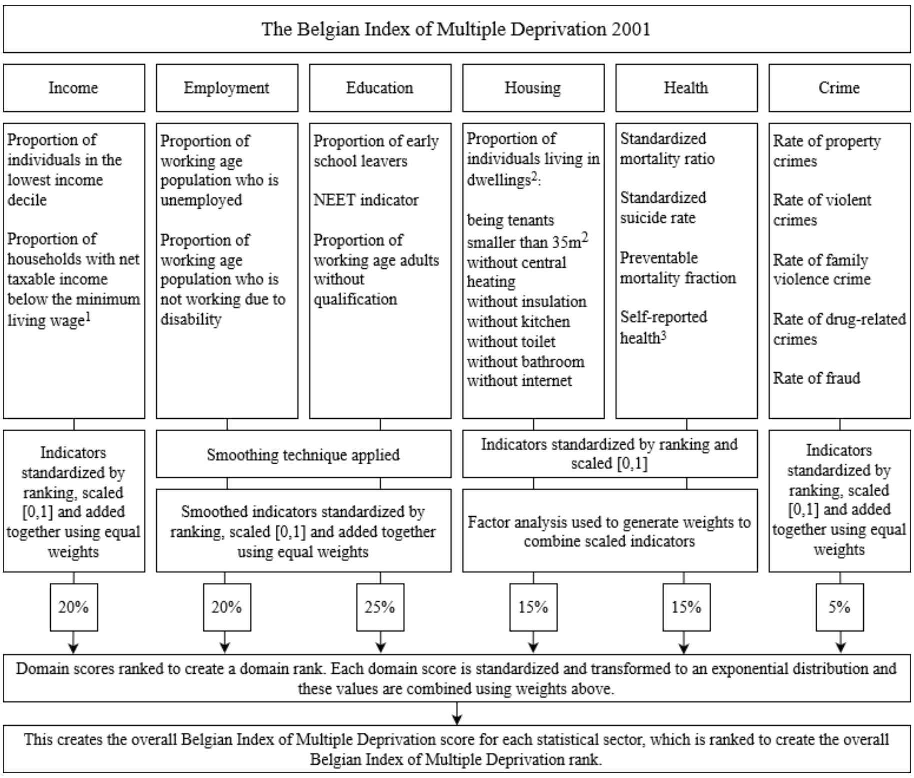

Figure 2.1 The model of the Belgian Index of Multiple Deprivation 2001

[1] In the BIMD2011, this indicator is weighted by the household size.

[2] The housing domain 2011 contains four indicators: proportion of individuals living dwellings with less than 0.5 room/person; without central heating; without bathroom; and proportion of tenants.

[3] The health domain 2011 does not contain the self-reported health indicator.

Geographical unit and timeframe

The BIMDs are presented at the level of the statistical sector, which is the smallest geographical unit of Belgium, resulting from the subdivision of municipalities (Statistics Belgium, 2017b).

By definition, a statistical sector may never extend over two municipalities and each geographical point of Belgium belongs to only one statistical sector. In 2001, the structure of the statistical sectors was revised by considering major changes in land use and municipal boundaries and a number of fictitious sectors have been created to determine special situations, such as to assign individuals with unknown sectors or diplomats stationed abroad. In total, there were 19,781 and 19,782 statistical sectors spread over 589 municipalities in 2001 and 2011, respectively (Jamagne et al., 2016). These sectors are heterogeneous in population size, with a median population of 299 in 2001 and 315 in 2011.

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, equalling 1,486 (7.5%) and 1,018 (5.2%) sectors, out of which 50.7% (2001) and 36.5% (2011) had zero inhabitants and corresponded to forest, parks, rivers, etc. The total amount of statistical sectors used in our study was therefore 18,295 (2001) and 18,764 (2011).

The BIMDs were created for the years 2001 and 2011 due to our limited data availability and accessibility for other years. The indices rely heavily on the Belgian national censuses that take place every ten years. Thus, the creation of the BIMD2021 is planned as soon as the data are available. Having indices for two-time points allows us to investigate temporal changes in deprivation in Belgium.

Domains and indicators

The selection of domains and indicators was based on work of Townsend, on the literature review of currently existing indices worldwide (Exeter et al., 2017; McLennan et al., 2019; Northern Ireland Statistics and Research Agency, 2017; Scottish Government, 2020; Townsend, 1987; Townsend et al., 1992), and on the discussion with Belgian stakeholders and experts involved in the follow-up committee of the ELLIS project (more information in Table S2.S31 in Supplementary Materials). Six domains of deprivation were selected: income, employment, education, housing, health, and crime (**Error! Reference source not found.** 2.1). Each domain consists of a number of indicators that aims to comprehensively capture various aspects of deprivation based on the available data (in total 24 indicators in 2001 and 19 indicators in 2011).

In the vast majority, indicators in the BIMD2001 and BIMD2011 are expressed as rates or proportions measuring the probability of an individual in a particular area experiencing a form of deprivation in 2001 or 2011. Due to poor data availability or accessibility for the year 2001, some of the indicators are based on data from the following years (e.g. the proportion of households with net taxable income below the minimum living wage). In addition, due to the small population numbers, some indicators are built with data collapsed over multiple years (e.g. standardized mortality ratios). All indicators measure major features of deprivation, are statistically robust, are available at the level of statistical sector level or municipality, refer to the period around 2001 and 2011 and can be updated for future iterations.

The *income domain* captures the proportion of the population that is experiencing deprivation related to low or no income. The *employment domain* measures the proportion of those who are unable to work due to unemployment or disability and who are, thus, excluded from the labor market. The *education domain* measures the paucity of educational attainment and skills in the overall population. The *housing domain* captures the shortcomings and poor quality of housing. The *health domain* captures poor physical or mental well-being in the Belgian population, and the *crime domain* measures the rate of material and personal victimization.

Table 2.1 Overview of indicators used in the BIMD2001 and BIMD2011

Domains and their indicators	BIMD2001	BIMD2011
Income		
The proportion of individuals in the lowest income decile	X	X
Proportion of households with net taxable income below the minimum living wage	X	X
Employment		
Proportion of working age population who is unemployed	X	X
Proportion of working age population who is not working due to disability	X	X
Education		
Proportion of early school leavers	X	X
NEET indicator	X	X

Proportion of working age adults without qualification	X	X
Housing		
Proportion of tenants	X	X
Proportion of individuals living in dwellings:		
smaller than 35 m2	X	
less than 0.5 room/person		X
without central heating	X	X
without insulation	X	
without kitchen	X	
without toilet	X	
without bathroom	X	X
without internet	X	

Health		
Standardized mortality ratio	X	X
Standardized suicide rate	X	X
Preventable mortality fraction	X	X
Self-reported health	X	
Crime		
Rate of property crimes	X	X
Rate of violent crimes	X	X
Rate of family violence crimes	X	X
Rate of fraud	X	X

Data

To build the income, employment, education, and housing domains, we used a pseudonymized dataset, built upon the demographic database produced by Statbel. Our database covers the period 1991-2020, and includes several administrative data sources, such as the 2001 and 2011 Belgian population censuses, data from the National Register on all-cause mortality and population structure, and data on cause-specific mortality from death certificates (Eggerickx et al., 2019; Statistics Belgium). Individuals in these data sources are deterministically linked by a multi-digit code specific to the project. The pseudonymization prevents linkages of the data with other administrative databases or databases located in other research centers. The database covers all persons officially residing in Belgium at the reference period when computed over multiple years or at the time of the census. Thus, individuals who lived in Belgium and were not officially registered were not included in our datasets.

The 2001 Belgian population census was conducted on October 1st, 2001 and was a semi-administrative census, with most of the socio-economic variables collected through a mandatory postal survey organized by the Federal Public Service Economy *(Statbel, 2022)*. In

2011, the individual survey was replaced by the use of data that were already available in administrative databases. Thus, the 2011 census was fully administrative and it was a snapshot of the Belgian population on January 1st, 2011.

In addition, aggregated data on the proportion of households below the minimum living wage at the statistical level, included in the income domains for 2001 and 2011, were obtained from Statbel.

While building the employment domain for 2011, we created an indicator of the proportion of health insurance beneficiaries (aged 20-64) who received long-term disability benefits utilizing data from the Intermutualistic Agency (IMA). These data are publicly available in the IMA Atlas database (https://atlas.ima-aim.be/databanken/).

Finally, counts of criminal crimes that occurred between 1 January 2001 and 31 December 2001, and 1 January 2011 and 31 December 2011, aggregated at the level of municipality, were provided by the Federal Police Belgium. They are publicly available at https://www.stat.policefederale.be/criminaliteitsstatistieken/interactief/grafiek-tijdslijn-criminele-figuren/.

More detailed information on data sources is found in Supplementary Materials.

Smoothing of indicators

When the population at-risk in the statistical sector is large, the variance is usually small and the direct estimates are robust and reliable. However, in statistical sectors with small populations, estimates are often unreliable. Although we excluded all statistical sectors with 10 or fewer inhabitants, the issue with the small number of events still arose when we calculated indicators referring to a subset of the population, such as the proportion of the working age population that is unemployed. To smooth these estimates, we fitted a simple space-time Bayesian model using the *smoothSurvey* function from the *SUMMER* package (Li et al., 2022; *R-INLA project*, 2022), as detailed in Supplementary Materials.

Combining indicators into domains

Several methods were explored to combine indicators into domains, such as maximum likelihood factor analysis (ML FA), principal component factor analysis (PCA), and the use of equal weights. The final, chosen method varied by domain. To decide on the method to be applied in each case, we conducted a thorough literature review on the methodology of deprivation indices worldwide, and multiple sensitivity analyses to empirically test the impact of various combination techniques.

When combining indicators into domains, the first step was the same across all indicators. To prevent large numbers or outliers from having a disproportionate effect on the overall scores, the indicators needed to be measured on comparable scales. The indicator values were therefore ranked from 1 to 18,295 in the BIMD2001 and 18,764 in the BIMD2011, from the least to the most deprived and transformed so their values ranged between 0 and 1.

Indicators of the income and employment domains were combined by simply adding them together (i.e. using equal weights). We tested the correlation of individual indicators with the housing domain which was constructed first (Otavova et al., 2022). This method was used by Exeter et al. when selecting the weights for indicators used in the deprivation index of New Zealand (Exeter et al., 2017). The income domain indicators were consistently, similarly correlated with the housing domain. In 2001 and 2011, the Spearman correlation coefficient between the housing domain and the indicator 'the proportion of individuals in the lowest income decile' corresponded to $\rho = 0.20$ and $\rho = 0.19$; and between the housing domain and the indicator ‘the proportion of households with net taxable income below the minimum living corresponded to $\rho = 0.19$ and $\rho = 0.16$.

Satisfactory stable Spearman correlation coefficients were also found for the employment domain. In 2001, the Spearman correlation coefficients between the housing domain and the indicators ‘the proportion of the working age population who is unemployed’ and ‘the proportion of the population who is not working due to disability’ was equally $\rho = 0.45$. In 2011, these Spearman correlation coefficients between the housing domain and the employment domain indicators corresponded to $\rho = 0.13$ and $\rho = 0.20$. Given the fact that indicators were standardized and showed stable associations with the housing domain, the least complex method was chosen for the income and employment domains, i.e. the indicators were combined using equal weights.

The education domains 2001 and 2011 were initially built using 1) equal weights and 2) weights derived by the ML FA. The latter method can only be used if there are at least three indicators, and an underlying factor is suspected – conditions satisfied by this domain. In addition, ML FA is most appropriate where indicators are not perfectly reliable or measured without error, and does not depend on the scale of measurement of the input indicators (Northern Ireland Statistics and Research Agency, 2017).

We then conducted multiple correlation tests. We tested the association between individual indicators (‘early school leavers’, ‘working-age adults without qualification’, and ‘the NEET’) and the housing domain scores (in 2001, $\rho = 0.42$, $\rho = 0.45$, $\rho = 0.48$; in 2011, $\rho = 0.57$, $\rho = 0.65$, $\rho = 0.60$), and the association between the domain scores created by equal weights and FA weights ($\rho > 0.90$ in both years 2001 and 2011). As the associations were stable across indicators and housing domain scores, and between the two education domain scores, we used the least complex method of equal weights.

The crime domain is the only domain that was constructed on the level of the municipality, implying that statistical sectors within a municipality obtained the same score. As in the case of the education domain, we compared two crime domain scores created by: 1) adding the rates together (i.e. equal weights) and 2) using the ML FA. The Spearman correlation coefficient between the two crime domain scores was 0.98. In addition, the crime domain scores were ranked and assigned to deciles, and a confusion matrix was used to see the matching in domain deciles. The results were highly satisfying – 96% match in the most deprived decile. Thus, the selected method was the one with equal weights.

Indicators of the housing and health domains were combined with weights obtained by maximum likelihood factor analysis (Northern Ireland Statistics and Research Agency, 2017).

We used the *fa* function from the *psych* package (Revelle, 2022). More information on transformation, combination of indicators, and ML FA can be found in Supplementary Materials.

Exponential transformation

Prior to integrating the domain scores into the overall indices of multiple deprivation, we ensured that the domain scores had a common distribution, were scale independent, and had an appropriate level of cancellation. The method of transformation of the ranks to an exponential distribution met these criteria (Noble et al., 2006). We followed a methodology of the exponential transformation used in existing indices worldwide (McLennan et al., 2019; Noble M & Avenell D, 2004; Northern Ireland Statistics and Research Agency, 2017; Scottish Government, 2020). The standardization involved ranking the domain scores from 1 to 18,295 in the BIMD2001 and 18,764 in the BIMD2011, from the least to the most deprived. The ranked scores were then scaled to the range [0,1], where R = 1/N for the least deprived, and R=N/N = 1 for the most deprived. N is the number of statistical sectors included in the BIMD2001 and BIMD2011 (Noble M & Avenell D, 2004). The exponential transformation is explained in Supplementary Materials. The exponentialized domain scores represent the final domain scores ranging from 0 (least deprived) to 100 (most deprived), with the most deprived 10 percent of statistical sectors obtaining scores between 50 and 100, covering 50% of the distribution of scores (McLennan et al., 2019).

Integration of domains into the Belgian Index of Multiple Deprivation (BIMD)

Integrating the different domains into an overall BIMD2001 and BIMD2011 involves weighting the domains (Exeter et al., 2017; McLennan et al., 2019; Northern Ireland Statistics and Research Agency, 2017; Scottish Government, 2020). Noble et al. (2006) described five possible approaches to domain weighting: based on existing literature on multiple deprivation; empirically driven; determined by policy relevance; determined by consensus; and entirely arbitrary (Noble et al., 2006). The distribution of our selected set of weights reflected the existing literature on deprivation indices and was supported by Belgian stakeholders and experts, as well as considered the ability of the domains to directly measure different forms of deprivation.

To investigate the impact of various weights on the overall indices, we conducted a sensitivity analysis by creating the BIMD2001 and BIMD2011 using different weights. These were 1) weights selected to reflect research and opinion of the Belgian stakeholders and experts (denoted as the final, chosen weights); 2) various weights used in the currently existing indices (for instance, in England, New Zealand, Scotland, and Northern Ireland) (Exeter et al., 2017; McLennan et al., 2019; Northern Ireland Statistics and Research Agency, 2017; Scottish Government, 2020); 3) weights generated by ML FA; and 4) weights as in 1 but in a reversed order.

Table 2.2 Overview of alternative weights applied in the BIMD2001 and the BIMD2011

Domains	England IMD	NZ IMD	Scotland IMD	Northern Ireland IMD	ML FA weights	Reversed final chosen weights	Final chosen weights
Income	24.5	28	12	25	4	15	20
Employment	24.5	28	12	25	42	15	20
Education	15	15	6	15	44	5	25
Housing	10.5	10	1	10	12	20	15
Health	15	14	6	15	5	20	15
Crime	10.5	5	2	10	3	25	5

Spearman’s rank correlation coefficient

We used Spearman’s rank correlation coefficient to describe a monotonic relationship between ranked indicators, domains, and overall BIMDs. The coefficient can assume values between $\rho = -1$ and $\rho = +1$ when two paired variables have a perfect monotonic and negative or positive relationship. The more the coefficient ρ approaches 0, the less the value pairs share a perfect monotonic relationship (Cleff, 2014).

Higher-level area summary measures

We produced multiple summary measures for the higher-level area geographies for the BIMD2001 and BIMD2011 and their domains. These include a simple measure, such as a proportion of statistical sectors in the most deprived 10 percent nationally; and a population-weighted measure, such as an average score, an average rank, and an extent (McLennan et al., 2019). The population-weighted measures take into account that statistical sectors' population sizes can vary. The methodology of the higher-area level summaries is described in detail in Supplementary Materials and follows the methods used worldwide (McLennan et al., 2019; Northern Ireland Statistics and Research Agency, 2017; Scottish Government, 2020).

Availability of the BIMD results

A full list of the data files and supporting documents is available via GitHub at https://github.com/bimd-project/bimd. The files contain the overall BIMDs and their domain scores, ranks, and deciles. We also publish the R codes allowing the end user to tailor the construction of BIMDs to their research or policy aims.

2.3 Results

Belgian indices of multiple deprivation and their deprivation domains

The distribution of deprivation by the BIMDs differed across space (the Belgian statistical sectors) and time. In Figure 2.2, a clear gradient is observed between Flanders and Wallonia, suggesting greater overall deprivation in the French-speaking region. The spatial distribution of the most and least deprived statistical sectors has not changed over time. In 2001 and 2011, about 78% of the most deprived statistical sectors were located in Wallonia, while 90% of the least deprived statistical sectors were in Flanders. The most deprived areas were more spatially concentrated and clustered together, which also reflects their greatest concentration in the municipality of Charleroi (containing 11% of all most deprived statistical sectors), whereas the least deprived areas showed greater spatial variations.

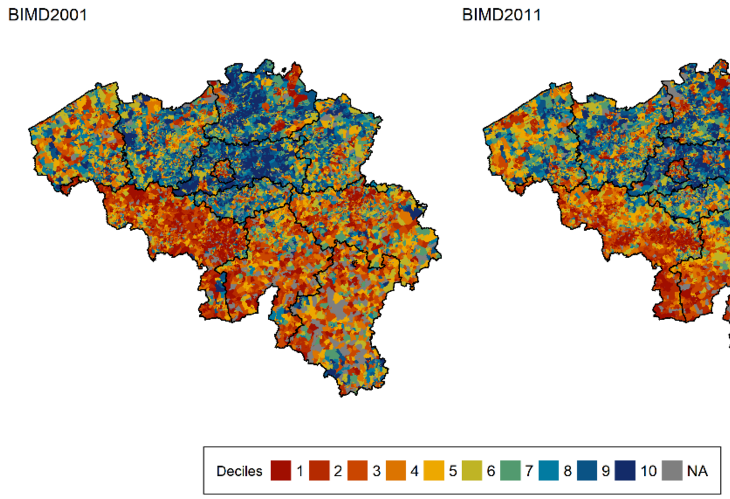

Figure 2.2 Distribution of the BIMD2001 and BIMD2011 deprivation deciles across Belgian statistical sectors in 2001 and 2011.

In 2001, the greatest number of most deprived statistical sectors in terms of income (5.5%), employment (10.6%), education (11.0%), housing (6.7%), and crime (8.0%) were located in the municipality of Charleroi, which is the municipality with the second highest number of statistical sectors in Belgium. The greatest number of most deprived statistical sectors in terms of health (7%) were located in the municipality of Liège. Across all six domains, most of the most deprived statistical sectors were in the region of Wallonia, ranging from 68% in terms of housing deprivation and up to 98% in terms of health deprivation (Figure 2.3). On the contrary, the spatial distribution of the least deprived statistical sectors varied greatly. Across all six domains, no evidence was found for a concentration of the least deprived statistical sectors in one municipality. Overall, the majority of the least deprived statistical sectors was found in Flanders, fluctuating between 60% in terms of housing deprivation and 95% in terms of employment. Interestingly, no least deprived statistical sector in terms of crime was identified in the Brussels-Capital region. Similar results were found in 2011, suggesting no significant change in the distribution of the most and least deprived statistical sectors.

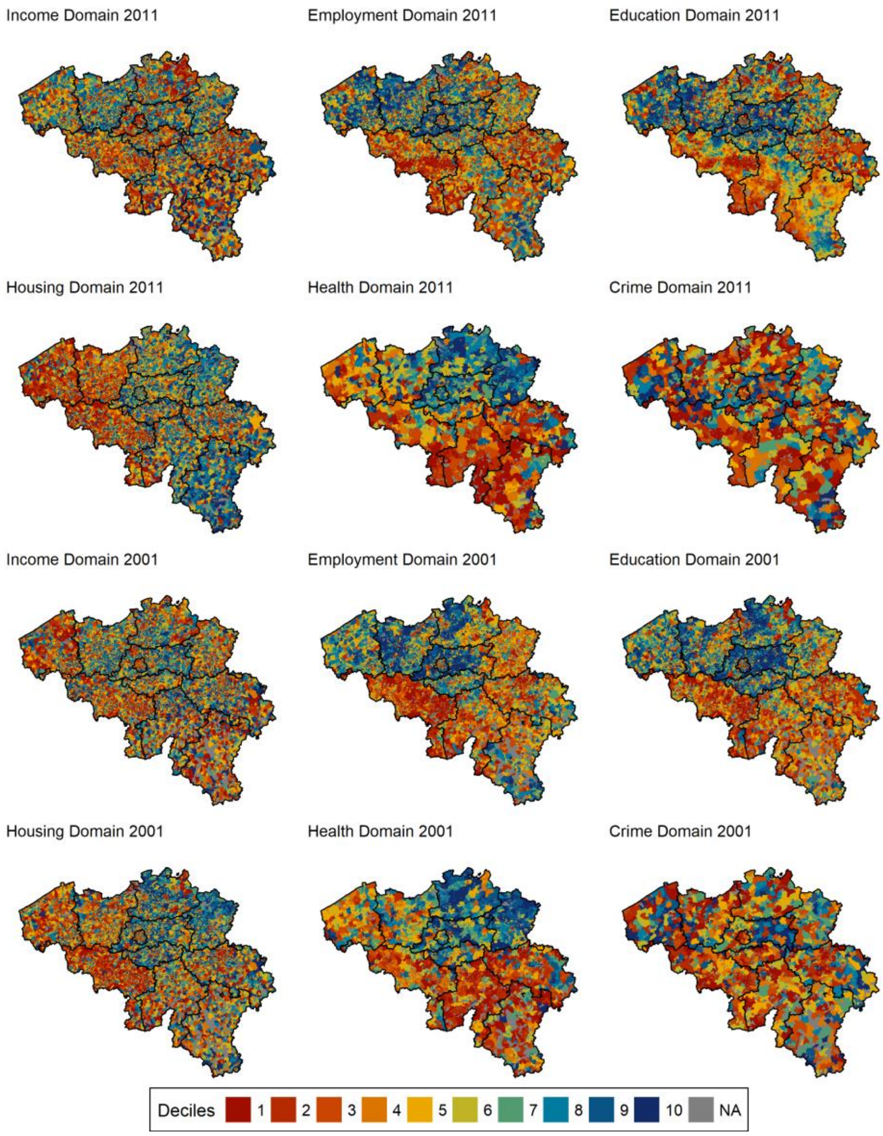

Figure 2.3 Distribution of the deprivation domain deciles across Belgian statistical sectors in 2001 and 2011.

Population-weighted higher-level summary measures, based on the BIMDs or domain scores or ranks, identified the municipality of Saint-

Josse-Ten-Noode, Farciennes, and Colfontaine among the ten most deprived, whereas the municipality of Hove, Herent, and Oud-Heverlee among the least deprived Belgian municipalities in 2001 and 2011. The municipality of Saint-Josse-Ten-Noode was also identified as the most deprived in terms of income, education, and housing. In 2011, the same municipality was still on the top of deprivation related to income and education, but the municipality of Mesen became the most deprived in housing. The municipalities of Colfontaine and Waarschoot were found the most deprived in terms of employment and crime, and the municipalities of Engis and Momignies in terms of health in 2001 and 2011. An overview of all Belgian municipalities and their deprivation on the BIMD2001 and BIMD2011 is shown in Supplementary Materials.

Population-weighted higher-level summaries, such as the ranked average score, can be used to measure deprivation at the higher area-division units. Figure 2.4 demonstrates the distribution of average score ranks by Belgian districts, which are the area-division units above municipalities. The 43 districts are ordered by the median average score rank (measured across municipalities) in descending levels of deprivation. In both years, the district of Mons had the lowest median average score ranks (45 in 2001 and 29 in 2011), while the district of

Antwerpen and Leuven had the highest median average score ranks in 2001 and 2011 (552 in 2001 and 541 in 2011).

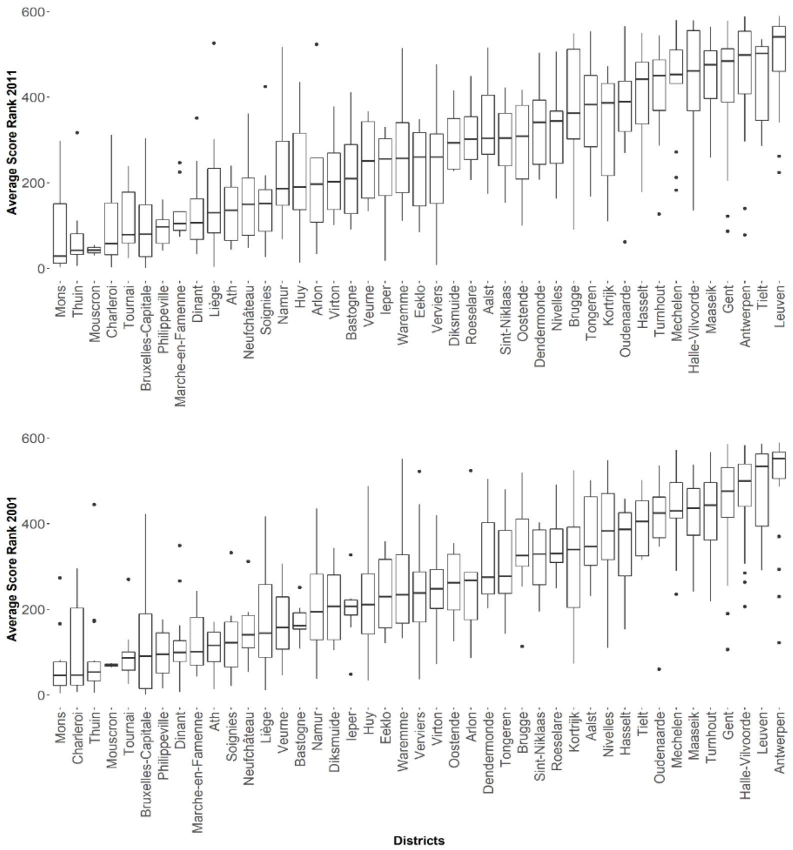

Figure 2.4 Distribution of the average score ranks across Belgian districts, from the most to the least deprived.

Using the BIMDs 2001 and 2011, the distribution of individual indicators by deprivation deciles was investigated. The results showed that the size of each indicator linearly increases with an increase in deprivation, measured by deprivation decile (i.e. the greatest proportions/rates were in the most deprived decile). This trend was observed in all indicators in 2001 and 2011. The absolute differences in the proportions between the most and least deprived areas, assigned to deprivation deciles, varied greatly. In 2001, the percentage of the population with the lowest income was almost two times higher in the most deprived areas, compared to the least deprived areas (10% against 5%). In 2011, the population with the lowest income was more than six times higher in the most deprived areas (27% against 4%). In 2001 and 2011, the unemployment rate was more than five times higher in the most deprived decile, compared to the least deprived decile (16% against 3% in 2001, 13% against 2% in 2011). The share of youth aged 15-24 who were neither in employment nor education or training (NEET indicator) was almost five times higher in 2001 (29% against 6%) and almost seven times higher in 2011 (20% against 3%). There were also stark differences in housing quality. In 2001, it was four times more common to live in a dwelling without a toilet or bathroom (similarly for both indicators 5% against 1%), if these dwellings were located in the most deprived areas. In 2001, overcrowding was four times more frequent in the most deprived areas (11% against 3% in the least deprived decile) and even six times higher in 2011 (13% against 2%). The percentage of the population without central heating was two times higher in 2001 (36% against 16%) and four times higher in 2011 (20% against 5%) in the most deprived areas, compared to the least deprived areas. Compared to the national mortality rates, in 2001 and 2011, individuals living in the most deprived areas suffered from 16% and 21% excess mortality, while risks of dying among those residing in the less deprived sector were 10% and 20% lower than the national average. In both years, the standardized suicide rate was about three times higher in the most deprived areas, compared to the least deprived. The preventable mortality fraction, i.e. the fraction of mortality that could be avoided if the public health policies focused on wider determinants of public health, such as lifestyle, was 20% and 19% in 2001, and 17% and 15% in 2011, in the most deprived, compared to least deprived areas. In 2001, individuals living in the most deprived areas reported were almost three times more likely to report poor health, compared to those living in the least deprived areas (11% against 4%). More details on the distribution of indicators by the overall BIMD2001 and BIMD2011 are in Supplementary Materials.

Our results showed that the age and sex population structure varied among deciles, but not between domains. In 2001 and 2011, the mean age of the male population living in the most deprived statistical sectors was 42.0 and 42.9 years, compared to 40.7 and 42.5 years in the least deprived statistical sectors. The mean age of the female population in the most and least deprived areas was higher, reaching 44.4 and 42.1 years in 2001, and 45 and 43.6 years in 2001 and 2011, respectively.

Although the deciles contained the same number of statistical sectors, the number of individuals across deprivation deciles varied. In 2001, the greatest proportion of the population was consistently identified in the most deprived decile in terms of crime (28%), education (17%), housing (15%), and employment (15%), suggesting that highly populated areas are at risk of deprivation. A similar trend was observed in the population allocation across deciles in 2011, with the greatest proportion of the population in the most deprived deciles, i.e., crime (29%), education (20%) and income (19 %), employment (13%). There were no significant differences in the proportions of men or women observed across deciles. Population pyramids are shown in Figures S2.S5 and S2.S6 in Supplementary Materials.

Correlations between the BIMD2001 and BIMD2011 and their respective domains at the statistical sector level

The Spearman's Rank Correlations, ρ, are presented in Table 2.3 and Table 2.4. All of the correlations are highly statistically significant ($\rho < 0.001$). The education and employment domain scores are very strongly associated with the overall BIMD scores, in both 2001 ($\rho = 0.85$ and $\rho = 0.80$) and 2011 ($\rho = 0.83$ and $\rho = 0.79$, respectively). Similarly, in 2001 the housing domain scores are strongly correlated with the overall BIMD scores ($\rho = 0.72$), while the income, health, and crime domain scores are only moderately correlated with the overall BIMD scores ($\rho = 0.56$, $\rho = 0.56$, $\rho = 0.40$). In 2011, the income domain scores are strongly correlated with the overall BIMD score ($\rho = 0.65$), whereas the crime, health, and housing domain scores are moderately correlated with the BIMD scores ($\rho = 0.50$, $\rho = 0.47$, $\rho = 0.42$).

In both indices, the employment's strongest association is with the education domain ($\rho = 0.77$ and $\rho = 0.70$), while the income's greatest associations in BIMD2001 are only weak with the education ($\rho = 0.29$), employment ($\rho = 0.24$) and housing domains ($\rho = 0.37$). In the

BIMD2011, the income domain’s strongest association is with the education domain ($\rho = 0.47$).

Table 2.3 Spearman correlation between the BIMD2001 and its domains

	BIMD2001	Income	Employment	Education	Housing	Crime
BIMD2001	1					
Income	0.56	1				
Employment	0.80	0.24	1			
Education	0.85	0.29	0.77	1		
Housing	0.72	0.37	0.51	0.56	1	
Crime	0.40	0.10	0.32	0.33	0.25	1
Health	0.56	0.07	0.38	0.36	0.35	0.23

Table 2.4 Spearman correlation between the BIMD2011 and its domains.

	BIMD2011 score	Income	Employment	Education	Housing	Crime
BIMD2011	1					
Income	0.65	1				

Employment	0.79	0.40	1			
Education	0.83	0.47	0.70	1		
Housing	0.42	0.14	0.23	0.19	1	
Crime	0.50	0.31	0.35	0.45	0.05	1
Health	0.47	0.07	0.31	0.20	0.21	0.18

We also explored the Spearman correlation between domains 2001 and 2011. The greatest association is between the crime (ρ = 0.88) and education domains (ρ = 0.84). The employment (ρ = 0.77) and housing domains (ρ = 0.66) are also strongly correlated, followed by the health (ρ = 0.58) and the income domains (ρ = 0.50). These two domains differ in indicators in the years 2001 and 2011, which may explain their moderate correlations.

2.4 Discussion

To our knowledge, this is the first study in Belgium employing multiple highly-reliable data sources to create an area-based, multidimensional deprivation measure. This represents a major methodological shift from the use of a simple measure of deprivation, such as income or education, at the individual level, to a more sophisticated composite measure of deprivation at the aggregate level of the smallest administrative unit in Belgium. The BIMD2001 and BIMD2011 are built on six domains of deprivation (income, employment, education, housing, health and crime), comprising 24 and 19 unique indicators, respectively. The process of combining indicators into domains, and domains into the overall BIMDs resulted in each statistical sector being given a domain and overall BIMDs score, rank, and decile. Using one of those, a statistical sector can easily be classified as deprived relative to other areas in either a particular dimension or in overall deprivation.

When constructing the indices, we had to make several crucial methodological choices. One of the first decisions regarded the units of our analysis, i.e. whether we should create the BIMDs using individuals or groups of people living in a clearly defined geographical area. We chose the latter for several reasons. Firstly, we were interested in capturing all three meanings of area deprivation: a compositional meaning, a collective meaning, and an environmental meaning (Sally Macintyre, 1997). The compositional meaning of area deprivation is that an area is considered deprived if it contains many deprived people. The collective and environmental meanings refer to the additional deprivation in an area which is beyond those attributable to the concentration of deprived people and they can be seen as synonymous with the 'neighborhood effect'. The neighborhood effects have been increasingly researched, specifically in relation to health or housing, and studies have shown that neighborhoods affect their inhabitants, even after accounting for individual risk factors (Cubbin et al., 2000; Duncan et al., 1999; Dunn & Hayes, 2000; Pickett & Pearl, 2001; Shaw, 2004). Evidence has been accumulating that the area where a person lives may influence various aspects of their lives, such as employment, child outcomes, criminal behavior, and other socio-economic phenomena (Dietz, 2002). By creating our indices at the level of the statistical sector, we were able to include all three dimensions. Secondly, using aggregate data enabled us to better accommodate the privacy, security, and confidentiality issues associated with using administrative and survey data. In addition, data on some crucial indicators were only obtainable at the aggregate level. Finally, as the sectors' characteristics are relatively stable over time, our aggregate approach allows more easily to identify areas in need of interventions that would benefit from area-based policies.

Belgium is administratively divided into regions, provinces, districts, municipalities, and statistical sectors. We aimed to construct the BIMDs at the smallest workable spatial scale, with the selected units being relatively homogeneous. This choice was also justified by the fact that statistical sectors are the official units in Belgium and thus, they represent actual communities or neighborhoods; their boundaries change little over time; and they are also in most cases large enough to provide statistically robust estimates of socio-economic or health indicators with limited smoothing required.

Measuring different aspects of deprivation and combining these into an overall multiple deprivation measure raised several concerns. A major concern regarded the issue of to which extent the same individuals should be represented in more than one indicator of the same domain or across multiple domains. For instance, an individual who is a tenant might also live in a dwelling smaller than $35m^2$, but he might also be unemployed. Our stance on that is that experiencing multiple forms of deprivation is worse than experiencing only one of its forms. Therefore, we did not aim to eliminate double counting either within or between domains.

Another concern involved the cancellation effect and its extent. For instance, if an area has high levels of education deprivation but low levels of employment deprivation, should the latter cancel out the former and to which extent? To control the cancellation effect, we used exponential transformation of the domain scores – a method commonly used in indices worldwide, for instance in the UK indices (McLennan et al., 2019). The exponential distribution does not eliminate the cancellation effect but it minimizes it by spreading out the most deprived distribution in the tail. This property ensures that indices are specifically constructed to identify deprivation and not affluence (McLennan et al., 2019; Noble et al., 2010; Northern Ireland Statistics and Research Agency, 2017; 2020).

Furthermore, we faced the issue of what weights should be attached to each domain. The results of our sensitivity analysis revealed that changes in weights make little difference to the overall BIMD2001 and BIMD2011. (Table S2.S21 in Supplementary Materials). We accredited the consistency in results to the high correlation between many domains. Based on our findings, our final choice of weight distribution was driven by existing research (Townsend, 1987; Townsend, 1991; Townsend et al., 1992) and consultations with Belgian stakeholders and experts. In addition, we considered the ability of the domains to directly measure different forms of deprivation in Belgium, and the quality and coverage of indicators in each domain. In the final version of the BIMDs, education, income, and employment domains have been given the largest weights, accounting for 65%. The education domain received the greatest weight (25%) as it is the most basic component of socio-economic status. Besides shaping future occupational opportunities and earning potential, education provides knowledge and life skills that prevent one from deprivation (Adler & Newman, 2002). The housing and health domains received a weight of 15%, whereas the crime domain received the smallest weight (5%) as it is modeled on the level of the municipality.

Strengths and limitations

A significant strength of the BIMDs is that the six domains may be used in combination or separately to explore their contribution to the overall BIMD in a given statistical sector. To facilitate a wide use of the BIMDs and domains, we publish their scores, ranks, and deprivation deciles at the statistical sector level. Moreover, we publish R codes and datasets that enable to build the BIMDs or compute higher-area level summaries. Publishing these materials opens the door to public health officials, policymakers, stakeholders, or researchers to measure geographical variations in housing inequality to guide policy decision-making. The availability of individual domains' scores enables to identify the type of deprivation that is prevalent in the neighborhood and changes the focus directly on the specific deprivation or geographical area. In case the research interest lies in exploring the association between health and deprivation, the publicly available domains can be combined without the health domain. Moreover, the indices can be updated using the most available datasets in the future, for example, once data from the next census are released.

Another strength of our study is the use of the highly reliable pseudonymized dataset from the 2001 and 2011 population censuses and the National Register to build most BIMDs' indicators. These indicators are represented by rates consisting of a numerator (e.g. the number of deprived people in the area) and a denominator (e.g. the total number of 'at risk' people living in the same area). Both are computed from the same data sources, ruling out any systematic error that arises from different datasets of different coverages. Working with administrative and exhaustive data gives an added advantage to our BIMDs as it enables us to minimize selection bias and reduce the risk of ecological fallacy. Exhaustiveness is, however, not effective for all variables as high non-response rates are observed for some variables (e.g., education level in some years or housing tenure). Coupling the census data and national register, we were able to impute missing information for some indicators, such as in the case of the housing domain. We should, however, acknowledge that our datasets exclude non-registered inhabitants of Belgium, who are typically more deprived and are not randomly distributed across the territory.

The variability in the level of non-responsiveness might relate to data collection across censuses. In 2001, data were collected through an individual questionnaire, while in 2011 administrative databases were used to update the previously existing information. This difference in data collection can lead to comparability issues for some variables.

Of particular concern is the absence of information on the educational level of new migrants in the 2011 census.

Although the final indices are at the level of the statistical sector, we were provided with the crime counts at the municipality level without specific geographical/address information, such as postcodes, map references, and address details. Such lack of information prevented us to obtain reliable and robust estimates for statistical sectors. The crime domain was thus built at the municipality level and statistical sectors falling into the same municipality received identical scores, rank and decile. Additional limitations regarding each domain are described in more detail in Supplementary Materials.

Many other indices worldwide include a domain referring to access to services, but the BIMD indices do not. This is because we were not able to access data that we could utilize to build this domain in 2001 and 2011. On the other hand, from the existing literature we know that when an index contains the ‘access to services’ domain, the weight given to this domain is always the lowest, e.g. 10% in the Northern Ireland MDI, or 2% in the New Zealand MDI. Given the high correlations between our domains and the overall index, including the ‘access to services’ domain would likely have a very little impact on the final score.

Our BIMDs also have limitations that need to be considered when interpreting the outcomes. We created area-based measures that can be used for comparing statistical sectors across Belgium, identifying the most deprived statistical sectors, exploring the types of deprivation via domains using the domain and BIMDs scores and ranks. The type of deprivation in an area and its scale can be identified by a domain score. Within the domain, the greater the score, the more deprived the area. The scores are, however, not an appropriate tool for a deprivation comparison across domains because they have different minimum and maximum values. Using the ranks, the statistical sectors can be compared in terms of deprivation domains and overall BIMDs. The findings should be reported with attention to their correct formulation. We can make a statement that ‘statistical sector A is more deprived than statistical sector B’, but we are restricted from making statements such as ‘statistical sector A is twice as deprived as statistical sector B’. In addition, the BIMDs are not designed to provide direct comparability between the 2001 and 2011 versions. The changes in deprivation between the two versions can however be described in relative terms, for example, a statistical sector was within the most deprived 30 percent of areas nationally according to the BIMD2011 but within the most deprived 10 percent according to the BIMD2001 (Department for Communities and Local Government).

Although the number of statistical sectors and their borders have changed only slightly over time, it is also crucial that researchers who wish to apply our estimates make use of the correct statistical sector definitions and shapefiles.

Finally, by creating an area-based spatial measure, we can identify areas as more or less deprived, but the tool is not suitable for making such inferences about individuals or specific groups of people. Most importantly, our indices are designed to identify various aspects of deprivation, not affluence. It means that a sector classified as less deprived is not necessarily among the most affluent sectors in Belgium.

2.5 Conclusion

We created the first composite and multidimensional tool for measuring deprivation in Belgium, the Belgian Indices of Multiple Deprivation for the years 2001 and 2011. The BIMDs are built on six domains that can be used in combination or separately to explore their contribution into the overall BIMD in a given geographical area. The domains are created by using a high-quality data and they can be easily updated when the most recent data become available. Although the BIMDs are computed at the level of the statistical sector, they can provide information on deprivation at a higher geographical level.

As we make the BIMDs publicly available, we hope that the indices will be used for analyzing patterns of deprivation and identifying areas that would benefit from special initiatives and programs. Policy makers, governmental departments, regional bodies and local authorities as well as academics are encouraged to use the indices to help target policies and funding to ultimately reduce inequalities across multiple domains.

Chapter 3 Inequalities in mortality associated with housing conditions in Belgium between 1991 and 2020[2]

3.1 Introduction

According to the United Nations, the right to housing is a basic human right, not just to a ‘basic shelter’ but to ‘adequate housing’ in terms of legal security of tenure, availability of services, materials, facilities and infrastructure, affordability, habitability, accessibility, location, and cultural adequacy (United Nations, 2021). Although improvements in housing have been central to many social policy interventions and are fundamental to tackling elements of poverty, over a billion people worldwide remain inadequately housed.

Housing affects health in numerous minor ways and can be considered an intermediate social determinant of health because it links poverty and well-being through various mechanisms (Braubach &

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Fairburn, 2010; Thiele, 2002). Epidemiological research suggests that poor housing can have a direct and indirect effect on health and mortality (Shaw, 2004). The direct effects may result from the material conditions of housing. For instance, depending on the climatic context, housing can, more often than not, be too cold or too hot for healthy living due to lack of ventilation, central heating, or air conditioning. Cold and humid environments caused by inadequate ventilation create conditions for the growth of mold and fungi that are associated with the incidence of diarrhea, headaches, fever, and respiratory diseases (Butler et al., 2003; Dales et al., 1991; Williamson et al., 1997). Furthermore, exposure to extreme cold and the absence of central heating is linked to a higher risk of dying in winter, whereas lack of air conditioning during extreme heat waves results in increased mortality during the summer months (Aylin et al., 2001; Gemmell, 2001). In addition to the material dimension, housing also has symbolic significance, referring to the fact that a house represents a place of refuge, is an essential part of one's identity, and plays a role in social interactions. Poor housing and a poor neighborhood environment may lead to pessimism and passivity, chronic stress, and a state of personal dissatisfaction – conditions that negatively affect physical and mental health (Bentley et al., 2022; Dunn, 2002; Howden-Chapman, 2004; Shaw, 2004).

The neighborhood in which housing is located and its natural and built environment, as well as the social and cultural norms present there, represent other indirect ways in which housing affects health (Shaw, 2004). For instance, in neighborhoods with high smoking rates, smoking might be considered the norm and deviation from such behavior a weakness (Stead et al., 2001).

Despite the wide range of possible negative impacts of inadequate housing on health, only a handful of studies have considered the relationship between housing conditions and variation in life expectancy. Housing tenure, one of the most commonly used indicators of housing and socio-economic status, has been found by several researchers to be associated with health outcomes. For instance, Filakti et al. reported that in England and Wales, premature mortality was 35% lower for male homeowners than for males living in social housing in the 1980s (Filakti & Fox, 1995), and, more recently, a study in Portugal reported that living in social housing is associated with increased mortality (Ribeiro & Barros, 2020). Strong associations between housing tenure and increased mortality or poor health were also reported by studies from Scotland (Macintyre et al., 2001) and the US (Saegert et al., 2003), while findings from Australia suggest that housing affordability stress has adverse impacts on wellbeing, especially mental health (Bentley et al., 2016). Findings from existing studies on the association between inadequate housing conditions in Belgium and adverse health outcomes are concurrent with findings reported worldwide (Damiens, 2020; Eggerickx et al., 2018; Gadeyne, 2006). For instance, a study by Damiens (2020) showed that mortality among tenants was about 25% higher than among homeowners, and a similar excess mortality was observed among those living in low-quality housing, defined by lack of elements such as a bathroom, central heating, or a kitchen, even after controlling for educational attainment, professional status, and income.

Although the Belgian Constitution includes the right to decent housing, and Wallonia, Flanders, and the Brussels-Capital Region share a common social policy, access to housing remains a major social differentiator (De Decker, 2008; De Decker & Dewilde, 2010; Vanneste et al., 2008). The differences in housing quality among the three regions are large, with housing quality being highest in the Flemish region and lowest in the Brussels-Capital Region, where the number of homeless and inadequately housed people has more than doubled since 2008 (Damiens, 2020; Eggerickx et al., 2018; Gadeyne, 2006; Winters & Heylen, 2014). A strikingly similar pattern in mortality was reported by Eggerickx et al. (2019), showing that, between 1991 and 2016, the highest levels of mortality were in the inner city of the Brussels-Capital Region and several Walloon cities, compared to the Flanders.

This paper aims to assess whether housing inequality is associated with increased mortality and to estimate the number of deaths that could be prevented if the entire population of Belgium faced the mortality rates of the least deprived areas in terms of housing. We use housing conditions as concrete manifestations of socio-economic deprivation and create composite, spatial, and time-specific housing deprivation indices for measuring deprivation levels at the smallest administrative unit in Belgium, the statistical sector. Then, we examine the association between housing inequality and mortality, using multiple health inequality measures.

3.2 Methods

Housing Deprivation Indices (HDI)

We used data on housing characteristics from the 1991, 2001, and 2011 Belgian population censuses to develop area-level housing deprivation indices at the level of the statistical sector for these three census years. Each index was built on a group of indicators encompassing multiple deprivation aspects. The selection of indicators was based on our literature review and on the premise that the indicators must be the best possible measure of housing deprivation in Belgium for the given period. The indicators retained vary across the selected years due to their relevance at the time, accessibility, and availability, and they always represent only the proportion of population who is deprived, not affluent.

For each indicator, the proportion of the population in a statistical sector that is deprived was calculated, for instance the proportion of individuals without central heating or internet connection. Maximum likelihood factor analysis (FA) was used to combine these indicators at the level of the statistical sector. Then, statistical sectors were ranked based on the resulting FA scores and assigned to deciles such that the most deprived statistical sectors fell into the first decile. This methodology was applied independently for the 1991, 2001, and 2011 indices. More details are provided in the Supplementary Materials.

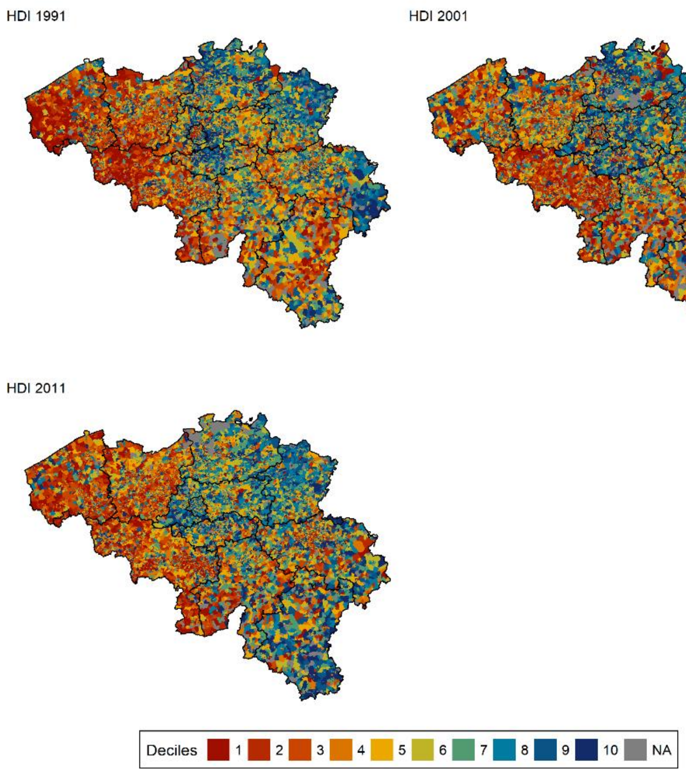


Figure 3.1 Distribution of housing deprivation deciles across Belgian statistical sectors in 1991, 2001, and 2011.

Geographical unit

The HDIs are presented at the level of the statistical sector, which is the smallest administrative unit of Belgium, resulting from the subdivision of municipalities (Statistics Belgium, 2017b). By definition, a statistical sector may never extend over two municipalities, and each geographical point in Belgium belongs to one and only one statistical sector (Jamagne et al., 2016). These sectors are heterogeneous in population size, with a median population of 300 persons.

In our study, only statistical sectors with more than 10 inhabitants were included to ensure obtaining stable estimates, to limit potential bias, and to safeguard data privacy. We excluded 1,464 (7.5%), 1,486 (7.5%), and 1,018 (5.1%) statistical sectors for 1991, 2001 and 2011 respectively. The final number of statistical sectors included in the analysis was therefore 17,909 for the period 1991–2000, 18,295 for the period 2001–2010, and 18,764 for the period 2011–2020.

Data

We used a pseudonymized dataset, built upon DEMOBEL, the demographic database produced by the Belgian Statistical Office (Eggerickx et al., 2019; Statistics Belgium). Our database covers the observation period 1991–2020 and includes several administrative data sources: the National Register, the 1991, 2001, and 2011 Belgian population censuses, and death certificates from the Civil Registry. Individuals in these data sources are linked by a multi-digit code specific to the research project. The pseudonymization prevents linkages of the data with other administrative databases or databases located in other research centers.

Missing data

The amount of missing information varied across indicators and censuses – 4%–12% for 1991, 6%–17% for 2001, and 2%–12% for 2011. Whenever possible, we identified individuals within the same household and imputed missing information based on other family members. Additionally, we imputed values based on the same housing profile – individuals in the same statistical sector had to share at least 75% of the housing characteristics. These two approaches resulted in a reduction of missing values to 2%–5% for 1991, 4%–9% for 2001, and 1%–6% for 2011 (Table S3.S2 in Supplementary Materials).

Mortality data

We used pseudonymized individual-level all-cause mortality data extracted from the National Register in Belgium relative to deaths that occurred between Jan. 1, 1991, and Dec. 31, 2020. Data included age, sex, and a unique personal identification number for each deceased individual. Multi-digit identification numbers were used for record linkage within the database to derive the last registered statistical sector of the deceased. Mid-year population estimates by statistical sector, sex, and single-year of age from 1991 to 2020 were obtained from the

National Register data, which includes all legal residents of Belgium and excludes irregular migrants and asylum seekers.

Inequality indices

First, we stratified the mortality and population data according to 5-year age group (with the lowest age group 0–4 and the open-ended age interval 95+), sex, housing deprivation deciles, and 10-year periods (1991–2000, 2001–2010, 2011–2020), yielding 1,260 strata. Housing deprivation indices were used as follows: the HDI 1991 was applied to the period 1991–2000, the HDI 2001 to 2001–2010, and the HDI 2011 to 2011–2020. We then computed sex- and age-standardized mortality rates (ASMR) per 100,000 person-years and at 95% confidence intervals (CI) for each stratum using the sex and age structure of the Belgian population in 2019. To show the changes over time, we calculated the absolute change in ASMR between the first (1991–2000) and last period (2011–2020). We plotted the adjusted Lorenz curve and computed Gini coefficients for each period to observe inequalities in ASMRs across the housing deprivation deciles. The Lorenz curve is a cumulative frequency curve (Peltzman, 2009) that, in our case, compares the distribution of sex- and age-standardized deaths across deciles, with a uniform distribution representing equality. The adjusted

Lorenz curve was plotted by using the cumulative proportion of sex- and age-specific deaths and cumulative proportion of population by housing deprivation deciles. We used the ASMRs to compute the sex- and age-specific number of deaths in each decile and consequently computed the cumulative percent of deaths. An example of our calculations is provided in Table S3.S4 in Supplementary Materials. Gini coefficients were computed using the Gini function from the DescTools package in R (Signorell, 2022).

Secondly, within each 5-year age group, sex, and 10-year period, the age-specific mortality rate of the least deprived decile was used as a reference group and applied to the other deciles to produce a number of expected deaths. We calculated the mortality associated with housing deprivation as the difference between the observed and expected deaths, expressed as a population attributable fraction (PAF) and a number of excess deaths. The 95% CIs were estimated using a Monte Carlo simulation, in which 10,000 deaths in each stratum were sampled from a Poisson distribution.

Thirdly, we constructed period life tables for each sex, housing deprivation decile, and 10-year period (Preston et al., 2001). The Arriaga method was used to decompose the differences in life expectancy between the most and least deprived deciles in men and women for all three decades separately. Finally, potential years of life lost (PYLLs) to inequality were calculated as the difference between the years lost due to death before age 75 in each cohort and the corresponding least deprived cohort.

All analyses were done in R version 4.1.1 (*R version 4.1.1*).

3.3 Results

Our study covered 310 million person-years in people aged 0–95+, with 3,161,490 deaths that occurred in Belgium between 1991 and 2020. Deprivation was defined by deciles of housing deprivation indices for 1991, 2001, and 2011 at the level of statistical sector. During the study period, ASMRs decreased for men and women in all deprivation deciles. Reduction in absolute ASMR was greatest for males in the most deprived decile (−406 per 100,000 person-years) and females in the least deprived deciles (−293 per 100,000 person-years), whereas relative reductions were greatest for males (−31%) and females (−25%) in the least deprived deciles (Table 3.1). Comparing the period 2011–2020 with 1991–2000, the gap between the most and least deprived deciles narrowed for men but widened for women.

Table 3.1 Trends in mortality inequality according to housing deprivation deciles.

	1991–2000	2001–2010	2011–2020	Change (%)
Age-standardized mortality rates per 100,000 person-years and 95% CI				
Male				
Most deprived	1,649 [1634–1664]	1,495 [1484–1506]	1,243 [1231–1254]	−24.62
Least deprived	1,193 [1181–1207]	923 [911–935]	826 [815–837]	−30.76
Difference	456	572	417	−8.55
Female				
Most deprived	1,402 [1389–1415]	1,271 [1262–1281]	1,140 [1130–1150]	−18.69
Least deprived	1,156 [1144–1170]	1,027 [1013–1041]	863 [851–875]	−25.34
Difference	246	244	277	12.60
Gini coefficient				
Male	0.05	0.08	0.07	

	[0.03–0.08]	[0.06–0.12]	[0.05–0.10]	
Female	0.03	0.04	0.04	
	[0.02–0.05]	[0.03–0.05]	[0.03–0.07]	
Mortality associated with housing inequality (%)				
Male	21.0	26.5	19.4	-7.6
	[20.12–21.85]	[25.13–27.99]	[18.33–20.47]	
Female	12.6	11.27	15.5	23.2
	[11.61–13.51]	[9.48–13.02]	[14.47–16.75]	
Mean number of Potential Years of Life Lost associated with housing inequality				
Male	1.50	1.58	0.92	−38.7
Female	0.61	0.69	0.46	−24.6

The adjusted Lorenz curves show that in 1991–2000, 9.9% and 9.1% of male and female deaths occurred in the most deprived decile, which only represents about 8.9% of the male and 8.5% of the female population. In the period 2001–2010, the first and most deprived deciles contained 13% and 12.5% of the male and female population, while accounting for 15.9% of male deaths and 13.9% of female deaths. Between 2011–2020, the first decile contained similarly 7.7% of the male and female population and accounted for 9.3% and 8.6% of male and female deaths.

The Gini coefficient, measuring the degree of 'bend' or inequality in the Lorenz curve, was slightly fluctuating for men (without statistical significance) but stayed almost constant for women over the periods under observation. The Gini coefficients are provided in Table 3.2 and the adjusted Lorenz curves are shown in Figure S3.S5 (in Supplementary Materials).

The proportion of mortality associated with housing inequality varied by period, sex, and age. Across all years under study, the PAF was higher in men than in women, first increasing sharply from 21.0% (95% CI, 20.1–21.9) to 26.5% (95% CI, 25.1–28.0) in the periods 1991–2000 and 2001–2011, then decreasing to 19.4% (95% CI, 18.3–20.5) in the period 2011–2020. In women, mortality associated with inequality has been increasing over time, from 12.6% (95% CI, 11.6–13.5) to 15.5% (95% CI, 14.5–16.8) between 1991–2000 and 2011–2020. In the most deprived deciles, the proportion of deaths associated with housing deprivation peaked in middle-aged men and women and accounted for more than half of all deaths occurring in the middle-aged population (Figures S3.S1, S3.S2, and S3.S3 in Supplementary Materials).

If the whole population of Belgium presented the same risk of mortality as the least deprived groups measured by the HDI in the three reference years 1991, 2001, and 2011, 568,605 fewer deaths would have occurred between 1991 and 2020. This represents about 18% of all deaths that could be associated with housing deprivation (Figure 3.2).

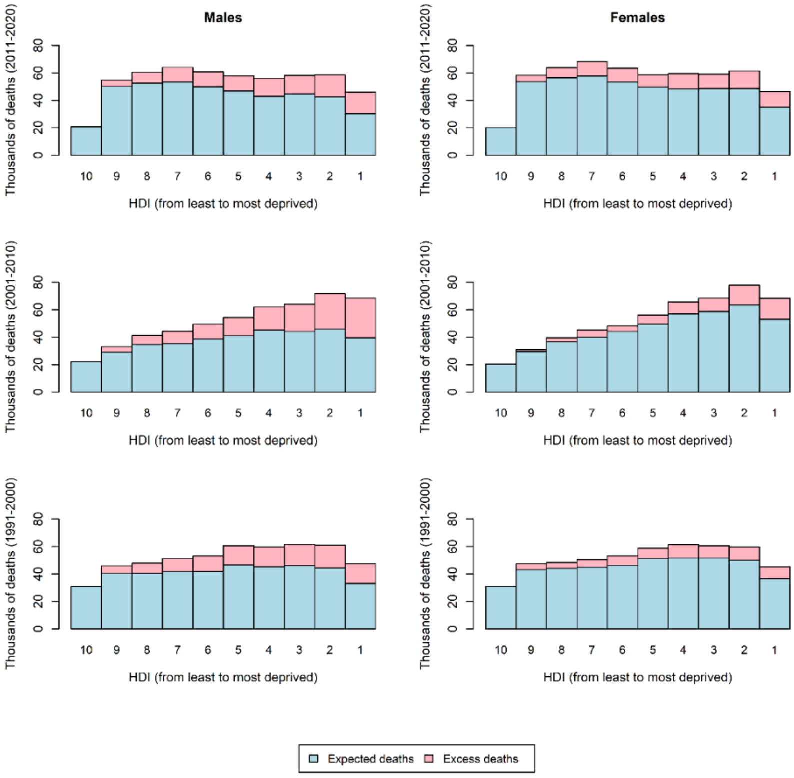


Figure 3.2 Mortality associated with housing inequality in Belgium by housing deprivation deciles.

The results of our life table calculation suggested that on average, men and women in the least deprived deciles live longer than in the most deprived deciles in all observed periods. For the period 1991–2000, men and women in the least deprived deciles were expected to live 78.1 and 82.8 years, respectively, compared to 72.7 and 79.9 years in the most deprived deciles (Table 3.2). The gap in life expectancy between the most and least deprived deciles was 5.4 and 2.9 years for men and women, respectively. In the subsequent periods of 2001–2010 and 2011–2020, the gaps between the most and least deprived groups for men and women increased to 7.1 and 4.0 years, and consequently decreased to 5 and 3.3 years, respectively.

Table 3.2 Life expectancies at birth in Belgium by the most and the least housing deprivation deciles for 1991–2000, 2001–2010, and 2011–2020.

	1991–2000[1]	2001–2010	2011–2020	Change in time (in years)
Male				
Most deprived	72.72	73.90	76.98	4.26
Least deprived	78.07	80.96	81.96	3.89
Difference	5.35	7.06	4.98	
Female				
Most deprived	79.88	80.68	82.53	2.65
Least deprived	82.78	84.65	85.84	3.06
Difference	2.90	3.97	3.31	

Over the three decades, life expectancy at birth increased for all deciles, but not at the same rate. Using the Arriaga method, we compared how differences in age-specific mortality contributed to the life expectancy gap between the most and least deprived deciles in each period under study. The increase in life expectancy is observed in all age groups, but it is driven mostly by declines in mortality in the age group 60–69 in men and 70–79 in women, in all three decades. These age groups contribute about 25% to the difference in life expectancy between the most and least deprived deciles in 1991–2000, 2001–2010, and 2011–2020 (Table S3.S3 in Supplementary Materials).

The results of our life table calculation also revealed that premature mortality associated with housing deprivation caused a mean of 4.7, 3.74, and 3.1 PYLLs per person in 1991–2000, 2001–2010, and 2011–2020 respectively. Sex-stratified results showed that the mean number of PYLLs has always been greater for men than women across all deciles, with a declining trend for both sexes (Figure 3.3). The mean PYLL for men and women, respectively, was 6.1 and 3.2 for the period 1991–2000, 4.8 and 2.7 for 2001–2010, and 3.9 and 2.3 years for 2011–2020. If everyone had the mortality risk of the least deprived groups measured by the HDI for 1991, 2001, and 2011, the PYLLs would decrease to 3.6, 2.6, and 2.4 years per person.

Our results also suggested that 23%, 30%, and 22% of PYLLs were associated with inequality for the years 1991, 2001, and 2011. In both sexes, this proportion peaked in the period 2001–2010, equally with 68% in men and women.

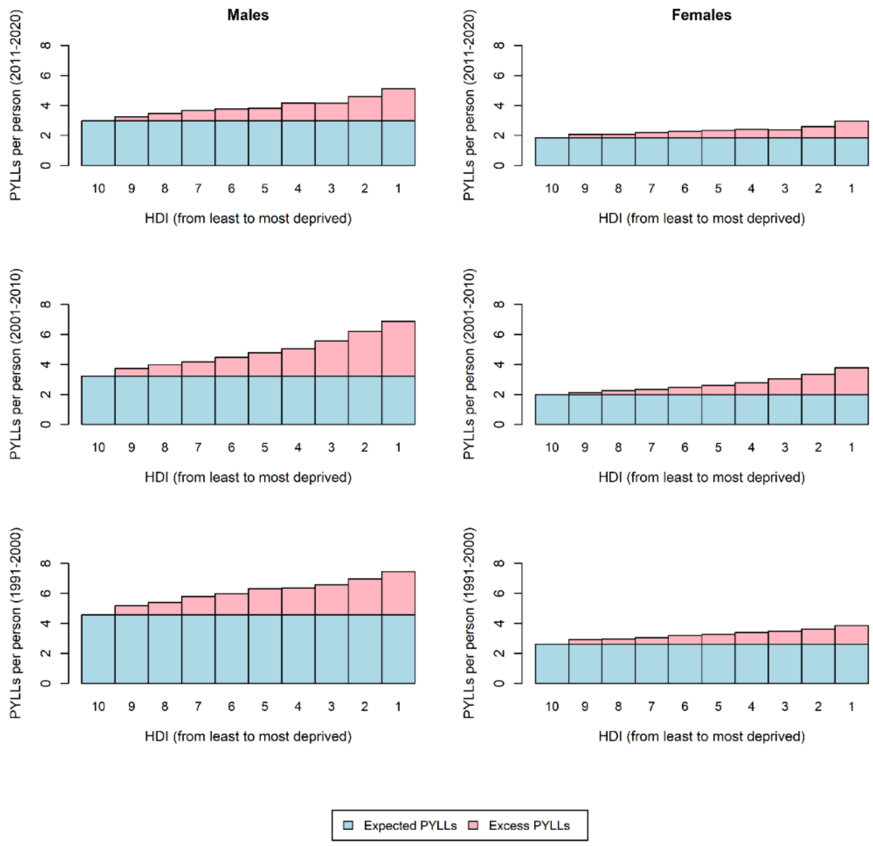


Figure 3.3 Potential years of life lost to housing inequality in Belgium by housing deprivation deciles

3.4 Discussion

To our knowledge, this is the first Belgian study investigating housing-driven inequalities in mortality using composite, spatial, and time-specific housing deprivation indices. The HDIs were created using data from the 1991, 2001, and 2011 population censuses, and the units of analysis were the smallest administrative units in Belgium, statistical sectors.

We conducted a cross-sectional study of 3,161,490 deaths that occurred in Belgium between 1991 and 2020, and we showed that one in five deaths could be associated with inequalities in housing measured by the HDIs. During the study period, the ASMRs declined in both sexes across all deprivation deciles, but inequality in mortality persisted. The differences in the ASMRs between the most and least deprived deciles were greatest for men in the study period of 2001–2010 and women in 2011–2020. Comparing the periods 1991–2000 and 2011–2020, we observed that the gap in the ASMRs between the most and least deprived deciles of the HDIs and the mortality associated with housing inequality decreased in men but increased in women, whereas the mean number of PYLLs associated with housing inequality decreased in both sexes. Life expectancy at birth increased in men and women across all housing deprivation deciles, mostly driven by declines in mortality at higher ages. The disparities in life expectancy at birth between the most and least deprived deciles decreased in men and increased in women.

In the period 2001–2010, we observed opposite trends in mortality associated with housing inequality and in the PYLLs. In men, the mortality associated with housing inequality and the PYLLs increased, but in women, both decreased. In addition, the gap between the most and least deprived housing deprivation deciles for the ASMRs increased in men but decreased in women, and for the life expectancy at birth increased for both sexes.

Findings of our study are consistent with results of prior studies that investigated variations in life expectancy by housing quality and housing tenure. Eggerickx et al. (2018) showed an increase in social and spatial inequalities in Belgium between 1991 and 2016, pointing out that inequalities are greatest among individuals aged 25 to 50 in line with our results depicting that mortality associated with housing inequality peaks between the ages of 40 and 49. The study by Damiens (2020) on the impact of housing conditions on mortality in Belgium concluded that low-quality housing may result in an increase in mortality rates by 25% after controlling for educational attainment, professional status, and income, whereas in our study, the difference between the most and least deprived groups ranged between 28%–40% for men and 18%–25% for women.

Although we are not able to explain why the time trends in inequality differ between men and women, our results might help to better understand the association between housing deprivation and health and guide housing policies. In Belgium, one weakness of public housing programs is the fact that housing policies are mostly centered on access to homeownership, while the stock of social housing remains insufficient. For instance, in Wallonia in 2007, 3.4% of households were awaiting social housing, and 75% of these were considered extremely poor (IWEPS, 2007). A similar situation was observed in Flanders and the Brussels-Capital Region (Loopmans et al., 2010). Moreover, the private rental sector is often characterized by poor housing conditions, as it receives the least public support (Winters & Heylen, 2014). Knowing that residing in inadequate housing is associated with adverse health outcomes, housing should be ranked as a priority health determinant in regional and national policies and surveillance systems. Achieving improvement might require a coordinated cross-departmental approach involving different spheres of policy targeting social determinants of housing.

Strengths and limitations

The key strength of our study is our development and use of spatial and time-specific indices of housing deprivation. The method we used to build our HDIs is easily replicable and can be updated in the future with the latest data. Indices as well as our population-level estimates of housing inequality in mortality were computed at the level of the statistical sector, but they can be aggregated to higher-area levels, such as municipalities. Our decision to build the HDIs at the aggregate level was supported on several points. We were interested in capturing area deprivation effects as conceptualized in three different meanings: as compositional, as collective, and as environmental (Sally Macintyre, 1997). A compositional meaning of area deprivation refers to poor housing conditions that are ultimately experienced by individuals and further translated into the proportions of deprived people living in an area. A collective meaning and an environmental meaning refer to additional deprivation in an area that is beyond that attributable to the concentration of deprived people; these can be seen as synonymous with neighborhood effects. Neighborhood effects have been increasingly researched, specifically in relation to health or housing, and studies have shown that neighborhoods affect their inhabitants, even after accounting for individual risk factors (Cubbin et al., 2000; Duncan et al., 1999; Dunn & Hayes, 2000; Pickett & Pearl, 2001; Shaw, 2004). Creating the HDIs at the level of the statistical sector, we were able to include all three dimensions, but it became difficult to isolate the individual effect and the neighborhood effect, as the housing characteristics are constructed on the aggregation of individual variables and not on environmental variables. Finally, as the sectors' characteristics are relatively stable over time, our aggregate approach allows for easier identification of areas in need of interventions that would benefit from area-based policies on housing and urban planning.

In choosing a suitable geographical area, we preferred the smallest administrative unit in Belgium, the statistical sector. This choice was also justified by the fact that statistical sectors are official administrative units; their boundaries change little over time; they are large enough to provide statistically robust estimates of housing or health indicators; and better homogeneity within their populations can be assumed, reducing the risk of ecological fallacy (Allik et al., 2020). In addition, the use of aggregate data was more practical as it enabled us to better accommodate the privacy, security, and confidentiality issues associated with using administrative and survey data.

Another real advantage of our study is the use of data from the whole population of Belgium to obtain population-level estimates of inequality measures. Using data from the whole population allowed us to avoid selection bias. All-cause mortality data from death registrations are exhaustive and highly reliable in Belgium (Mikkelsen et al., 2015). Our data can be broken down by geographical area to pinpoint the areas with the greatest health inequalities to ensure their sufficient allocation of public health resources.

This study has limitations that need to be considered when interpreting the results. While the statistical sector is the smallest geographical unit available in Belgium, we should be mindful of problems such as any remaining risk of ecological fallacy (Sedgwick, 2015). Inferences about individuals cannot be drawn from this analysis, as it looks at the effect of group-level characteristics. It would be false to assume that all individuals living in highly deprived areas must themselves be highly deprived, and conversely, that individuals living in relatively less deprived areas must themselves be less deprived.

The HDIs are built on housing characteristics that were recorded on the respective dates of the 1991, 2001, and 2011 population censuses, but they are applied to the 10-year periods that follow each of these. As Spearman’s rank correlations between the overall HDI scores were about 0.7 and correlations between the individual indicators mostly around 0.8 (Table S3.S5 and Table S3.S6 in Supplementary Materials), we assumed that the HDIs are fairly stable over time. However, we cannot eliminate a change in the level of housing deprivation across statistical sectors during 10 years.

Another limitation of our study relates to the fact that information on housing conditions was collected differently in the three censuses. In 1991 and 2001, data were collected through an individual questionnaire, while in 2011 administrative databases were used to update the previously existing information. This difference in data collection can result in comparability issues. Another concern is the absence of information concerning individuals living in communal living facilities, such as nursing homes. The proportion of missing information on housing for those individuals was equal to 75%, 95%, and 89% in the 1991, 2001, and 2011 censuses respectively. For this reason, we have excluded them from our analysis. The amount of missing information on individual housing indicators differed highly across the three censuses. Linking the census data with the national register, we were able to impute missing information based on other family members living in the same household. In addition, we imputed values based on similar profiles – matching individual profiles within a given statistical sector. Although we were able to partially impute some information, missing values still ranged between 2% and 6% in 1991 and 2011, and between 4% and 10% in 2001. Ignoring the missing cases and including only legal residents in our analysis likely led to a slight underestimation of housing inequalities across Belgium. Non-response was shown to be selective in regards of vulnerable individuals of a lower socio-economic status or individuals in poor health (Renard et al., 2019). Illegal residents of Belgium often reside in dwellings of modest or poor quality (Gsir, 2016).

As we use housing conditions as a concrete manifestation of socio-economic status, a question of correlation between housing quality and other factors might arise. Previous studies showed that inequalities in housing are closely related to differences in income or education, and it is possible that some of the inequalities observed here refer to these dimensions. We are currently working on developing a Belgian index of multiple deprivation (BIMD) that integrates the issues of housing, income, education, employment, and crime. Tools such as the BIMD will enable us to isolate the specific contribution of housing conditions – a task currently beyond the scope of this study. It is also very likely that the impact of housing deprivation on health is mediated by lifestyle factors such as tobacco smoking or alcohol consumption.

People living in deprived circumstances generally have higher tobacco and alcohol consumption (Hiscock et al., 2012), and thus, some of these deaths could also be attributed to housing deprivation (Stringhini & Bovet, 2017). Moreover, a debate exists about the extent to which poor health precedes or results from inadequate housing, and evidence supporting both causal directions exist; however this is not a key issue in our study because either pathway confirms the close relationship between inadequate housing and health (Shaw, 2004).

We aimed to measure the extent of health inequality associated with housing conditions rather than capture a causal effect of housing deprivation on health. The design of our cross-sectional study does not allow us to assess the causal relationship between housing deprivation and mortality rates and is not suitable for showing that any of the indicators of the HDIs have caused death or that their improvement would result in a decrease in mortality. Instead, we showed a scenario in which everyone in Belgium had the same mortality as the least deprived decile of the HDIs, without suggesting how this scenario could be achieved. By its very nature, the study is designed to show the scale of health inequalities associated with inadequate housing rather than the cause of the health inequalities.

3.5 Conclusions

Our findings provide a better understanding of the extent to which housing inequalities are associated with mortality and suggest that important socio-spatial inequalities still exist in Belgium. Using composite housing deprivation indices and multiple measures of health inequality, we showed that every year thousands of deaths in Belgium could be avoided if Belgium had the mortality rate of the least deprived decile. Finally, our findings can help the Belgian government and local politicians to locate hotspots of poor housing and their associated health inequalities for better-targeted public action.

Chapter 4 Trends in socioeconomic inequalities in cause-specific premature mortality in Belgium, 1998-2019[3]

4.1 Introduction

Social justice is an essential factor that profoundly impacts our lives and determines our well-being, susceptibility to illnesses, and risk of premature death. The poorest of the poor tend to experience the greatest levels of illness and premature mortality, but a social gradient is evident across most countries, where lower socioeconomic positions correlate with poorer well-being (Marmot et al., 2008).

The association of health and mortality with socioeconomic status has been demonstrated worldwide (Chetty et al., 2016; Datta et al., 2010; Lewer et al., 2020; Schwandt et al., 2021; Stringhini et al., 2011; Zeki Al Hazzouri et al., 2011). Studies of changes in health inequalities over recent decades have shown a widening or persistence

[3] This chapter is published in: Otavova M, Masquelier B, Faes C, Van den Borre L, Vandeninden B, De Clercq E, , Devleesschauwer B. (2023). *Trends in socioeconomic inequalities in cause-specific premature mortality in Belgium, 1998-2019*. BMC Public Health 24, 470 (2024). https://doi.org/10.1186/s12889-024-17933-z. It is reproduced here as in the published version.

in the difference between rich and poor (Leyland et al., 2007; Mackenbach, 2012; Mackenbach et al., 2003; Turrell & Mathers, 2001). For instance, Mackenbach et al. (2003) unveiled an increase in relative inequalities in total mortality in Finland, Sweden, Norway, Denmark, England/Wales, and Italy in the period 1990-2010 (Mackenbach et al., 2003). A study from Canada reported that premature mortality attributable to inequality increased in the years 1995-2005, and about 40% of premature deaths were attributable to deprivation (Saint-Jacques et al., 2014). A more recent study by Lewer et al. (2020) reported that premature mortality rates in England have increased between 2003 and 2018, particularly for women living in the most deprived areas (Lewer et al., 2020).

In Belgium, Renard et al. (2014) studied regional disparities in premature mortality in 1993-2009 and reported an impressive improvement in premature mortality from the leading causes of death in men and women, but also substantial disparities between the regions (Renard et al., 2014). In another study, Renard et al. (2016) used the level of education as a proxy of socioeconomic status (SES) and confirmed a reduction in premature mortality in men and women in the period of 1991-2001, and an increase in relative inequalities in both sexes (Renard, Gadeyne, et al., 2017). Eggerickx et al. (2018) studied the evolution of social differences in mortality in Belgium between 1991 and 2016. They used a multidimensional indicator of deprivation at the individual level and observed a significant increase in social inequalities since the 1990s. In 2021, our team published a study in which we used housing conditions as concrete manifestations of socioeconomic deprivation in Belgium and investigated their association with mortality. Our results showed a decrease in mortality rates but a rise in inequality from 1991 to 2020 (Otavova et al., 2022).

Building on this work, the main objective of this study is to assess the overall magnitude of socioeconomic inequality in all-cause and cause-specific premature mortality between the years 1998 and 2019 in Belgium. The novelty of our study is the use of the Belgian indices of deprivation, measuring the aggregate scale of socioeconomic inequality at the level of the smallest administrative unit in Belgium, the statistical sector (Otavova et al., 2023). By using health metrics, such as premature mortality rates, population attributable fractions, and potential years of life lost, we introduce the scale of the socioeconomic inequality in Belgium in a way that is easy to communicate to policymakers and the public; track health inequality developments over time; and disaggregate the inequality by sex, level of deprivation, and cause of death.

4.2 Methods

Belgian Indices of Multiple Deprivation 2001 and 2011 (BIMD2001 and BIMD2011)

The Belgian indices of multiple deprivation (BIMDs) are time- and spatial-specific tools for measuring multiple deprivation at the level of the statistical sector (Otavova et al., 2023). The BIMDs encompass six domains of deprivation: income, education, employment, housing, health, and crime. These domains are combined to obtain a single score for each geographical area. The scores are then ranked and assigned to deprivation deciles from the most (1) to the least (10) deprived. Figure 4.1 shows the distribution of deprivation deciles in 2001 and 2011. To avoid a correlation between the indices with the health domain and the health outcomes, we re-built the BIMDs without the health domains for this study. The BIMDs are available via https://github.com/bimd-project/bimd, the interactive tool can be found at https://bimd.sciensano.be/tool and more details on the methodology are found in the paper by Otavova et. al. (2023).

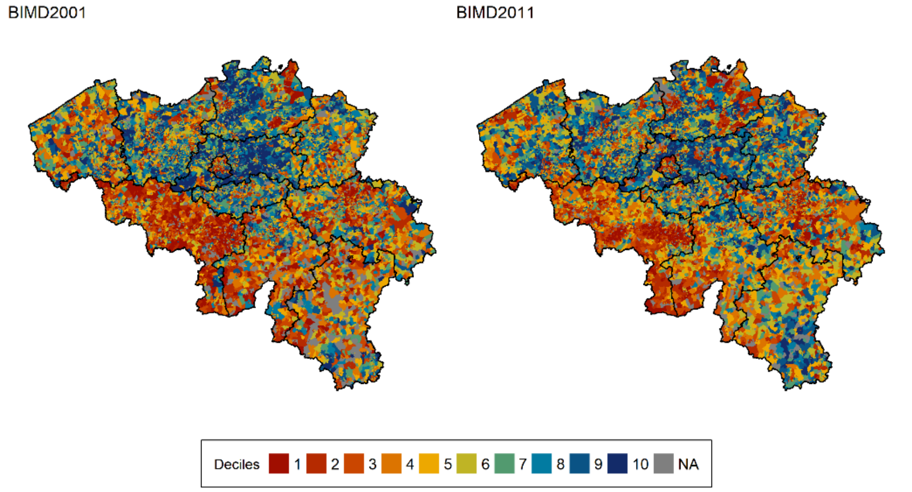


Figure 4.1 Distribution of the BIMD2001 and BIMD2011 deprivation deciles across Belgian statistical sectors in 2001 and 2011.

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 2001 and 2011, equaling to 1,486 (7.5%) and 1,018 (5.2%) statistical sectors, out of which 50.7% (2001) and 36.5% (2011) had zero inhabitants and corresponded to forest, parks, rivers, etc... The total amount of statistical sectors used in our study was therefore 18,295 (in 2001) and 18,764 (in 2011). These statistical sectors are heterogeneous in population size, with a median population of 344 (1st quartile of 133 and 3rd quartile of 759) in 2001 and 347 (1st quartile of 130 and 3rd quartile of 781) in 2011.

The BIMDs were used to categorize deaths and population exposure by deprivation level based on the place of residence at the time of death. We used the BIMD2001 for the periods 1998-2003 and 2004-2008, and the BIMD2011 for the periods 2009-2013 and 2014-2019.

Data

We used pseudonymized individual-level all-cause and cause-specific mortality data extracted from the Civil Registry in Belgium relative to deaths that occurred between Jan. 1, 1998, and Dec. 31, 2019 in people aged 1 to 74 years. Infant deaths were excluded from the present study due two reasons. First, an infant death is officially registered in the National Register (our data source) only when an infant lives through the January 1st. Including the age 0 in our analysis might result in underestimating the infant mortality. Additionally, infant mortality arises from factors that are specific to this age group, and there are more suitable indicators available that better capture mortality within this age group (Renard et al., 2015).

Data included age, sex, the underlying cause of death by International Classification of Diseases-10 code, and a place of residence of the deceased, defined by the statistical sector. Mid-year population estimates by statistical sector, sex, and single-year of age from 1998 to 2019 were obtained from the National Register data, which includes all legal residents of Belgium and excludes irregular migrants and asylum seekers.

Grouping of the causes of deaths

The causes of deaths were grouped using a three-level hierarchy. First, we subset all-cause and all-age deaths to premature deaths (deaths before age of 75), and then we grouped them by ICD-10 chapters (such as I00-I99: circulatory diseases). Second, if a chapter included subcategories responsible for more than 1,000 deaths between 1998 and 2019 (such as I20-I25: ischaemic heart disease), we created a second level showing these subcategories. Finally, if the subcategory included any three-digit diagnosis responsible for more than 1,000 deaths (such as I20: acute myocardial infarction), we created a third level for these diagnoses. Although the threshold of 1,000 deaths was chosen arbitrarily, it corresponded to death counts that were large enough to ensure reliable estimates.

Age-standardized premature mortality rates

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 deaths after the age of 75 are less reliable because of more frequent competing causes of death in older people (Nolte & McKee, 2003). Second, such upper-limit is consistent with the recent definition of avoidable mortality (OECD/Eurostat, 2019).

We stratified the overall and cause-specific mortality and population data to 5-year age groups (except the lowest age group made of children aged 1–4), sex, BIMDs' deprivation deciles, and periods 1998-2003, 2004-2008, 2009-2013, and 2014-2019. We then computed sex- and age-standardized premature mortality rates per 100,000 person-years for each stratum using the sex and age structure of the European standard population 2018.

In addition, a z-test was performed to assess the statistical difference in ASMR between two compared populations. The evaluation between the first and last period and between the most and least deprived deciles is expressed in absolute and relative differences; e.g., (Rate 4^{th} – Rate 1^{st})/rate 1st.

More on the computational approach is included in Supplementary Materials.

Population attributable fraction

We computed the population attributable fraction (PAF) to measure the impact of the inequality in the whole population, and to suggest the percentage of improvement that could be expected, if the whole of Belgium had the premature mortality rates of the least deprived areas. Within each age group, sex, and period, the premature mortality rates of the least deprived decile were used as reference groups and applied to remaining deciles to produce a number of expected deaths under this counterfactual scenario. The mortality attributable to socioeconomic inequality represents the difference between the observed and expected deaths.

A Monte Carlo simulation approach was used to estimate the 95% uncertainty interval (UI). Specifically, we performed 10,000 iterations of random sampling of deaths in each sex, period, decile, and cause of death. The sampling was carried out from a Poisson distribution, with the mean number of deaths serving as the distribution parameter, determined from the observed data. Death rates were computed by dividing the simulated deaths by the corresponding populations at risk, and the death rates of the least deprived decile were then applied to the corresponding population at risk in each stratum to compute the expected number of deaths. Attributable deaths were determined by taking the difference between simulated deaths and expected deaths. The sum of attributable deaths was calculated across all iterations of the Monte Carlo simulation, and the PAF, the ratio of attributable deaths to the total simulated deaths, was computed. The 95% CI for the PAF was obtained by computing quantiles of the PAF distribution.

Potential years of life lost

The potential years of life lost (PYLL) is a summary measure of premature mortality that estimates the years of potential life lost due to premature deaths. We computed crude PYLL for all-cause and cause-specific mortality, stratified by sex, period, and deprivation decile. The number of PYLL was calculated in each stratum by summing the number of deaths at each age between 1-74 years, multiplied by the number of years of life remaining up to the 75th birthday (Romeder & McWhinnie, 1978). The PYLL due to inequality was then computed as an absolute and relative difference between the PYLL in the least deprived decile and the remaining deciles. We report the uncorrected number of PYLL due to our interest in the actual number of deaths distributed by age, sex, and cause, not in the number of deaths in the theoretical standard population obtained by multiplying the specific death rates by the standard population.

In addition, we calculated the age-standardized PYLL per 100,000 persons using the European Standard Population 2018, stratified by sex, period, and deprivation decile. These were introduced to facilitate comparisons between different areas, specifically, between the most and least deprived.

All analyses were done in R version 4.1.1 (*R version 4.1.1*).

4.3 Results

All-cause and cause-specific premature mortality rates, their disparities in time and across deprivation deciles

Table 4.1 presents age-standardized premature mortality rates by sex, deprivation decile, and period (1998-2003, 2004-2008, 2009-2013, and 2014-2019). Over the whole period, the overall premature mortality rate in men and women living in areas considered as the most deprived was 745 (95% CI 741-749) and 381 (95% CI 378-384) per 100,000 person-years, respectively. Premature mortality rates were significantly lower in men and women living in the least deprived areas, estimated at 380 (95% CI 378-384) and 213 (95% CI 210-216) per 100,000 person-years. The ratio of the most/least deprived premature mortality rates in men (1.97; 95% CI 1.96-1.98) differed significantly from the ratio in women (1.79; 95% CI 1.78-1.79).

Comparing 1998-2003 with 2014-2019, the overall premature mortality rates decreased over time in both sexes and across all deciles. The relative difference in the most and least deprived deciles over time was greater in men (25.09% and 36.63%) than in women (15.47% and 25.51%). The relative difference in premature mortality between the most and least deprived deciles increased in men (1998-2003; 82.10% and 2014-2019; 115.28%) as well as in women (1998-2003; 67.61% and 2014-2019; 90.21%). In 1998-2003, mortality rates of men and women living in the most deprived areas were, respectively, 1.82 (95% CI 1.79-1.85) and 1.68 (95% CI 1.64-1.72) higher than in those living in the least deprived areas. In 2014-2019, these ratios increased to 2.15 (95% CI 2.10-2.20) in men and 1.90 (95% CI 1.85-1.96) in women.

Table 4.1 Standardized premature mortality rates per 100,000 person-years.

	1998-2003	2004-2008	2009-2013	2014-2019	All years	Absolute change in time	Relative change in time
Men							
Most deprived	865 (857-874)	775 (767-784)	711 (703-718)	648 (641-654)	745 (741-749)	-217	-25.09%
Least deprived	475 (467-482)	397 (389-405)	343 (335-351)	301 (295-308)	380 (378-384)	-175	-36.63%
Absolute difference	390	378	367	347	365		
Relative difference	82.10%	95.21%	107.29%	115.28%	96.05%		
Women							

Most deprived	414 (408-420)	389 (383-395)	374 (369-380)	350 (345-355)	381 (378-384)	-64	-15.47%
Least deprived	247 (241-253)	216 (211-222)	203 (197-209)	184 (179-189)	213 (210-216)	-63	-25.51%
Absolute difference	167	173	172	166	153		
Relative difference	67.61%	80.10%	84.73%	90.21%	71.83%		

Premature mortality rates are standardized using the European Standard Population 2018. Rates for other deciles are not shown for brevity, and lie monotonically between these values. Change = a relative change in values from 1998-2003 to 2014-2019. Most deprived and least deprived refer to the 1st and 10th deciles as measured in 1998-2003 and 2004-2008 with the BIMD2001; and in 2009-2013 and 2014-2019 with the BIMD2011.

Important differences were observed in cause-specific premature mortality in men and women living in areas identified as most and least deprived by the BIMDs. We ranked the causes of death according to the male and female premature mortality rates. The top 10 causes of death for each sex as ranked in the first period (1998-2003) with their premature mortality rates in the most and least deprived are displayed in Figure 4.2 and Figure 4.3.

In men and women across all causes of death, the most deprived areas had greater premature mortality rates than the least deprived areas. For most causes of death, we observed a reduction in cause-specific premature mortality in the most and least deprived decile in 2014-2019 compared to 1998-2003. This reduction was always greater in the least than most deprived areas, but rates of decline varied by cause of death. For the majority of causes of death in men and women, the relative difference between the most and least deprived areas was greater in the last period under observation (2014-2019), due to a slower decrease in premature mortality in men living in the most deprived, compared to those living in the least deprived areas. For instance, the premature mortality of men caused by neoplasms decreased by 22.01% in the most deprived groups (2014-2019 vs. 1998-2003), and by 32.38% in the least deprived group. As a result, the gap between the most and least deprived in 1998-2003 and 2014-2019 increased, from 42.02% to 63.82%. Similar results were observed in premature mortality rates of neoplasms in women, greater reduction in least deprived areas (20.29% vs. 5.76%) and an increase in the gap between the most and least deprived areas. In 2014-2019, women living in the most deprived areas had 41.17% greater premature mortality rates caused by neoplasms compared to women living in the least deprived areas, whereas in 1998-2003 this difference equaled to 19.40%.

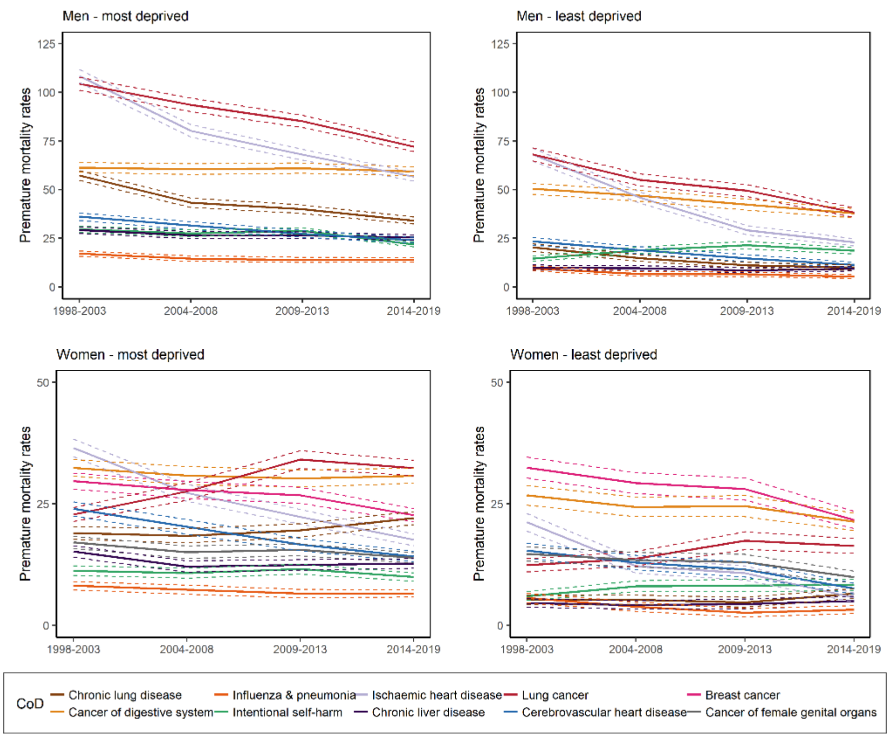


Figure 4.2 Causes of death (CoD) with the highest rates of premature mortality and their development over time for men and women living in the most and least deprived areas.

For a few causes of death, we observed increases in premature mortality risks over time, in both the most and least deprived areas. In women, mortality rates of lung cancer in the most and least deprived areas increased by 41.94% and 32.04% in 2014-2019 vs 1998-2003, whereas mortality rates of chronic lung disease (COPD) increased by 16.11% and 26.34% (Figure 4.2). Mortality increases were also observed when deaths were caused by chronic diseases and conditions related to unhealthy lifestyle behavior, such as drugs and alcohol. For instance, the proportion of deaths caused by drugs or alcohol poisoning doubled and tripled in the most and least deprived deciles.

Another pattern worth mentioning was that some causes of death showed a reduction in the premature mortality rates in the most deprived areas, but an increase in the least deprived areas (1998-2003 vs 2014-2019). For instance, mortality from intentional self-harm demonstrated a decrease by -26.44% and -11.48% among men and women living in the most deprived areas and an increase of 28.00% and

38.70% among men and women in the least deprived areas (1998-2003 vs 2014-2019).

Standardized rate ratios (SRR) of the most/the least deprived premature mortality rates were computed for each category of death in the period 1998-2003 and 2014-2019. A majority of causes of death had an SRR significantly greater in the last period compared to the first period, suggesting that health inequalities have amplified. Some causes demonstrated however a significant decrease in inequality. This was the case of psychoactive substance use by men, and intentional self-harm in men and women

Table 4.2 Top 10 causes of death of premature death (before 75 years of age) in men and their evolution over time in most and least deprived areas in Belgium (1998-2019)

	Period	ASMR (D_1)	ASMR (D_{10})	Absolute difference	Relative difference	ASMR RATIO (95%CI)	p-value (ASMR RATIO)
Premature mortality (men)	1998-2003	865.72 (857.4-874.03)	474.83 (467.19-482.47)	390.89	82.32%	1.82 (1.79-1.85)	<0.001
	2014-2019	647.80 (641.35-654.26)	301.79 (294.95-308.63)	346.01	114.65%	2.15 (2.10-2.20)	<0.001
	Absolute difference	-217.92	-173.04				
	Relative difference	-25.17%	-36.44%				
Ischemic heart disease	1998-2003	108.34 (104.98-111.72)	68.05 (64.74-71.35)	40.30	59.22%	1.59 (1.51-1.65)	<0.001
	2014-2019	56.60 (54.37-58.83)	22.86 (21.00-24.71)	33.74	147.60%	2.48 (2.29-2.68)	<0.001

	Absolute difference	-51.74	-45.19				
	Relative difference	-47.76%	-66.41%				
Lung cancer	1998-2003	104.41 (101.09-107.73)	68.07 (64.74-71.38)	36.34	53.38%	1.53 (1.45-1.60)	<0.001
	2014-2019	72.06 (69.54-74.58)	38.20 (35.81-40.60)	33.85	88.61%	1.89 (1.77-2.01)	<0.001
	Absolute difference	-32.35	-29.87				
	Relative difference	-30.99%	-43.88%				
Neoplasm of digestive system	1998-2003	61.34 (58.79-63.88)	50.39 (47.57-53.21)	10.95	21.73%	1.21 (1.14-1.29)	<0.001
	2014-2019	59.36 (57.07-61.65)	37.86 (35.49-40.23)	21.50	56.81%	1.57 (1.46-1.68)	<0.001

	Absolute difference	-1.98	-12.53				
	Relative difference	-3.22%	-24.86%				
Chronic lung disease	1998-2003	57.20 (54.72-59.67)	20.27 (18.40-22.15)	36.93	182.19%	2.82 (2.59-2.99)	<0.001
	2014-2019	34.07 (32.30-35.85)	9.97 (8.72-11.22)	24.10	241.73%	3.42 (3.06-3.82)	<0.001
	Absolute difference	-23.13	-10.30				
	Relative difference	-40.44%	-50.81%				
Accidents	1998-2003	36.75 (34.99-38.51)	17.27 (15.77-18.76)	19.48	112.79%	2.12 (1.95-2.31)	<0.001
	2014-2019	33.32 (31.75-34.89)	13.79 (12.31-15.27)	19.53	141.62%	2.42 (2.19-2.66)	<0.001
	Absolute difference	-3.43	-3.48				

	Relative difference	-9.3%	-20.15%				
Cerebrovascular heart disease (Stroke)	1998-2003	36.08 (34.12-38.03)	23.46 (21.49-25.43)	12.62	53.79%	1.54 (1.40-1.65)	<0.001
	2014-2019	23.98 (21.49-25.43)	11.34 (9.98-12.7)	12.64	111.46%	2.11 (1.88-2.38)	<0.001
	Absolute difference	-12.10	-12.12				
	Relative difference	-33.54%	-51.66%				
Chronic liver disease	1998-2003	29.23 (27.53-30.93)	9.98 (8.76-11.20)	19.25	192.88%	2.93 (2.61-3.25)	<0.001
	2014-2019	25.34 (23.91-26.77)	9.29 (8.13-10.45)	16.05	172.76%	2.73 (2.43-3.06)	<0.001
	Absolute difference	-3.89	-0.69				

	Relative difference	-13.30%	-6.91%				
Intentional self-harm	1998-2003	29.61 (28.03-31.20)	14.50 (13.14-15.85)	15.11	104.21%	2.04 (1.85-2.25)	<0.001
	2014-2019	21.78 (20.55-23.00)	18.56 (16.88-20.24)	3.22	17.35%	1.17 (1.06-1.30)	<0.001
	Absolute difference	-7.83	4.06				
	Relative difference	-26.44%	28.00%				
Influenza & Pneumonia	1998-2003	17.06 (15.72-18.41)	9.49 (8.17-10.80)	7.57	79.78%	1.80 (1.55-2.02)	<0.001
	2014-2019	13.93 (12.80-15.06)	5.26 (4.29-6.22)	8.67	164.82%	2.65 (2.24-3.13)	<0.001
	Absolute difference	-3.13	-4.23				
	Relative difference	-18.35%	-44.57%				

Neoplasm of urinary system	1998-2003	14.56 (13.31-15.82)	12.51 (11.08-13.93)	2.05	16.39%	1.16 (1.01-1.31)	<0.001
	2014-2019	12.29 (11.23-13.36)	9.32 (8.11-10.54)	2.97	31.87%	1.32 (1.13-1.53)	<0.001
	Absolute difference	-2.27	-3.19				
	Relative difference	-15.60%	-25.49%				

Table 4.3 Top 10 causes of death of premature death (before 75 years of age) in women and their evolution over time in most and least deprived areas in Belgium (1998-2019)

	Period	ASMR (D_1)	ASMR (D_{10})	Absolute difference	Relative difference	ASMR RATIO (95%CI)	p-value (ASMR RATIO)
Premature mortality (women)	1998-2003	413.95 (408.20-419.71)	246.97 (241.43-252.51)	166.98	67.61%	1.68 (1.64-1.72)	<0.001

	2014-2019	349.91 (345.08-354.74)	183.86 (178.50-189.21)	166.02	90.31%	1.90 (1.85-1.96)	<0.001
	Absolute difference	-64.04	-63.11				
	Relative difference	-15.47%	-25.55%				
Ischemic heart disease	1998-2003	36.50 (34.72-38.29)	21.20 (19.39-23.01)	15.30	72.17%	1.72 (1.57-1.88)	<0.001
	2014-2019	17.59 (16.40-18.78)	5.72 (4.79-6.64)	11.87	207.52%	3.08 (2.67-3.55)	<0.001
	Absolute difference	-18.91	-15.48				
	Relative difference	-51.8%	-73.0%				
Neoplasm of digestive system	1998-2003	32.40 (30.70-34.10)	26.75 (24.72-28.77)	5.65	21.12%	1.21 (1.10-1.32)	<0.001
	2014-2019	30.77 (29.20-32.34)	21.30 (19.52-23.08)	9.47	44.46%	1.44 (1.32-1.58)	<0.001

	Absolute difference	-1.63	-5.45				
	Relative difference	-5.10%	-20.40%				
Breast cancer	1998-2003	29.64 (28.01-31.28)	32.45 (30.30-34.60)	2.81	8.65%	0.91 (0.84-0.99)	<0.001
	2014-2019	22.65 (21.32-23.99)	21.66 (19.88-23.44)	0.99	4.57%	1.05 (0.95-1.16)	<0.001
	Absolute difference	-6.99	-10.79				
	Relative difference	-23.58%	-33.25%				
Lung cancer	1998-2003	22.79 (21.35-24.23)	12.36 (11.00-13.73)	10.43	84.39%	1.84 (1.64-2.09)	<0.001
	2014-2019	32.35 (30.76-33.95)	16.32 (14.78-17.86)	16.03	98.22%	1.98 (1.80-2.18)	<0.001
	Absolute difference	9.56	3.96				

	Relative difference	41.94%	32.04%				
Cerebrovascular heart disease (Stroke)	1998-2003	23.97 (22.52-25.43)	15.39 (13.84-16.93)	8.58	55.75%	1.84 (1.64-2.09)	<0.001
	2014-2019	14.17 (13.10-15.25)	7.58 (6.46-8.69)	6.59	86.95%	1.98 (1.80-2.18)	<0.001
	Absolute difference	-9.8	-7.81				
	Relative difference	-40.88%	-50.74%				
Chronic lung disease (COPD + Asthma)	1998-2003	18.99 (17.69-20.29)	5.2 (4.27-6.14)	13.79	265.19%	3.65 (3.14-4.28)	<0.001
	2014-2019	22.05 (20.72-23.39)	6.57 (5.55-7.59)	15.48	235.61%	3.36 (2.94-3.83)	<0.001
	Absolute difference	3.06	1.37				
	Relative difference	16.11%	26.34%				

Female genital organs cancer	1998-2003	17.05	14.69	2.36	16.06%	1.16	<0.001
		(15.81-18.29)	(13.22-16.15)			(1.03-1.28)	
	2014-2019	13.91	9.91	4	40.36%	1.40	<0.001
		(12.87-14.96)	(8.69-11.14)			(1.22-1.61)	
	Absolute difference	-3.14	-4.78				
	Relative difference	-18.42%	-32.53%				
Chronic liver disease	1998-2003	15.18	4.59	2.31	230.72%	3.30	<0.001
		(13.99-16.37)	(3.74-5.45)			(2.80-3.85)	
	2014-2019	12.74	5.02	7.72	153.78%	2.54	<0.001
		(11.74-13.73)	(4.10-5.93)			(2.16-2.98)	
	Absolute difference	-2.44	0.43				
	Relative difference	-16.07%	9.37%				
Intentional self-harm	1998-2003	11.23	6.02	5.21	86.54%	1.86	<0.001
		(10.24-12.21)	(5.09-6.95)			(1.58-2.22)	
	2014-2019	9.94	8.35	1.59	19.04%	1.19	<0.001

		(9.09-10.79)	(7.18-9.51)			(1.02-1.39)	
	Absolute difference	-1.29	2.33				
	Relative difference	-11.48%	38.70				
Influenza & Pneumonia	1998-2003	8.16	5.65	2.51	44.43%	1.45	<0.001
		(7.29-9.04)	(4.62-6.67)			(1.19-1.70)	
	2014-2019	6.57	3.24	3.33	102.78%	2.0	<0.001
		(5.83-7.31)	(2.45-4.02)			(1.61-2.55)	
	Absolute difference	-1.59	-2.41				
	Relative difference	-19.49%	-42.65%				

The detailed analysis of inequalities in cause-specific premature mortality across age groups, measured by the SRR, revealed that the magnitude and location differ by cause of death, sex, and period studied. For several causes of death, the inequality has moved toward the higher ages over time, but their peaks were more pronounced in 1998-2003, compared to 2014-2019. This trend was observed for instance in male deaths caused by chronic lung disease and chronic liver disease with their highest points of inequality moving from the age group of 50-54 to 65-69, and from 40-44 to 50-54 during the twenty years under study. In women, the same trend was observed in deaths by chronic liver disease or intentional self-harm, for which the peak of inequality moved from the age group of 45-49 to 50-54, and from 25-29 to 35-39. On the contrary, some causes of death showed greater inequality peak at higher ages spreading across several age groups in the last period compared to the first period studied. This trend was observed in deaths by cancer of the digestive or respiratory system, stroke, or accident in men; in deaths by breast cancer in women; and deaths by ischaemic heart disease in both.

Lastly, for several causes of death, the level of inequality in the first period studied was consistently higher across all ages compared to the last period, such as hypertension or certain types of cancer (cancer of mouth, lymphoid, bone and articular cartilage), in both, men and women. A more comprehensive overview of cause-specific premature mortality rates in men and women is provided in Tables S4.S2 and S4.S3 in Supplementary Materials.

Overall and cause-specific premature mortality attributable to socioeconomic inequality in Belgium

We computed the proportion (PAF) of premature mortality attributable to socio-economic inequality for both all-cause and cause-specific premature mortality. Of the 789,666 premature deaths that occurred in Belgium between 1998-2019, 27.6% (95% CI 27.1-28.2) were attributable to socioeconomic inequality. The PAF was greater in men (29.1%, 95% CI 28.4 – 29.8) compared to women (25.1%, 95% CI 24.2-26.1).

Table 4.4 Population attributable fraction of premature mortality associated with socioeconomic inequality by sex and period and 95%CI.

	1998-2003	2004-2008	2009-2013	2014-2019	All years	Relative difference between 1st and 4th period
Men	25.5 (24.2-26.8)	28.0 (26.6-29.5)	31.9 (30.4-33.5)	34.2 (32.8-35.6)	29.1 (28.4-29.8)	34.04%
Women	21.8 (19.9-23.6)	24.2 (22.2-26.2)	26.4 (24.2-28.5)	29.9 (28.1-31.9)	25.1 (24.2-26.1)	26.23%
Absolute difference	3.75	3.81	5.52	4.20	4.00	

Our results also showed an increase in premature mortality attributable to inequality over time (Table 4.4). The overall PAF has increased from 24.2% (95% CI 23.1-25.2) in 1998-2003 up to 32.6% (95% CI 31.5-33.7) in 2014-2019. Sex differences were observed in PAF development over time. In 1998-2003 and 2014-2019, premature mortality attributable to SE inequality was greater in men (25.5%, 95% CI 24.2-26.8; 34.2%, 95% CI 32.8-35.6) than in women (21.8%, 95% CI 19.9-23.6; 29.9%, 95% CI 28.1-31.9). These numbers, however, suggested a similar increase in women (8.2%) as in men (8.6%). From 1998 to 2019, the greatest proportion of overall premature deaths attributable to inequality occurred in men aged 40-59 years (around 60%), and in women aged 40-54 years (more than 50%), living in the most deprived areas, respectively (Figure S4.S4 in Supplementary Materials).

Considering the leading causes of death, the greatest inequality was observed for deaths due to psychoactive substance use (50.9%, 95% CI 44.9-56.8), chronic lung disease (47%, 95% CI 44.5-49.5), and chronic liver disease (43%, 95% CI 40-46.2). Almost half of these deaths were attributable to inequality. External causes of death, such as deaths due to accidents (33.7%, 95% CI 31.1-36.3) showed high inequalities as well. Almost one-fourth of the deaths caused by diseases of the circulatory system could be attributable to inequality, with leading causes of ischaemic heart diseases (26%, 95% CI 24-28) and cerebrovascular heart disease or stroke (22%, 95% CI 19.2-25.1). Causes of death with the greatest proportion of premature mortality attributable to inequality are shown in Figure 4.3.

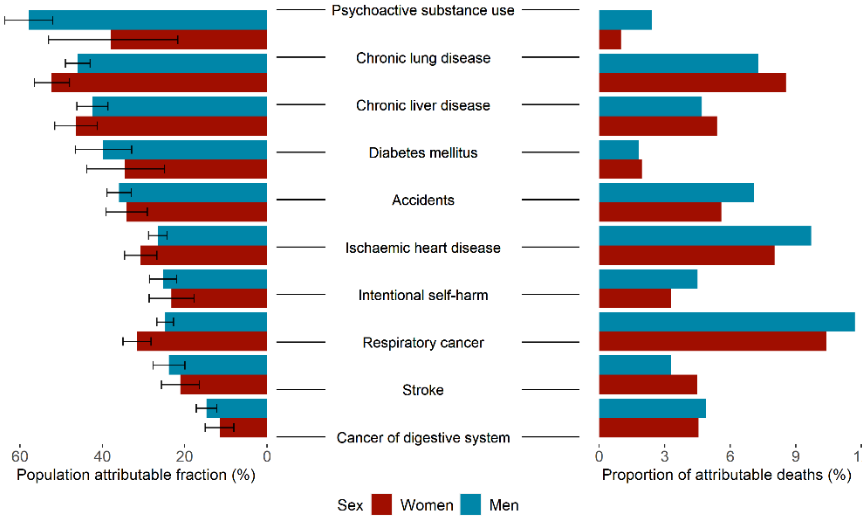


Figure 4.3 Causes of death with the greatest proportion of premature mortality attributable to socioeconomic inequality and their contributions to the total number of attributable deaths, 1998-2019.

Neoplasms generally have low inequality, but neoplasms of liver and intrahepatic bile ducts (28.1%, 95% CI 22.6-33.5), neoplasms of mouth (26.4%, 95% CI 20.5-32.1), lung (25%, 95% CI 22.6-26.2) and larynx (23.3%, 95% CI 14.5-32.6) were exceptions, with higher proportions of deaths attributable to inequality. The contribution of considered diseases to the total number of attributable deaths, was greatest for lung cancer, ischaemic heart disease, and chronic lung diseases, equaling about 10%.

Our results showed only a few significant differences in PAF of major ICD10 chapters in men and women and across periods. In men, circulatory diseases, neoplasms, and respiratory diseases increased by 15%, 8%, and 10% in the 4th period under study, compared to the 1st period. In women, only circulatory diseases and neoplasms showed an increase of 16% and 10% in premature mortality attributable to inequality over time. Across all major causes of death, middle-aged men and women in the most deprived groups had the greatest proportion of premature mortality attributable to inequality.

The contribution of diseases to the total number of attributable deaths was similar for men and women across all periods under study. Table S4.S4 in Supplementary Materials shows a detailed overview of the cause-specific PAF.

Crude PYLL due to inequality in Belgium since 1998

From 1998 to 2019, a total number of 11,221,841 potential years of life (PYLL) were lost in Belgium, about 64.5% (7,243,567) in men and 35.5% (3,978,274) in women. Using the deprivation deciles, we computed the expected number of PYLL in Belgian men (4,899,798) and women (2,892,879), if all had the same mortality rates as those living in the least deprived areas. Potential years of life lost due to inequality represented 32.3% (2,343,769) of all PYLL in men and 27.3% (1,085,395) of all PYLL in women.

In both sexes, the greatest contributors to the overall PYLL were deaths by neoplasms, contributing by 29.4% in men and 40.9% in women. However, after decomposing the ICD-10 chapters into smaller subgroups of deaths, the results showed the following causes of death contributed the most to the overall PYLL. In men – deaths by accident (11.4%), intentional self-harm (10.1%), lung cancer (9.4%), ischaemic heart disease (8%), cancer of the digestive system (7.5%), and chronic liver disease (3.7%). In women, the following causes of death contributed the most to the overall PYLL – deaths by breast cancer (10.3%), lung cancer (7.4%), deaths by accident (6.7%), intentional self-harm (6.5%), cancer of female genital organs (4.7%), ischaemic heart disease (4.3%), stroke (4%), and chronic liver disease (3.3%).

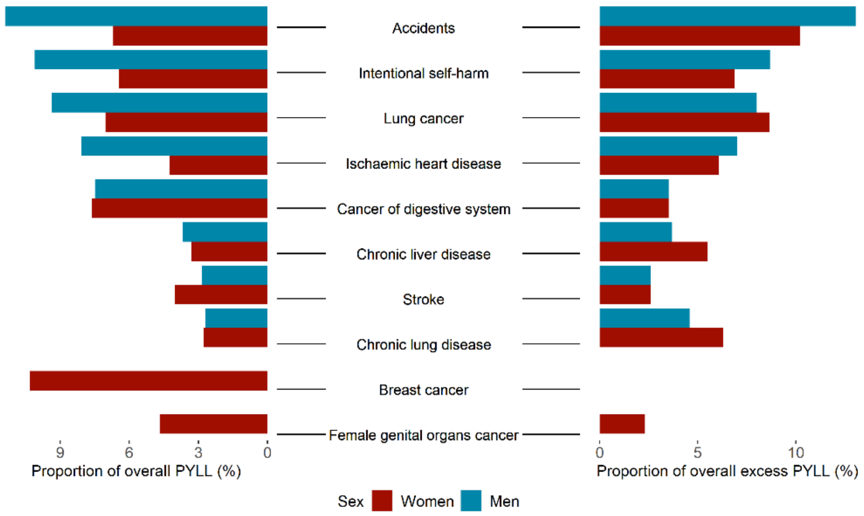


Figure 4.4 Causes of death with greatest contribution to the overall crude PYLL (left) and their contribution to the excess number of PYLL (right).

The subgroups of cause-specific deaths contributing the most (with more than 5%) to the excess PYLL (Figure 4.4) were in men the deaths by accident (305,755 - 13.5%), intentional self-harm (203,386 - 8.7 %), lung cancer (187,816 - 8.01%), ischaemic heart disease (164,408 - 7.1%), chronic liver disease (129,064 - 5.5%). In women, the causes of deaths contributing with more than 5% to the overall excess PYLL included deaths by lung cancer (71,876 – 8.7%), intentional self-harm (74,472 – 6.9%), chronic lung disease (68,325 – 6.3%), and ischaemic heart disease (65,888 – 9.1%).

Age-standardized PYLL due inequality in Belgium since 1998

We computed the age-standardized PYLL per 100,000 by sex, deciles and period. In the period studied, 6,474 PYLL and 3,418 PYLL per 100,000 men and women were observed. In men and women, PYLL were decreasing over time across all deprivation deciles. The decrease was greater among the least deprived, peaking in men (-36%). The relative difference in the most and least deprived stayed almost constant. More details are provided in Table 4.5.

Table 4.5 Overview of age-standardized PYLL per 100,000 persons by sex, period and the most and least deprived deciles.

	All years	1998-2003	2004-2008	2009-2013	2014-2019	Absolute difference	Relative difference
Overall	5,485	6,408	5,674	5,208	4,648	-1,760	-27.47%
Men	6,474	8,261	7,283	6,398	5,592	-2,613	-30.89%
most deprived	10,192	12,076	10,792	9,564	8,337	-3,739	-30.96%
least deprived	4,817	5,944	5,070	4,449	3,804	-2,140	-36.00%
Absolute difference	-5,376	-6,131	-5,723	-5,116	-4,533	1,598	-26.06%
Relative difference	-52.7%	-50.8%	-53.0%	-53.5%	-54.3%		
Women	3,418	4,242	3,914	3,631	3,336	-902	-20.78%
most deprived	5,351	5,919	5,490	5,292	4,701	-1,218	-20.58%
least deprived	2,856	3,331	2,925	2,725	2,445	-885	-26.58%
Absolute difference	-2,494	-2,589	-2,566	-2,567	-2,256	333	-12.86%

Relative difference	-46.1%	-43.7%	-46.7%	-48.1%	-49.0%

The number of observed and expected PYLL per 100,000 persons has been decreasing over time in both sexes, the relative difference in observed vs expected has increased in men from 27.9% up to 31.6% and in women from 22.4% to 26.7%, 1998-2003 vs 2014-2019.

A detailed overview of the number of observed and expected PYLL per 100,000 person-years is presented in Table S4.S5 in Supplementary Materials, whereas crude PYLL by causes of death stratified by men and women is shown in Tables S4.S6 and S4.S7 in Supplementary Materials.

4.4 Discussion

This is the first Belgian study that investigates deprivation-driven inequalities in premature mortality using the 2001 and 2011 Belgian indices of multiple deprivation to shed light on pronounced socioeconomic inequalities in several health indicators. Compared to men and women living in the least deprived statistical sectors, those living in the most deprived statistical sectors had a 96% and 78% greater chance of dying prematurely. Almost 28% of all premature deaths were attributable to socioeconomic inequality, corresponding to 1 person dying prematurely every hour in Belgium since 1998. About 30% of potential years lost due to socioeconomic inequality would be saved if the whole of Belgium had the premature mortality rates of the least deprived areas. The relative decrease in premature mortality was greater in men than in women (25% vs 15%), and in the most and least deprived deciles (36% vs 25%). The inequality has increased due to a faster pace of decrease in the least deprived areas compared to the most deprived areas. The relative difference between the most and least deprived areas increased in men and women by about 8%.

We observed the greatest inequality in premature mortality for respiratory, mental and behavioral, and digestive diseases, whereas much less inequality was observed for neoplasms, musculoskeletal, and nervous diseases. The greatest inequality measured by the PAF and PYLL was observed in psychoactive substance use, chronic lung and liver disease, obesity, and diabetes mellitus, which are causes of death linked to increased opiate, alcohol, and tobacco consumption, or poor diet. The PAF tended to increase with age and peaked in men and women in the late middle age (ages 45-64).

Our study confirms findings from previous studies that reported a decrease in premature mortality rates and an increase in health inequality in Belgium over time (Damiens, 2020; Eggerickx et al., 2018; Renard, Gadeyne, et al., 2017; Renard et al., 2014, 2015). The findings of the current study also represent a valuable extension to our previous study (Otavova et al. 2022) in which we used area-based housing indices, later integrated into the BIMDs, to investigate the association between poor housing and all-ages mortality (Otavova et al., 2022). The greater magnitude of inequality reported in the current study might suggest that housing indices only partially capture inequalities and the role of other factors, such as education and income must be considered to have a more comprehensive picture.

Although our study design does not allow us to assess a causal relationship between deprivation and health, some reasonable hypotheses can be derived to interpret the trends we observe. The substantial decrease in deaths caused by ischaemic heart disease in the most and least deprived deciles suggests a positive impact of health policies, and successful education of the population regarding healthy diet and healthy lifestyle (Amine et al., 2003; Sørensen et al., 2012), or improvements in prevention (screening strategy) followed by adequate medical treatment. A fall in deaths by road accidents reflects the drastic measures in road security policies (De Pauw et al., 2014). Development of more effective treatments (hormone, chemo, or immunotherapy) and successful implementation of screening programs led to a decrease in deaths by breast cancer (Goossens et al., 2019), male and female genital cancer (Van Kerrebroeck & Makar, 2016), colorectal cancer (Tran et al., 2023), lymphoid and hematological cancer by more than one third in the most and least deprived deciles.

Almost 40% and 20% increase in premature deaths caused by liver cancer in men in the most and least deprived deciles might result from a change in reporting (Renard et al., 2014), but other factors, could play a role. Thus, further studies should be conducted to explain this change.

Smoking represents the main risk factor for lung cancer, accounting for 80-90% of all cases (Walser et al., 2008). In Belgium, lung cancer in men has been decreasing since the 1990s (Renard et al., 2014), and our results show a similar trend – a decrease across all deprivation groups and an increase in premature rates with age. Over recent decades smoking prevalence has declined faster in upper than lower socioeconomic groups in northern Europe, resulting in strong socioeconomic gradients in smoking (Cavelaars et al., 2000; Van der Heyden et al., 2009). Our results also show that deaths by lung cancer decreased faster in men in the least deprived groups (-44%) compared to the most deprived groups (-31%). On the contrary, the female lung cancer premature rates increased by 42% for those living in the most deprived areas and by 32% for those living in the least deprived areas.

This reflects the well-known sex differences in the timing of the smoking epidemic (Dai et al., 2022).

Strengths and limitations

Our study has two major strengths: the utilization of the Belgian indices of multiple deprivation and the cause-specific analysis of carefully selected health indicators. We used BIMDs that combine data on income, education, employment, housing, and crime to provide insight into health inequalities associated with upstream socioeconomic circumstances. Our decision to use these indices and measure inequality at the aggregate level was justified by several arguments. A main benefit of the BIMD use is the wider range of disadvantageous circumstances covered. The intersection of various disadvantages can concurrently influence health and health behavior, and given the diversity of Belgian society, researchers in population health must consider the interplay between different dimensions of disadvantage – a task for which the BIMDs are well-suited. We were also interested in capturing area deprivation effects as conceptualized in three different meanings: as compositional (i.e. a proportion of deprived people living in the area), as collective, and as environmental (i.e. socio-cultural and historical features of communities or environmental features, synonymous with neighborhood effect) (Sally Macintyre, 1997). It has been shown that, even after accounting for individual risk factors, neighborhoods still strongly affect their inhabitants (Cubbin et al., 2000; Duncan et al., 1999; Dunn & Hayes, 2000; Pickett & Pearl, 2001; Shaw, 2004). Using the BIMD, we were able to include all three dimensions, but it became difficult to isolate individual effects, as the tool is constructed on the aggregation of individual variables. Furthermore, an inherent strength of the indices is their easy replicability, allowing for future updates with the most recent data, and hence, a follow-up study can be conducted to track future developments in health inequalities since 2019 in Belgium.

Another major benefit of our study is a detailed cause-specific analysis of health inequalities by premature mortality, population attributable fraction, and potential years of life lost. Whereas the PAF offers an estimate of the potential reduction in premature mortality if socioeconomic inequalities were eliminated, the PYLL completes the picture by weighting the burden of each condition with the loss of quantity of life (Renard et al., 2014). To compute these population-level estimates of inequality, we utilized cause-specific data from the whole population of Belgium, ensuring the maximum statistical power and avoidance of selection bias. The method of computing the premature mortality associated with inequality is replicable in other settings and can be used to make comparison studies. Our results can be disintegrated by cause of death, and, due to our aggregate approach, we can spatially identify the most prevalent causes of death and pinpoint geographical areas in need of interventions reducing health inequalities. By ranking the causes of premature deaths based on premature mortality rates, PAF, and PYLL we are able to help setting up priorities for policy makers.

In choosing a suitable geographical area, we preferred the smallest administrative unit in Belgium, the statistical sector. This choice was validated by the fact that statistical sectors are official administrative units; their boundaries change little over time (Otavova et al., 2023); they are large enough to provide statistically robust estimates; and better homogeneity within their populations can be assumed, reducing the risk of ecological fallacy (Allik et al., 2016; Allik et al., 2020). Additionally, the use of aggregate data was more practical and enabled us to accommodate the privacy, security, and confidentiality issues associated with a use of the administrative and survey data more easily. We were also given an access to data that were used for the crime and health domains, that would otherwise be unavailable or the process of obtaining them would be too lengthy.

The study has limitations that need to be considered when interpreting the results. As we investigate the association between deprivation and health at the aggregate level, inferences about individuals cannot be drawn. An ecological fallacy would be committed (Sedgwick, 2015) by falsely assuming that individuals living in the most deprived areas must themselves be highly deprived, and conversely, that those living in the least deprived areas must themselves be less deprived.

The indices are built on census and register data related mostly to years 2001 and 2011, but the BIMD2001 and BIMD2011 are applied to the period 1998-2008 and 2009-2019. As the Spearman's rank correlation coefficient between the indices is 0.9, we assume that the BIMDs are fairly stable over time. However, we cannot eliminate a possible change in the level of deprivation across statistical sectors during the periods under study.

Another limitation of the current study is that we are unable to capture morbidity or quality of life aspects based on the death registration data. There is also a risk of misclassification as mortality data rely on death certificate data of which quality is questionable for certain groups and certain causes of death (Aelvoet et al., 2005). By restricting our analysis to data from 1998 to 2019 and by limiting the scope to premature deaths (1-74 years), we avoided the more questionable periods and higher age groups in which the causes of deaths are reported with more errors and multi-morbidity plays an increasing role.

Our analysis accounted for differences in age and sex between deprivation groups but were not able to adjust for other variables, such as migrant status. The migrant status might be a confounder for diseases with a strong genetic or migration-related risk (Bhopal et al., 2018; Smith et al., 2010). Internal mobility was also not considered as the deprivation deciles could only be assigned once to the deceived, i.e. at the time of death. The place of death was identified as the place where a deceased was officially registered, but it might not correspond to the place he or she was exposed to specific risk factors across the life course.

In the current study, we measured the extent of health inequality associated with socioeconomic deprivation as defined by the BIMDs but we could not capture a causal effect of deprivation on health. The design of our cross-sectional study does not allow us to assess the causal relationship between deprivation and premature mortality and is not suitable for showing that any of the domains of the BIMDs have caused death or that their improvement would result in a decrease in premature mortality. Instead, we showed a scenario in which the whole of Belgium had the same premature mortality rates as the least deprived deciles of the BIMDs, without suggesting how this scenario would be achieved. By its very nature, the study is designed to show the scale of health inequalities associated with deprivation rather than the cause of the health inequalities.

4.5 Conclusion

We studied the trends and disparities in premature mortality in Belgium and provided a better understanding of the extent to which area-level deprivation is associated with premature deaths. Our study showed that premature mortality decreased but health inequalities increased over time and every year, thousands of deaths in Belgium could be avoided if Belgium had the premature mortality rates of the least deprived decile. The greatest inequality in causes of death is related to behavior risk factors, such as alcohol consumption or tobacco and illicit drug use. These results emphasize the importance of a more in-depth evaluation of health and social policies, and a need of new, country-level interventions that aim to protect those with a lower socioeconomic status more effectively from health-deteriorating lifestyles and environments.

Chapter 5 Spatial variation in cause-specific premature mortality and association with socioeconomic deprivation in Belgium from 2000 to 2019[4]

5.1 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 (Lewer et al., 2020; Marmot et al., 2008; World Health Organization, 2013). 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, poor housing, environmental conditions, and health. Thus, addressing the spatio-temporal variation in premature mortality

[4] This chapter has not been published yet.

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 (Gadeyne, 2006; Van Oyen et al., 2011). 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. 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. 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).

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. 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. 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.

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 (Hagedoorn, Vandenheede, Willaert, et al., 2016; Hamad et al., 2020; Signorello et al., 2014; Van der Heyden et al., 2009). 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 (Pickett & Pearl, 2001) and mortality (Meijer et al., 2012). Other explanations of regional differences include environmental factors, 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 (Deboosere & Gadeyne, 2002).

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) (Otavova et al., 2023), 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:

- Which geographical areas exhibit the highest risk of dying prematurely?
- Is the subnational variation in cause-specific risk of premature death decreasing or increasing?
- What effects do overall socioeconomic deprivation or domain-specific deprivation have on subnational variations in the cause-specific risk of premature death?

5.2 Methods

Belgian Index of Multiple Deprivation (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 (Otavova et al., 2023). 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 amount of statistical sectors was therefore 18,764.

In this study, the BIMD2011 scores were then used for 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 dividing 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 with an increase in an average deprivation score, deprivation increases. Figure 5.1 shows the distribution of the average deprivation scores assigned to deprivation deciles at the municipal level. More details on the distribution of the overall and domain-specific average deprivation scores can be found in Figure S5.S1 and Table S5.S1 in the Supplementary materials.

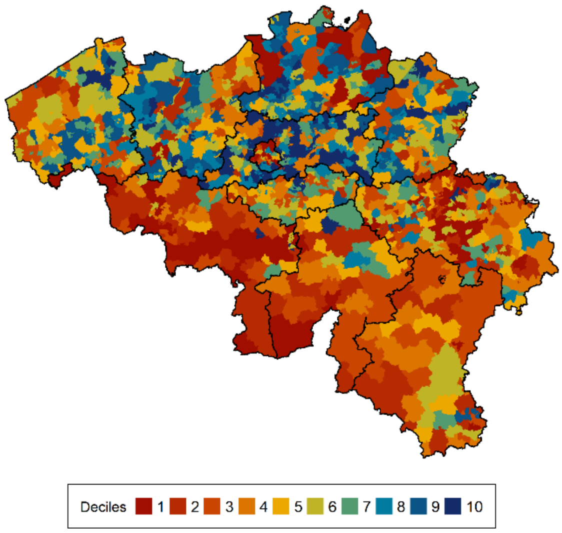


Figure 5.1. Distribution of average deprivation scores assigned to deciles from 1 (most deprived) to 10 (least deprived) in 2011.

Geographical and administrative division of Belgium

Reporting subnational results requires a brief introduction to the country's geographical division between the years 2000-2019. 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 Jan. 1, 2000, and Dec. 31, 2019, in people aged 1 to 74 years. Infant deaths were excluded from the present study for two reasons. First, an infant's death is officially recorded in the National Register (our data source) 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 death 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-10 code, 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 (Nolte & McKee, 2003). Second, such an upper limit is consistent with the recent definition of avoidable mortality (OECD/Eurostat, 2019). Premature mortality represents a small fraction of all deaths – between 2000 and 2019, 34.7% of all deaths were.

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 oesophageal cancer (referred to as mouth cancer throughout the article); (3) colorectal cancer; (4) diabetes mellitus; (5) 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 5.1). The selected causes of death represent a relevant public health problem because of the large number of corresponding deaths, possibly avoidable through effective prevention or treatment (OECD, 2019; Sciensano, 2024a).

Table 5.1 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 Oesophageal 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

Standardized mortality ratios (SMR)

For each municipality *m*, *m* = 1,…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,…,4, referring to 2000-2004, 2005-2009, 2010-2014, and 2015-2019. It can be expressed as follows:

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

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 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 modelling

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 the limited sample sizes. In contrast, modeling techniques are preferred 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 small sample sizes (Gelfand et al., 2010). Therefore, a common approach is to model the observed counts $Y_i, i = 1, \ldots, n,$ 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:

$$Y_{smp} \sim Poisson\left(E_{smp}\theta_{smp}\right)$$

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

We assume a Poisson distribution for the number of deaths, Y_{smp}, for sex *s*, municipality *m*, and period *p*, 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 (R Core Team and contributors worldwide), with independent variables average deprivation score (numerical) and period (categorical).

Moran's I statistic was used to check the presence of spatial autocorrelation, (Moran, 1950). It is given by:

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

where r_m denotes the residual for the *m^th^* municipality. In addition, w_{mn} denotes whether

the pair of municipalities (*m,n*) is 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 strong 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 a presence of spatio-temporal correlation, the popular Besag-York-Mollié (BYM) model with a spatial structure and a spatio-temporal model proposed by Bernardinelli et al. (1995) were fitted (Bernardinelli et al., 1995; Besag et al., 1991). The selection of the final model was based on the deviance information criterion DIC (Spiegelhalter et al., 2002).

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

$$log(\theta_{smp}) = \alpha + \beta_1 x_{smp} + \beta_2\, period + \mu_{smp} + v_{smp} + \gamma_{smp}$$

where $\mu_m + v_m$ are the spatially structured and unstructured random effects for municipality *m*; γ_p is the main temporal random effect for period *p*. The spatially structured random effect μ_m is assigned a Conditional Autoregressive distribution smoothing the data according to a neighborhood structure. The unstructured component v_m models uncorrelated noice $v_m \sim (0, \sigma_v^2)$. We used the Gamma prior for the precision of the random effect μ_m. The Gamma prior is defined as:

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

.

Implementation in R - INLA method

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 (Rue et al., 2018). 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 (*R version 4.1.1*).

5.3 Results

Which geographical areas exhibit the highest risk of dying prematurely?

Figure 5.2 displays the relative risk of premature mortality for each Belgian municipality during the study's first (2000-2004) and last (2015-2019) periods, with estimates presented separately for men and women. The figure reveals temporal and spatial variations in relative risks of premature death across Belgian municipalities. A clear North-South gradient was observed between Flanders and Wallonia, with Wallonia exhibiting higher relative risks of premature death. Areas with elevated relative risks were spatially concentrated, forming a continuous belt that began near the French border in municipalities within the districts of Tournai and Mons, extended through Thuin, Charleroi, Namur, Huy, and Liège, and terminated at the German border in the district of Verviers.

In both the initial 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.

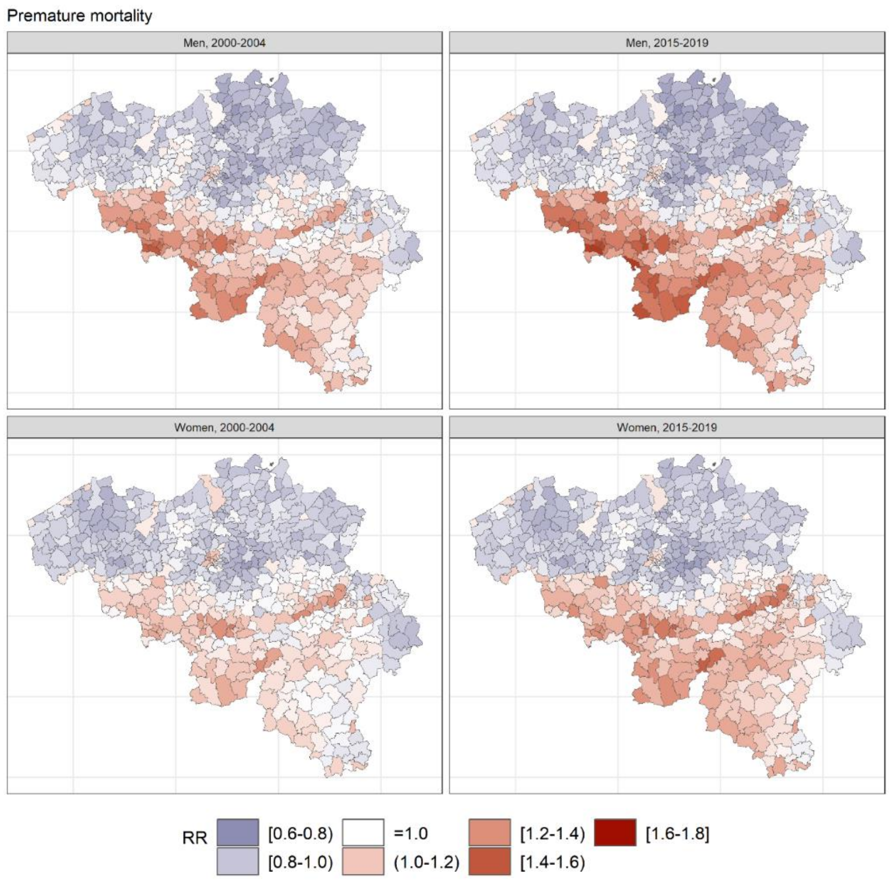


Figure 5.2 Spatial and temporal distribution of RR of premature mortality in Belgium in the first period (2000-2004) and last period (2015-2019) studied, by sex.

The spatial distribution of cause-specific relative risks exhibited various patterns, including North-South, Northwest-Southeast, and West-East gradients, and mixed patterns. Several causes of premature death—cardiovascular diseases (Figure S5.S2), cerebrovascular diseases (Figure S5.S3), alcohol consumption (Figure S5.S4), COPD (Figure S5.S5), diabetes mellitus (Figure S5.S6), mental and neurological diseases (Figure S5.S7), non-transport accidents (Figure S5.S8), and lung cancer (Figure S5.S9)—showed a similar spatial distribution to the overall relative risk of premature mortality, with a clear North-South gradient. In these cases, higher relative risks were predominantly found in Walloon municipalities, while Flemish municipalities exhibited relative risks below 1.

The relative risks of premature mortality due to lip, oral cavity, pharynx, larynx, and oesophageal cancer (Figure 5.3) and suicide (Figure S5.S10) showed a North West-South East gradient. Figure 5.3 also highlights sex differences in the distribution of relative risks. For men, the highest relative risks were concentrated in the provinces of Hainaut, East Flanders, and West Flanders, while for women, the greatest relative risks were found in Hainaut, Liège, and Namur. Conversely, both men and women exhibited similar patterns for the lowest relative risks, predominantly located in Limburg, Antwerp, and Liège.

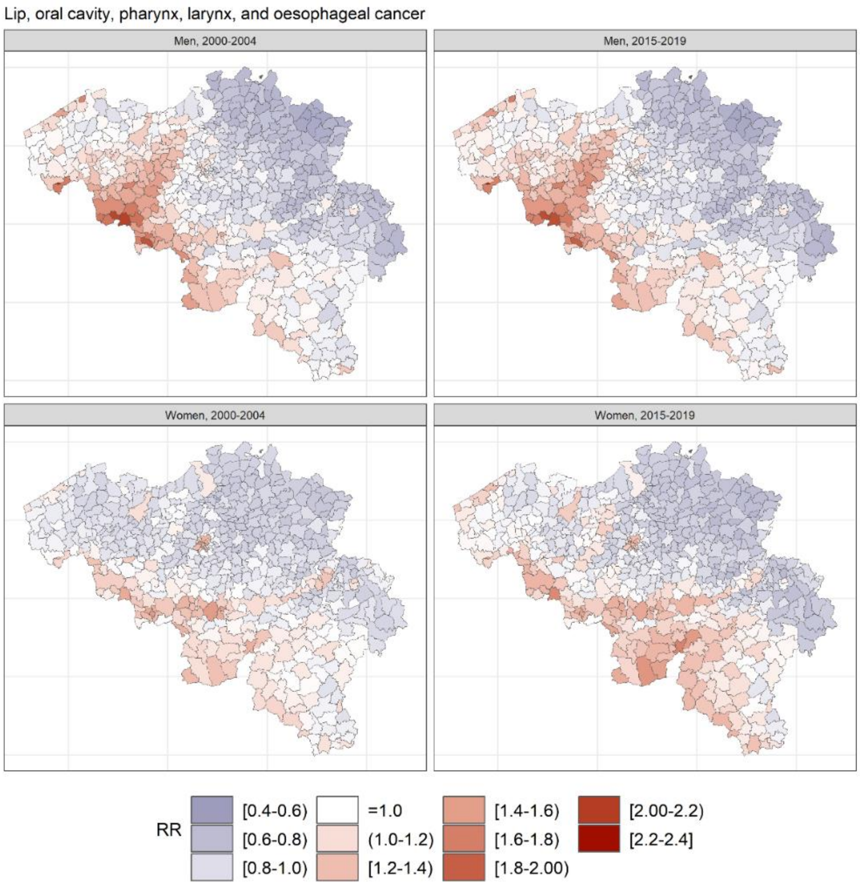


Figure 5.3 Spatial and temporal distribution of RR of premature mortality due to cancer of the lip, oral cavity, pharynx, larynx, and esophagus in Belgium in the first (2000-2004) and last period (2015-2019) studied, by sex.

A distinct West-East gradient was evident in the distribution of relative risks for breast cancer (Figure 5.4). 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 similar pattern was seen in the relative risk of premature death due to colorectal cancer (Figure S5.S11).

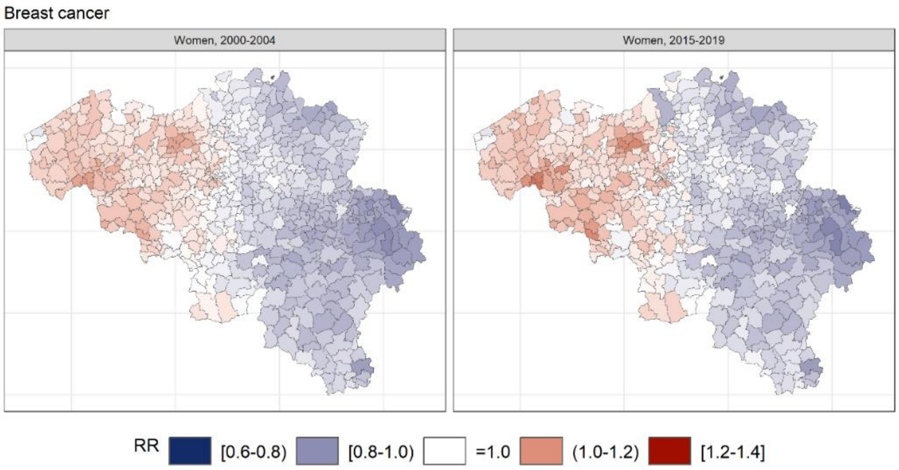


Figure 5.4 Spatial and temporal distribution of RR of premature mortality due to breast cancer in Belgium in the first (2000-2004) and last period (2015-2019) studied, in women.

A mixed pattern is observed in the distribution of relative risks for premature death due to road accidents. High relative risks were concentrated in the districts of Dinant, Bastogne, Huy, and Neufchâteau, with the largest relative risks found in the municipalities of Jodoigne and Ramillies in the district of Nivelles, as well as Houthulst and Lo-Reninge in the district of Diksmuide. This pattern extended across both Walloon and Flemish municipalities, including areas in the provinces of West Flanders and Limburg (Figure 5.5). In contrast, relative risks below 1 were observed in the districts of Antwerp, Halle-Vilvoorde, and Brussels-Capital, with the lowest relative risks recorded in the municipalities of Saint-Gilles, Ixelles, and Etterbeek, all located within the Brussels-Capital district.

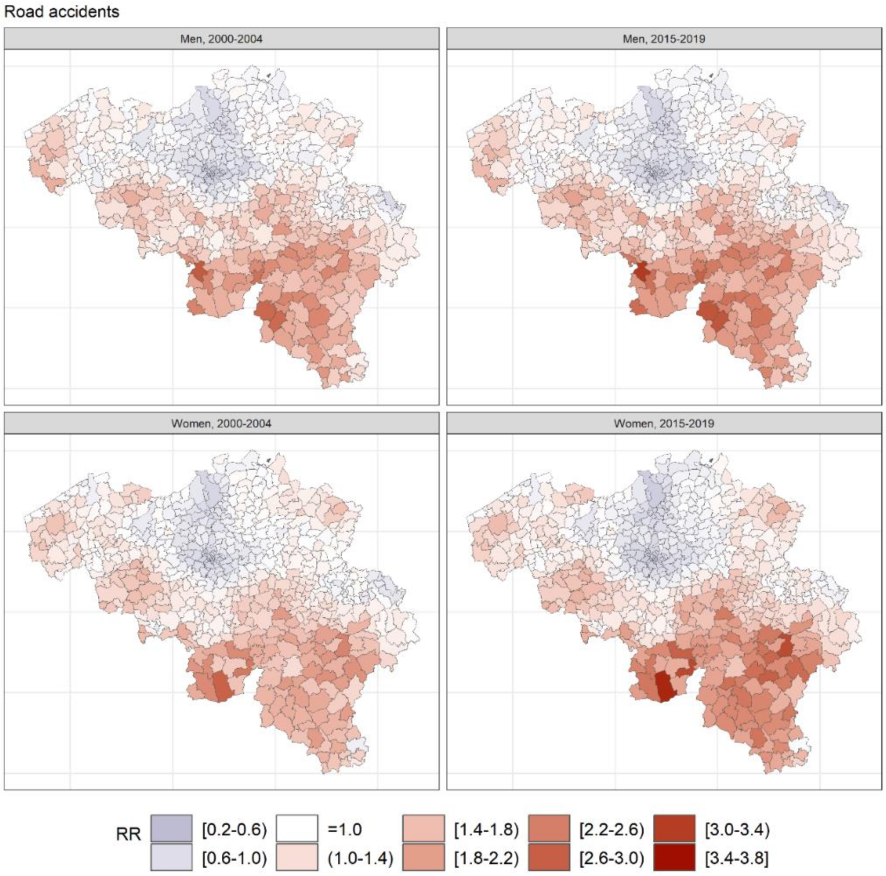


Figure 5.5 Spatial and temporal distribution of RR of premature mortality due to road accidents in Belgium in the first (2000-2004) and last period (2015-2019) studied, by sex.

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

Figure 5.6 shows the standard deviation (SD) estimates of modeled relative risks and their 95%CI for each study period. The heterogeneity in relative risk values across periods can be assessed by comparing the SD estimates and their 95% credible intervals. An increase in the period-specific standard deviation of the relative risk reflects an increase in the risk heterogeneity in that period. Assuming that increased SE deprivation is associated with an increase in the risk of dying prematurely, the increase in heterogeneity may translate into a large gap between the highest and lowest SMR.

The results in Figure 5.6 indicate a clear shift to the right, suggesting higher heterogeneity in municipal premature mortality levels in the most recent period compared with previous periods. For men, relative risks of premature death from COPD, diabetes mellitus, mouth cancer, non-transport accidents, and road accidents showed an insignificant increase in subnational variability. A small but significant shift was observed between the first (2000-2004) and last period (2015-2019) for cardiovascular diseases (0.065, 95%CI 0.063-0.069 vs 0.081, 95%CI 0.077-0.084) cerebrovascular diseases (0.082, 95%CI 0.079-0.083 vs 0.095, 95%CI 0.092-0.097), colorectal cancer (0.080, 95%CI 0.079-0.081 vs 0.095, 95%CI 0.093-0.097), mental-neurological diseases (0.134, 95%CI 0.130-0.140 vs 0.145, 95%CI 0.143-0.149), and suicide (0.104, 95%CI 0.101-0.108 vs 0.133, 95%CI 0.128-0.137). For women, we observed a significant increase in the standard deviation between the first and last period in the relative risk of premature mortality (0.040, 95%CI 0.039-0.041 vs 0.044, 95%CI 0.042-0.045), lung cancer (0.101, 95%CI 0.098-0.105 vs 0.110, 95%CI 0.107-0.115), mental-neurological diseases (0.145, 95%CI 0.141-0.149 vs 0.167, 95%CI 0.162-0.171), non-transport accidents (0.130, 95%CI 0.123-0.136 vs 0.145, 95%CI 0.138-0.154), road accidents (0.243, 95%CI, 0.236-0.255) and suicides (0.125, 95%CI 0.122-0.128 vs 0.170, 95%CI 0.165-0.173). A significant shift in standard deviation between each period was seen for breast cancer, cerebrovascular diseases, colorectal cancer, and mouth cancer. Our results show that risk heterogeneity for women, compared to men, has been greater for all causes since the first period studied, except for mouth cancer and colorectal cancer. The level of standard deviation of colorectal cancer in women reached the level of its male counterpart in the third period studied (2010-2014), whereas the standard deviation of relative risk of mouth cancer reached the male standard deviation of mouth cancer only in the last period (2015-2019). A detailed overview of SD by cause of death and sex can be found in Table S5.S2 and Table S5.S3 in Supplementary Materials.

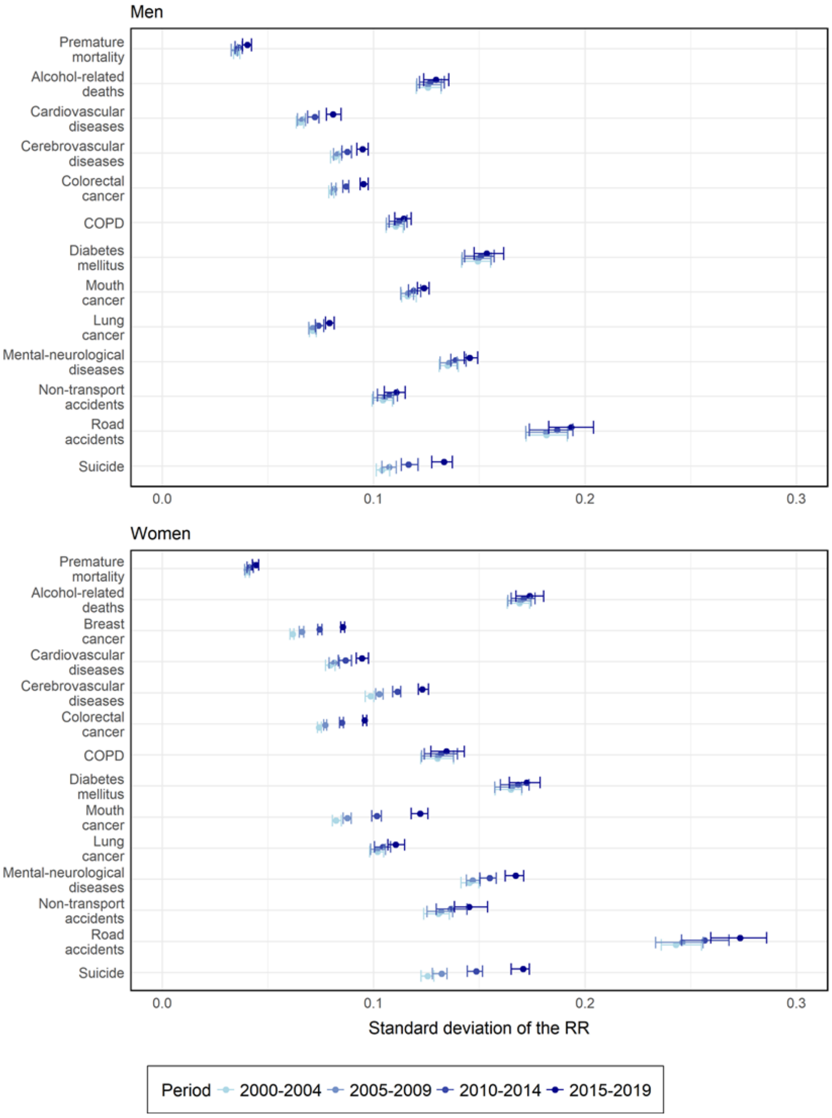
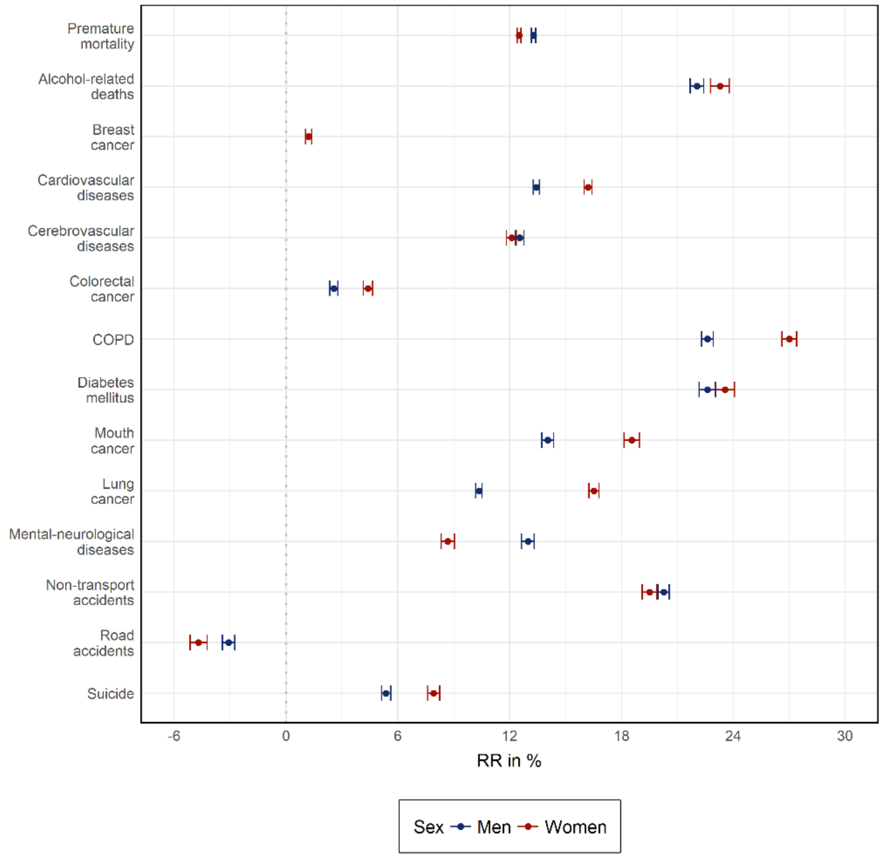


Figure 5.6 Standard deviation of estimated cause-specific relative risks, by sex.

What effects do overall socioeconomic deprivation or domain-specific deprivation have on subnational variations in the cause-specific risk of premature death?

Exponentialized fixed effect estimates, i.e. posterior mean and 95% credible intervals (CI) of the average deprivation score or domain-specific score extracted from each fitted model were used to answer this question. The effect of deprivation on all-cause and cause-specific mortality risks is quantified as a relative risk related to a fixed increase ξ in the covariate value. We used the standard deviation (*SD*) of the average deprivation score (*SD* = 10.04) as the unit increase ξ, representing a realistic increase in the value of the deprivation score. Since the average score distribution is similar across domains, the same unit increase was applied to domain-specific results to maintain consistency across the outcomes.



5.7 shows a positive relationship between deprivation and the risk of all-cause premature mortality and the majority of cause-specific premature mortality at the municipal level. An increase in the deprivation score by one *SD* unit, i.e. 10.04 units, increased the risks of dying prematurely by 13.28% (95%CI, 13.17-13.39) and 12.51% (95%CI, 12.40-12.61) for men and women at the municipal level, respectively. In both sexes, the greatest effect of socioeconomic deprivation on the municipal relative risk was observed for COPD and diabetes mellitus, suggesting that if deprivation increased by 10.04 units, the risk of dying prematurely increased by 22.61% (95%CI, 22.30-22.92) and 22.61% (95%CI, 23.16-23.06) in men, and 27.00% (95%CI, 26.60-27.40) and 23.55% (95%CI, 23.02-24.07) in women. These results showed a significant sex difference and cause-specific impact of deprivation that became evident across all causes studied. Although with increasing deprivation the risk of dying prematurely at the municipal level increased more for men than for women, the effect of deprivation on the relative risk of selected causes was mostly greater for women, except for cerebrovascular diseases, mental-neurological diseases, and non-transport accidents. The largest sex differences were observed for lung cancer (RR 6% higher in women), mouth cancer (RR 4% higher in women), and COPD (RR 4% higher in women).

We also observed the opposite effect, suggesting that increased deprivation reduced the municipal risk of dying from road accidents by 3.09% (95%CI, 2.76-3.42) and 4.70% (95%CI, 4.24-5.15) for men and women, respectively.

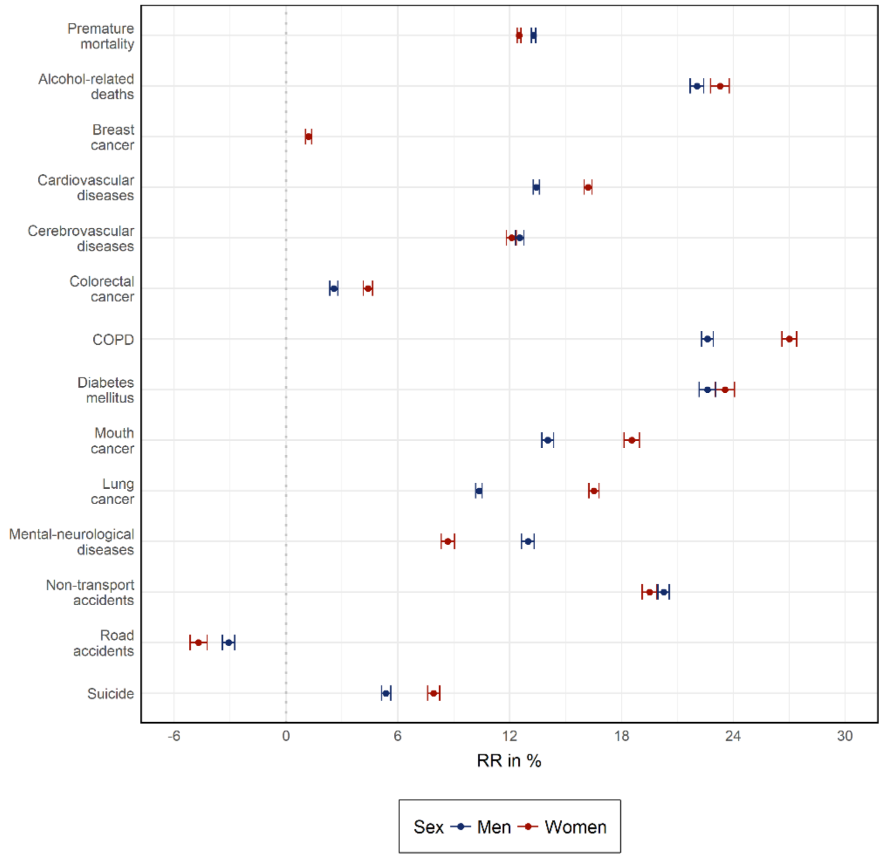


Figure 5.7 Estimated mean point estimates of relative risks and their 95% confidence intervals for all-cause and cause-specific premature mortality associated with a unit increase (i.e. 10.04) in the overall average deprivation score, by sex.

For men and women, the trend and magnitude of the effect at the municipal level associated with an increase in domain-specific deprivation scores were similar across most all-cause and cause-specific premature mortality (Figure 5.8 and Figure 5.9). The largest effects on municipal premature mortality risks were observed for the employment and housing domains, followed by the education and income domains. The crime domain had the smallest impact on the relative risk of dying prematurely for most causes of death across. For 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, 17.50-18.08), for deaths by COPD by 18.18% (95%CI, 17.93-18.42), and diabetes mellitus by 16.70% (95%CI, 16.33-17.07). For women, an increase of 10.04 units in the housing average deprivation score raised the relative risk of premature death due to diabetes mellitus by 22.85% (95%CI, 22.24-23.46), whereas a similar increase in the employment average deprivation score increased relative risk of dying due to COPD by 21.98% (95%CI, 21.66-22.31) and relative risk of alcohol-related deaths by 18.20% (95%CI, 17.81-18.60). An opposite effect was observed for the relative risk of death due to road accidents. An increased income average deprivation score decreased relative risk due to road accidents by 5.50% for men and women – lower relative risk was also seen for an increase in education and crime average deprivation scores for men and women, and employment average deprivation scores for women. More results can be found in Tables S5.S4, S5.S5, S5.S6, and S5.S7 in Supplementary Materials.

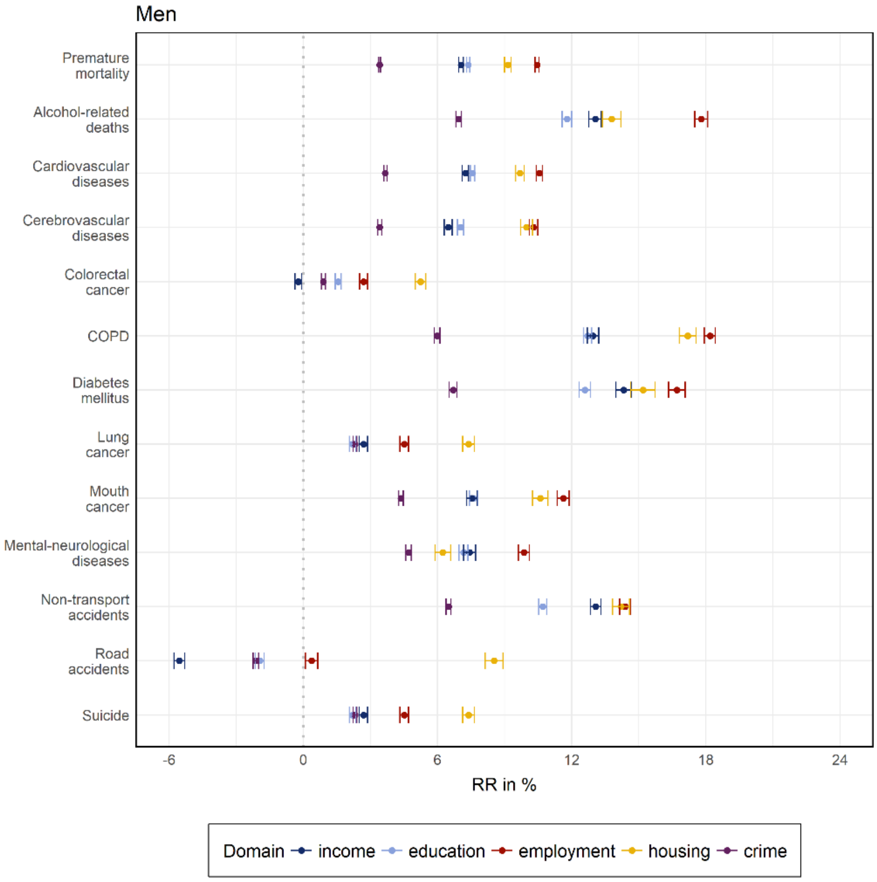


Figure 5.8 Estimated mean point estimates of relative risks and their 95% confidence intervals for all-cause and cause-specific premature mortality associated with a unit increase (i.e. 10.04) in the domain-specific average deprivation score, for men.

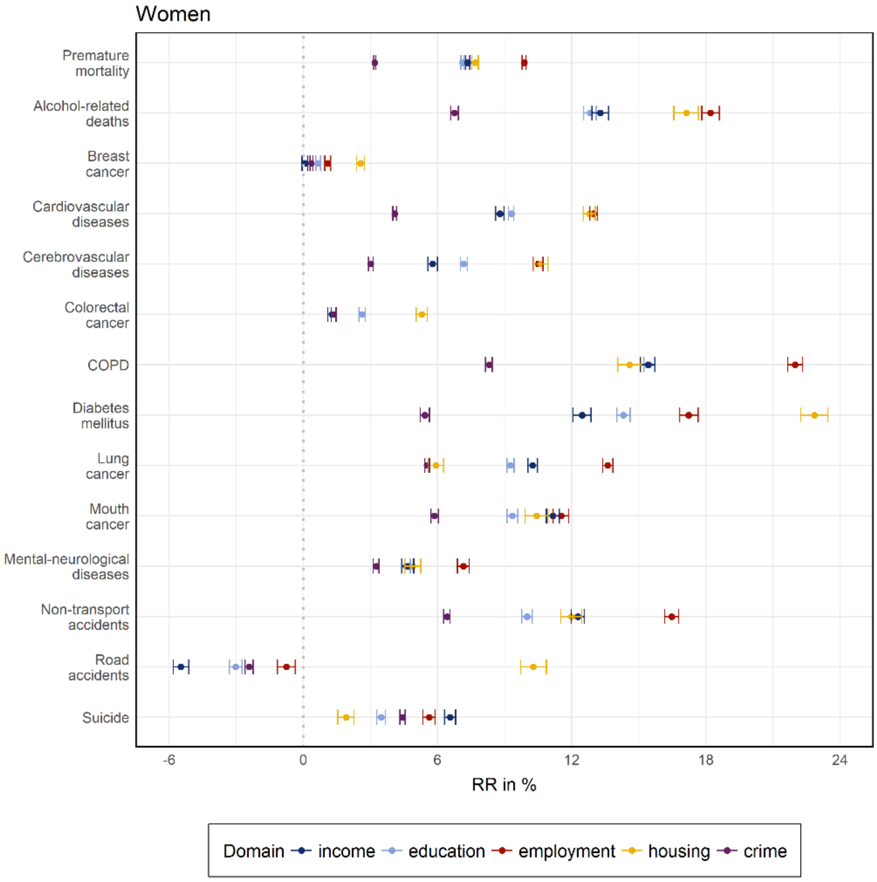


Figure 5.9 Estimated mean point estimates of relative risks and their 95% confidence intervals for all-cause and cause-specific premature mortality associated with a unit increase (i.e. 10.04) in the domain-specific average deprivation score, for women.

5.4 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 domain-specific deprivation and premature mortality in Belgium.

Although the geographical patterns of low and high relative risks of premature mortality vary by cause, most spatial patterns include the distribution of the highest relative risks in a narrow band, known as the 'Walloon axis' (Halleux, 2011). The Walloon axis follows the river of Meuse from Liege to Namur, and continues to the West along the river of Sambre to Charleroi, extending towards the Haine Valley and Mons-Borinage. This band is known for a high population concentration - nearly half of the Walloon population was concentrated in this area in 2010, and high deprivation – the BIMD2011 classified most of the statistical sectors in this area among the most deprived in Belgium (Otavova et al., 2023).

A different pattern, the West-East gradient, was observed in the relative risk of premature deaths by breast cancer suggesting a higher relative risk for those living in less deprived areas of Belgium – an atypical gradient, as for most other causes of death the association with deprivation is as expected. Similar results have already been reported in a study by Renard et al. (2015) but without a satisfactory explanation. Studies from other countries suggest that the narrowing socioeconomic differences in breast cancer mortality may be influenced by various factors (Faggiano et al., 1997; Heck & Pamuk, 1997). For instance, a period effect associated with the introduction of breast cancer screening programs may disproportionately benefit women with higher education levels (Martikainen & Valkonen, 2000). Additionally, changes in reproductive behavior, such as the trend among women in higher socioeconomic groups to delay motherhood, may also play a role. It’s important to note that breast cancer etiology varies by age, with different risk factors before and after menopause, which may lead to socioeconomic differences in mortality favoring less-educated women only at older ages (Hulka & Stark, 1995). Investigating the causes behind the reversed gradient in the relative risk of premature death due to breast cancer is, however, 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 increased. In 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 observed. The common factor for these causes of death is unhealthy lifestyle behavior, such as alcohol consumption, tobacco use, or poor diet. Although these behavioral risk factors are often referred to as ‘proximate’ determinants, their distribution across different socioeconomic strata is likely influenced by structural factors, such as limited access to behavior change support or material deprivation (Lynch, Kaplan, & Salonen, 1997; Stronks et al., 1997). Reducing the risk heterogeneity will therefore require a combination of individual and population-level interventions that target not only health education but also the removal of barriers to healthy behavior. Causes related to alcohol consumption, tobacco use, and high-fat diet have been identified in Belgium (Otavova et al., 2024) and other countries (Mackenbach, 2012; Mackenbach et al., 2003; Mackenbach et al., 2016) as those driving the increase in inequalities, which also means that a possible reduction in their inequalities would have the maximal impact on Belgian all-cause premature mortality.

Our findings revealed a positive correlation between the average deprivation scores (overall or domain-specific) and most all-cause or cause-specific relative risk of premature death, with the greatest impact on risks of premature death due to COPD, alcohol consumption, and diabetes mellitus. A rare negative association was observed between deprivation and the relative risk of premature deaths due to road accidents. This trend can be explained by the fact that road traffic mortality is associated with distance traveled and higher speed – two elements we see in Belgian municipalities with a higher proportion of rural areas. Densely populated municipalities with higher average deprivation scores have a high density of public transport, which reduces car use, and limits the distance and speed traveled (Renard et al., 2015).

Strengths and limitations

Our study has three main strengths: utilizing both overall and domain-specific average deprivation score, modeling of relative risks using the spatio-temporal model, and the analysis of cause-specific relative risks at the municipal level by sex. The average deprivation score is a population-weighted score computed for all 589 Belgian municipalities, and it is based on the global BIMD2011 scores or the deprivation domains included in the BIMD2011. The BIMD2011 combines data on income, education, employment, housing, and crime to provide 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. Additionally, a notable advantage of the BIMD2011 and the average deprivation score is that they are easily replicable and can be updated with the most recent data. This will allow follow-up studies to monitor changes in relative risks in premature mortality in Belgium from 2019 onwards (Otavova et al., 2023).

Another strength of our study is the use of spatio-temporal modeling enabling a more reliable and robust estimation of relative risks, even when the number of cases in the municipality is small (Kang et al., 2016). The applied model accounts for spatial correlation, recognizing that observations in neighboring areas may be more similar than those in distant areas. It incorporates covariates and leverages information from neighboring regions, improving local estimates and smoothing out extreme relative risk values – an issue often present in SMRs computed for small populations.

A major advantage of our study is the modeling of cause-specific relative risks at the municipal level 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 specific relative risks of all-cause premature mortality in Belgian municipalities, and identify geographical areas in need of interventions that would reduce the cause-specific specific relative risks. To compute the population-level relative risk estimates, we used cause-specific data from the entire Belgian population to ensure the maximum statistical power and avoid selection bias.

In choosing a suitable geographical area, we preferred the second smallest administrative units in Belgium, the municipalities. This choice was validated by the fact that the municipal boundaries did not change between 2000 and 2019; they are large enough to provide statistically robust estimates, and better homogeneity within their populations can be assumed, reducing the risk of ecological fallacy. Additionally, the use of aggregate data was more practical and allowed us to address the privacy, security, and confidentiality issues associated with the use of administrative data more easily (Jamagne et al., 2016).

The findings of our study have certain limitations that should be taken into account when interpreting the results. As we focus on examining the effect of deprivation on the RR of premature death at an aggregate level, conclusions cannot be extrapolated to individuals. An ecological fallacy would be committed (Sedgwick, 2015) 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 specific relative risks, and alternatively, that those living in municipalities with low average deprivation score must themselves be less deprived and have lower relative risks.

5.5 Conclusion

We investigated the spatial distribution of relative risks of all-cause and cause-specific premature mortality and their association 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. Finally, 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.

Chapter 6 Uncovering socioeconomic disparities in modal age at death and its dispersion in Belgium since 2000[5]

6.1 Introduction

Since the mid-twentieth century, most developed countries have experienced a shift in the distribution of mortality towards older age and a concentration of deaths within a progressively shorter age interval. These changes characterize the ongoing stage of mortality transition – the era of delayed aging, an era that is also known for significant advancements in medicine, public health (Kannisto, 2001), and social conditions – helping people to live longer, healthier lives, which results in increased life expectancy, and better physical and cognitive health with a delay in the onset of chronic diseases and disabilities (Christensen et al., 2009; Crimmins, 2015; Olshansky et al., 2001; Rowe & Kahn, 1997).

Lower mortality at higher ages has led to the aging of populations with increased numbers of centenarians and

[5] This chapter has not been published yet.

supercentenarians (Robine & Paccaud, 2005), a rise in the maximum recorded life span, and the uninterrupted long historical increase in life expectancy (Oeppen & Vaupel, 2002). These events increased interest in longevity studies concerning monitoring and analyzing longevity trends or differentials by investigating lifespan indicators. Life expectancy at birth (e_0) has been the most commonly researched longevity indicator and its remarkable increase has been considered one of the greatest human accomplishments of the past century. The world went from having no countries with e_0 of more than 50 years to having many countries with e_0 of 80 years only in one hundred years (Crimmins, 2015). This nearly doubling of e_0 resulted from two key factors: 1) a significant reduction in deaths from infectious diseases among the young, and 2) a substantial decline in mortality from heart disease. During the nineteenth century and the first part of the twentieth century, when infant mortality rates were high and represented the main public health issue, e_0 was the most useful indicator. However, the emergence of the aging population has raised questions about the ability of e_0 to provide relevant information on death distribution among the higher ages. Due to its dependency on early-age mortality, many demographers consider e_0 ill-suited for measuring longevity in countries experiencing delayed aging. Instead, they regard the modal age at death (*M*) indicator as essential for investigating survival to old age and longevity (Canudas-Romo, 2008; Canudas-Romo, 2010; Kannisto, 2001).

Although not as well-known and widely used as life expectancy at birth, the significance of *M* was highlighted in the 19th century by influential figures such as Quetelet (Quetelet, 1835, 1848; Quetelet, 1994) or Lexis (Kannisto, 2000). Throughout the 20th century, numerous researchers studied the age distribution of deaths to better understand the human lifespan (Benjamin, 1964; Benjamin, 1982a, 1982b, 1988; Elderton, 1903; Gumbel, 1937). However, it was not until 2000, with the work of Kannisto (Kannisto, 2000), that the *M* and its dispersion measure emerged as an essential set of tools to summarize and monitor mortality changes at older ages over time (Canudas-Romo, 2008; Cheung & Robine, 2007; Cheung et al., 2005; Cheung et al., 2008; Ouellette & Bourbeau, 2011; Thatcher et al., 1998).

The dispersion of deaths beyond *M* is measured by the standard deviation above the modal age at death *(SD(M+))*. A decrease in the *SD(M+)* reflects a reduction in the variability of *M*, commonly referred to as compression of mortality (Wilmoth, 2000). This means that deaths are concentrated in a shorter age interval, the dispersion of the *M* distribution is reduced, and the downward slope of the survival curve becomes steeper, resulting in a more rectangular shape. This phenomenon is known as the rectangularization of the survival curve. A few studies have already explored the rectangularization of the survival trends, compression of mortality, trends and changes in modal age at death in different settings (Brown et al., 2012; Canudas-Romo, 2008; Cheung & Robine, 2007; Cheung et al., 2005; Cheung et al., 2008; Gurven & Kaplan, 2007; Horiuchi et al., 2013; Ouellette & Bourbeau, 2011), as well as similarities or differences in patterns between *M* and e_0 (Canudas-Romo, 2010; Cheung & Robine, 2007; Kannisto, 2001), but even fewer studies used *M* to assess socioeconomic disparities in mortality at higher ages (Brown et al., 2012; Diaconu et al., 2022; Zarulli et al., 2012). By today, there are only a few studies investigating the evolution of *M* in Belgium (Alvarez & Vaupel, 2023; Anson, 2018; Janssen & de Beer, 2019), but none investigating differences in modal age at death between different deprivation groups.

Thus, in the current study, we aim to fill this gap in longevity research by examining the trends and levels of the modal age at death and standard deviation above the modal age at death across Belgian statistical sectors, grouped by their deprivation levels into deprivation deciles, between 2000 and 2019. We compute the Belgian, sex- and deprivation-specific *M* and *SD(M+)* estimates from P-spline smoothed age-at-death distributions obtained from detailed population and mortality data, a method introduced by Ouellette and Bourbeau (2011) (Ouellette & Bourbeau, 2011). The first objective of this study is to investigate the disparities among men and women living in different deprivation deciles and answer questions such as *What is the most common age at death in a given year in the most and least deprived deciles? How has the M evolved? How does M differ between the most and least deprived deciles?* In addition, time trends in standard deviation above the modal age at death will provide answers to equally important questions such as *How has it changed between the years 2000 and 2019?* Besides all-cause estimates, we also provide the first available estimates of *M* and *SD(M+)* for six leading causes of death among Belgian men and women: cerebrovascular diseases, heart diseases, and four types of cancers, namely colorectal, lung, breast (women), and prostate (men) cancer. Since we consider both lifespan indicators (*M* and e_0) and their dispersion measures to be complementary and equally important for describing the human lifespan, our study also presents e_0 and *SD* of e_0 by year, sex, and deprivation decile.

6.2 Methods

Belgian Indices of Multiple Deprivation 2011 (BIMD2011)

We measured the socioeconomic deprivation at the level of the smallest geographical unit in Belgium (i.e., the statistical sector) by the newly developed Index of Multiple Deprivation (BIMD2011). The original BIMD2011 encompasses six domains of deprivation: income, education, employment, housing, health, and crime. The domains are combined to obtain a single score for each geographical area, and these scores are then ranked, and assigned to deprivation deciles from the most (1) to the least (10) deprived. The BIMD2011 tool is available via https://github.com/bimd-project/bimd, and more details can be found elsewhere (Otavova et al., 2023). For this study, we re-created the BIMD2011 without the Health Domain to avoid bias (Figure 6.1).

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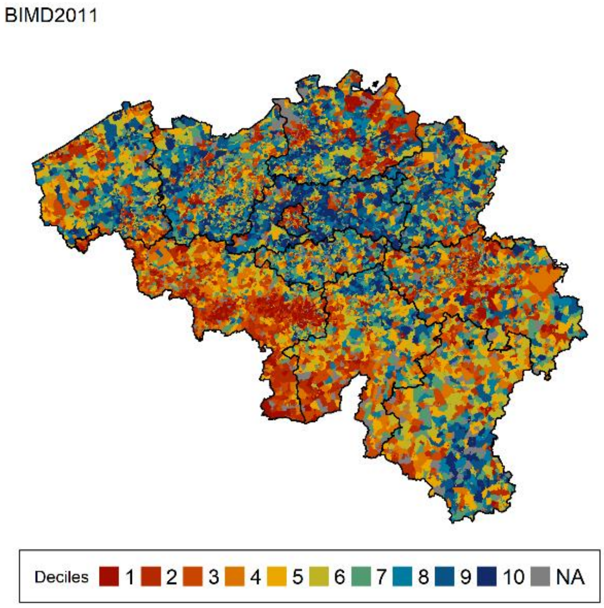


Figure 6.1 Distribution of the BIMD2011 deprivation deciles across Belgian statistical sectors in 2011. The most and least deprived statistical sectors fall into the first (dark red) and the tenth (dark blue) deprivation deciles.

Data

We used pseudonymized individual-level all-cause and cause-specific mortality data extracted from the Civil Registry in Belgium that occurred between Jan. 1, 2000, and Dec. 31, 2019. The data consisted of death counts by single year of age (0-110+) and included sex, the underlying cause of death according to the 10th revision of the International Classification of Diseases (WHO, 2011), and the place of residence of the deceased, defined by the statistical sector. Corresponding mid-year population estimates by statistical sector, sex, and single years of age from 2000 to 2019 were obtained from the National Register data. Our dataset includes all legal residents of Belgium and excludes irregular migrants and asylum seekers.

Period life tables and life expectancy at birth

Values for e_0 were extracted from period life tables that we constructed using a methodology as close as described in the Methods Protocol for the Human Mortality database (Wilmoth et al., 2021). We first smoothed observed death rates M_x at older ages (80 and above) by fitting the Kannisto model of old-age mortality (Thatcher et al., 1998):

$$\mu_x\,(a,b) \;=\; \frac{ae^{b(x-80)}}{1 \;+\; ae^{b(x-80)}}$$

Where a ≥ 0 and b ≥ 0. We used observed deaths, D_x, and exposures, E_x, for ages x = 80, 81, …,110+ (any pre-selected open-end category) to arrive parameter estimates $\hat{a}$ and $\hat{b}$ by maximizing the following log-likelihood function:

$$log\;L\,(a,b) \;=\; \sum_{x\,=\,80}^{110+}[D_x log\;\mu_{x\,+\,0.5}(a,b) \;-\; E_x\mu_{x\,+\,0.5}(a,b)] \;+\; constant$$

The smoothed M_x for ages 80 up to 110+ replaced the observed M_x in the period life table calculations. Next, we converted the life table death rates, $M_x = m_x$, into probabilities of dying q_x according to the following formula:

$$q_x = \frac{n\, m_x}{1 + (n - a_x)\, m_x}$$

$$q_{110+} = 1$$

Where n_x is the length of the age interval, and a_x is the average number of years lived within the age interval [x, x+1) for people dying at that age. We assume $a_x = ½$ for all single-year ages except age 0. We used a revised version of the formulas for a_0 suggested by Andreev and Kingkade (2015) (Andreev & Kingkade, 2015) as presented in Table 6.1.

Table 6.1 Andreev-Kingkade formulas for computing a_0 given m_0

	m_0 *range*	Formula: $a_0 = a + b\, m_0$
Males	[0, 0.02300)	0.14929 – 1.99545 m_0
	[0.02300, 0.08307)	0.02832 + 3.26021 m_0
	[0.08307, ∞)	0.29915
Females	[0, 0.01724)	0.14903 – 2.05527 m_0
	[0.01724, 0.06891)	0.04667 + 3.88089 m_0
	[0.06891, ∞)	0.31411

Using q_x we computed p_x – the probability of surviving from age x to age x + n, that is defined as $p_x = 1 - q_x$. The number of survivors to age x in the cohort, l_x, was computed $l_{x+n} = l_x\, p_x$, where $l_0 =$ 100,000. The number of deaths between age x and age x + n, d_x, was equal to the difference between the number of survivors to age x and the number of survivors to age x + n, equaling to $d_x = l_x - l_{x+n}$. Consequently, L_x or the person-years lived between ages x and x + n was computed: $L_x =$ n $l_{x+n} + a_x\, d_x$. By summing up the person-years lived between ages x and x + n, we computed the person-years lived above age x, $T_x = \sum_{a=x}^{\infty} L_a$. The life expectancy, $e_x^0 = \frac{T_x}{l_x}$.

We built separate life tables for each calendar year, sex, and deprivation decile (400 life tables) and extracted the life expectancy at birth. The 95% confidence intervals were built by using the standard Chiang variance model (Chiang, 1984; Lo et al., 2016):

$$\mathrm{Var(LE)} = \sum_{x=0}^{w-1} (p_{0x})^2 [(1 - a_x) n_x LE_{x+1}]^2 [\frac{q_x^2 (1 - q_x)}{D_x}]$$

Where p_{0x} is the survival probability from age 0 to age x, a_x is the fraction of the age interval lived, n_x is the width of the age interval, LE_{x+1} is the life expectancy from age x + 1, and q_x is the probability of dying in age interval *x*. The Chiang *LE* variance represents the sum of variance contributions corresponding to each age interval except the last denoted *w-1*.

Modal age at death

For estimating the values of *M*, we used a P-spline approach, a flexible nonparametric smoothing method introduced by Ouellette and Bourbeau (2011) (Ouellette & Bourbeau, 2011). Instead of smoothing the age distribution of life table deaths, the P-spline approach uses the observed deaths and person-years lived in each 1-year interval to obtain a smoothed force of mortality from which we can derive the corresponding smoothed age-at-death distribution. The age range of smoothing spanned from age 10 to age a, where a is the highest age for which the number of deaths exceeds 10. The value of a differed by sex, year, and deprivation decile.

Given the relationship between the force of mortality, survival and density function, the smoothed density function at age a and time y describing the age-at-death distribution is expressed as:

$$\hat{d}(a,y) \ = \ \hat{\mu}(a,y) * \hat{l}(a,y) \ = \hat{\mu}(a,y) * exp(-\int_{0}^{a} \hat{\mu}(u,y)d(u))$$

The estimated modal age at death is given by $\widehat{M} \ = \ max\ _{a}\hat{d}\ (a,y)$. We utilized the *Mort1Dsmooth fit* function from the *MortalitySmooth* package in R to apply a one-dimensional smoothing model to age-specific mortality data, incorporating variables such as age, death events, and exposure time. A narrow age interval (delta = 0.001) was defined as a sequence of ages within the observed range, and the log hazard function was predicted for the age interval using the fitted Mort1Dsmooth model. The cumulative hazard function (l.hat) and hazard function (d.hat) were computed based on the predicted log hazard. The mode of the hazard function, representing the age at which the hazard was maximized, was then identified.

More details on the R routine for computing M estimates from P-spline-smoothed mortality curves can be found in a paper by Horiuchi et al. (2013) (Horiuchi et al., 2013).

Computing the cause-specific M was more complex, as the competing mortality risks needed to be taken into consideration. Assuming that the causes of death are mutually exclusive and exhaustive (Preston et al., 2001), the all-cause force of mortality is derived by summing up the cause-specific forces of mortality. The cause-cause specific force of mortality is defined as:

$$\mu_k(a, y) = lim_{\triangle \to 0} \frac{\text{Pr } (\text{a} < \text{A} < \text{a } + \triangle a, K = k | A > a}{\triangle a}$$

Where the survival at age a and time y and cause of death k are treated as random variables, and μ_k represents the instantaneous risk of dying from cause k. The cause-specific density function provides information on the risk of dying at age a from cause k and describes the distribution of deaths across ages and it is defined as:

$$f_k(a, y) \;=\; \mu_k(a, y)S(a, y)$$

Where $S(a, y)$ describes the all-cause survival function that is derived through summation of cause-specific forces of mortality:

$$S(a, y) = \; exp[-\int_0^a \mu(u, y)du]$$

The cause-specific *M* is obtained by maximizing the corresponding density function $M_k \;=\; max_x f_k(a, y)$. A more detailed description of cause-specific modal age-at-death derivation is found elsewhere (Sullivan et al., 2017). The 95% confidence intervals for *M* were also computed for each stratum using a residual or non-parametric bootstrap approach. The method by Koissi et al. (2006) (Koissi et al., 2006) was adapted by Ouellette et al. (2012) to the P-splines modeling and allowed us to estimate the variability of the *M*. Using the fitted force of mortality μ, we obtained the matrix of fitted death counts *D*, and computed deviance residuals (Pregibon, 1984) .

$$r = sign(D - \widehat{D}) * \sqrt{2\,[\,D\,ln(\frac{D}{\widehat{D}})\; - \;D\; + \widehat{D}\,]}$$

Using the deviance residuals, we sampled a new set of bootstrapped residuals r_b^*. By replacing the deviance residuals r by r_b^* in the formula above, we obtained a new matrix of bootstrapped deaths $\widehat{D}_b^*$. The bootstrapped deaths were then used together with the matrix of population data in the P-spline framework to obtain a smoothed bootstrapped density function and bootstrapped *M*. The procedure was repeated 1,000 times and resulted in a bootstrapped distribution of $\widehat{M}\ (y)$ from which we extracted 2.5th and 97.5th percentile (lower and upper bound) for the 95% bootstrap confidence interval.

Standard deviation above the modal age at death

We measured the dispersion of deaths at older ages using the standard deviation above the modal age at death (*SD(M+*)). That is,

$$SD(\widehat{M}+)(y)\; = \sqrt{\frac{\int_{\widehat{M}(y)}^{\infty}(a\; - \;\widehat{M}(y))\text{^}2\,\hat{f}(a,y)da}{\int_{\widehat{M(y)}}^{\infty}\hat{f}\,(a,y)\;da}}$$

Where $\hat{f}$ is a function of ages and years, *M* and (*SD(M+*)) are functions of years (Ouellette et al., 2012).

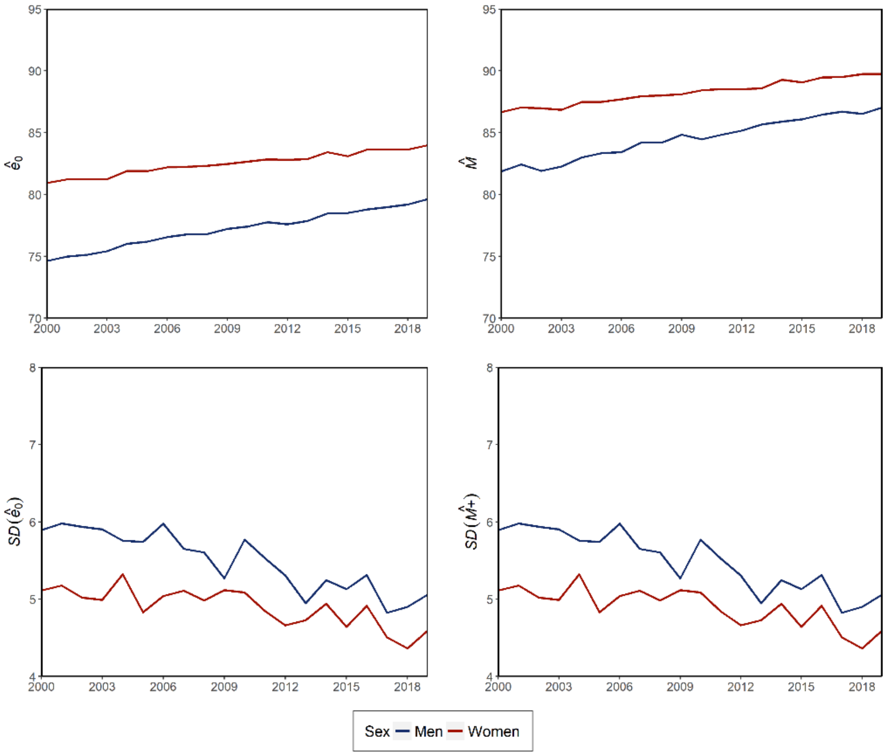
Causes-of-death

For the cause-specific analysis of *M*, the following leading causes of death were selected: cerebrovascular diseases (I60-I69), heart diseases (I00-I09, I11, I13, I20-I51), trachea, bronchus, and lung cancer (C33-C34), prostate cancer (C61), breast cancer (C50), and colorectal cancer (C18-C21).

All analyses were done in R version 4.1.1 (*R version 4.1.1*).

6.3 Results

Life expectancy at birth and modal age-at-death estimates for the whole population of Belgium



6.2 shows changes in e_0 and *M* and their respective dispersion measures in Belgium between 2000 and 2019. Men and women born in 2000 were expected to live 74.63 (95%CI, 74.60-74.66) and 80.95 (95%CI, 80.92-80.97) years, but their most common age at death was estimated to be 81.86 (95%CI, 81.30-82.42) and 86.66 (95%CI, 86.40-86.88) years. Both e_0 and *M* increased during the studied period, reaching e_0 of 79.63

(95%CI, 79.61-79.66) and 83.99 (95%CI, 83.96-84.01) years, and *M* of 87.05 (95%CI, 86.68-97.28) and 89.76 (95%CI, 89.57-89.97) in men and women, respectively. It corresponds to a similar increase of about 5 and 3 years in male and female e_0 and *M*. The overtime trend of $SD(e_0)$ and $SD(M)$ showed a decrease. In the period 2000-2019, the standard deviation of life expectancy at birth fell from 5.9 to 5.0 years in men and from 5.12 to 4.6 years in women, whereas the standard deviation above the mode fell from 7.10 to 6.04 years in men and from 6.32 to 5.72 years in women.

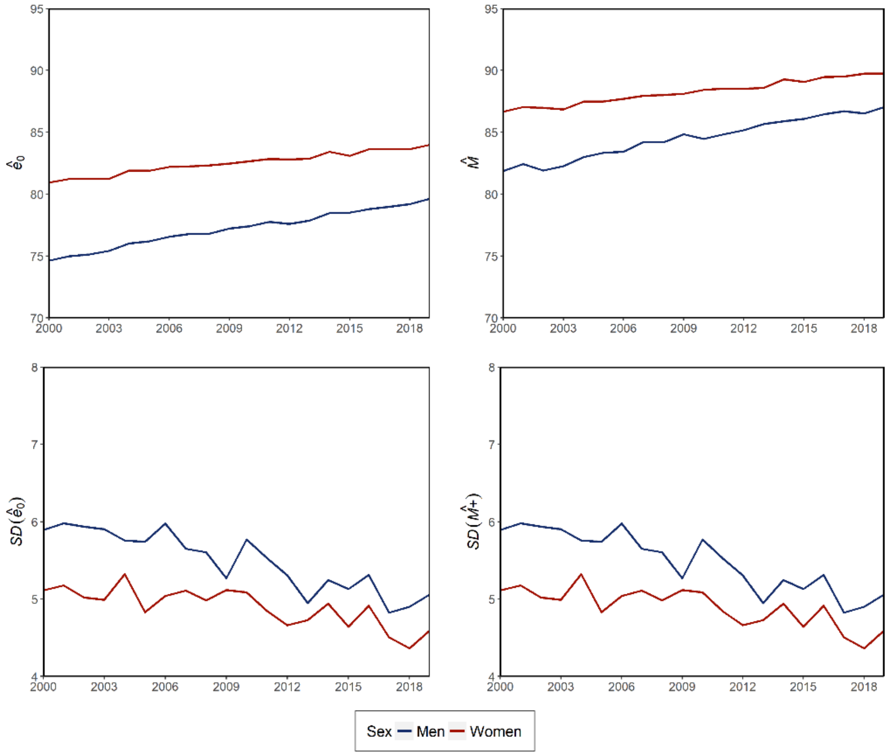


Figure 6.2 Estimated life expectancy at birth, modal age at death, standard deviation of life expectancy at birth, and standard deviation above the modal age at death for the whole of Belgian population, by year and sex.

Life expectancy at birth and modal age-at-death estimates across the deprivation deciles

Figure 6.3 presents sex- and decile-specific changes in *e0* and *M* in Belgium between 2000 and 2019. It reveals that *e0* and *M* increased for men and women in all deprivation deciles during the period studied. The life expectancy at birth increased from 71.54 (95%CI 71.48-71.61) to 76.26 (95%CI 76.19-76.32) years among men living in the most deprived areas, and from 77.26 (95%CI 77.10-77.31) to 81.90 (95%CI 81.79-82.01) years among men living in the least deprived areas, and from 79.32 (95%CI 79.26-79.38) to 81.74 (95%CI 81.68-81.80) years among the most deprived and from 82.07 (95%CI 81.97-82.18) to 86.20 (95%CI 86.09-86.28) years among the women living in the least deprived areas. The average increase in e_0 of those living in the most and least deprived areas was 2.8 (most deprived) and 3.3 (least deprived) months per year for men and 1.5 (most deprived) and 2.5 (least deprived) months per year for women. These results suggest that the relative difference in e_0 between the most and least deprived areas increased from 7.36% to 7.90% in men, and from 3.71% to 5.47% in women.

In 2000, Belgian males living in the most deprived areas typically died at the age of 79.92 (95%CI 78.35-80.17), that is, almost 4 years earlier than men living in the least deprived areas. Thanks to an average growth rate of 2.3 (most deprived) and 2.7 (least deprived) months per year between 2000 and 2019, the male *M* reached 83.7 (95%CI 82.60-83.78) years and 88.5 years (95%CI 88.02-88.79) in 2019 in the most and least deprived areas. On the contrary to a distinctive gap observed between male *M* of the most and least deprived areas during the whole period under study, we noted an overlap of decile-specific female *M* in the early years studied, followed by a clear divergence in 2004 onwards. In 2000, the majority of Belgian women living in the most deprived areas died at the age of 86.59 (95%CI 86.25-86.94), similar to women in the least deprived areas 86.95 (95%CI 86.30-87.55). Later on, in 2019, the peak of female deaths moved to the age of 88.67 (95%CI 88.28-89.08) and 90.41 (90.31-91.26), in the most and least deprived. As in men, *M* of women living in the most deprived areas increased slower – on average by 1.3 months per year compared to 2.3 months per year of women living in the least deprived areas. The relative difference between the most vs least deprived M has increased for both sexes, from 4.90% to 5.41% in men, with a greater increase from 0.07% to 1.91% in women.

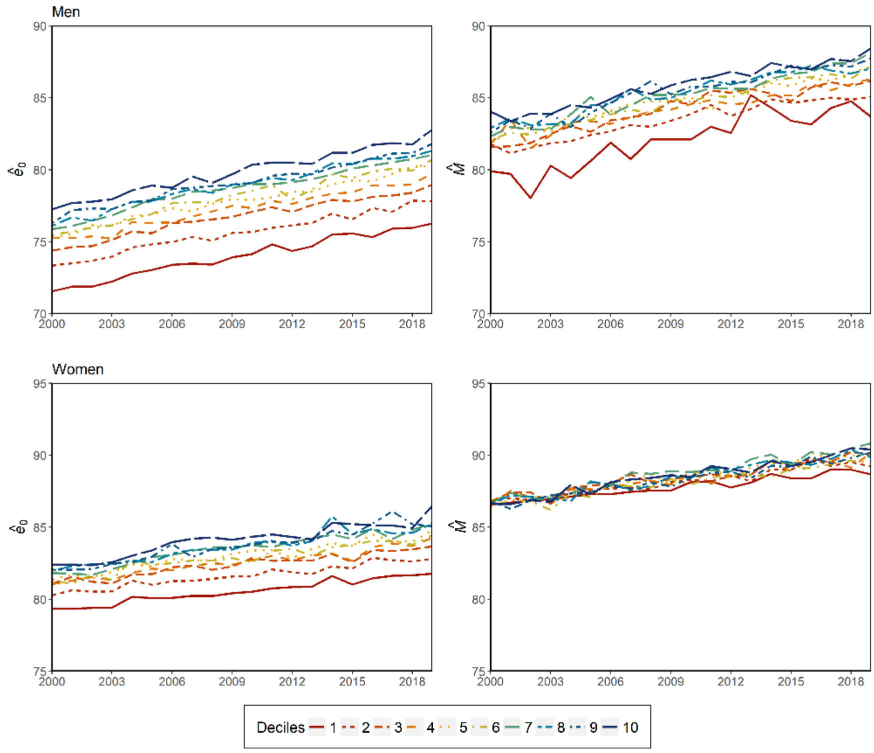


Figure 6.3 Estimated life expectancy at birth and modal age at death by deprivation deciles and sex in Belgium, 2000 to 2019. The most deprived are located in the first (full red line) and the least deprived in the tenth decile (full blue line).

To assess the significant differences in the pace of growth of e_0 and M, we modeled e_0 and M trends as a linear function of time. Results presented in Figure 6.4 indicate that the *M* of women in the least deprived areas shows a significantly faster increase than those in the most deprived areas. A similar pace of growth with no significant differences was observed in female and male e_0 and male *M* in the most and least deprived areas. In regards to sex differences, men in the most and least deprived areas experienced a more rapid increase in e_0 and *M* than women.

Absolute difference in e_0 and *M* between the least and most deprived areas and its trend from 2000 until 2019 is shown in Figure S6.S1 in Supplementary Materials.

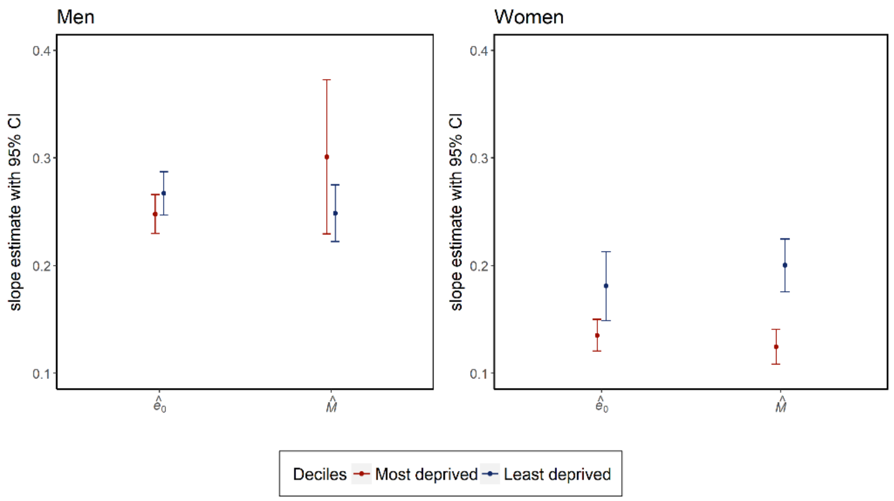


Figure 6.4 Estimated linear slopes of M and 95% CI for men and women in the most and least deprived deprivation deciles, 2000 to 2019.

The standard deviation of life expectancy at birth and standard deviation above the mode

Figure 6.5 displays sex- and decile-specific trends for *SD*(e_0) and *SD(M+)*. In men and women in the most and least deprived deciles, both indicators were smaller in 2019 than in 2000, and across the whole period studied, the most deprived areas had greater *SD*(e_0) and *SD(M+)* than the least deprived areas.

The left panels in Figure 6.5 present *SD*(e_0) by sex and deprivation deciles. In the period studied, the relative decline in *SD*(e_0) was greatest for men (-9.98%) and women (-7.72%) living in the most deprived areas, falling from 16.65 to 14.99 years and 15.41 and 14.22 years compared to men (8.65%) and women (1.10%) living in the least deprived areas. While the decline in *SD*(e_0) of men in the most deprived areas was steadier over time, the decline in female *SD*(e_0) in the same areas was rockier, alternating between a small decrease and an increase. Between 2006 and 2013, female *SD*(e_0) values stagnated around 14.50 years, before they started decreasing again, reaching 14.21 years in 2019. The *SD*(e_0) of men living in the least deprived areas revealed a decrease from 14.22 years in 2000 until 2004, followed by an increase in 2005-2006, and once again a decrease for the rest of the period studied, reaching 12.99 years in 2019. The values of female $SD(e_0)$ living in the least deprived areas equaled 12.77 years in 2000, only 0.15 years more than in 2019, corresponding to 12.62 years.

The *SD(M+)* decreased from 7.92 (95%CI 7.59-8.63) to 7.17 (95%CI 7.16-7.99) years and from 6.57 (95%CI 6.42-6.85) to 6.06 (95%CI 5.86-6.25) years for men and women living in the most deprived areas; in the least deprived areas, male *SD(M+)* decreased from 6.07 (95%CI 5.96-6.57) to 5.65 (95%CI 5.27-5.89) years and female *SD(M+)* decreased from 5.97 (95%CI 5.48-6.10) to 5.51 (95%CI 4.99-5.78) years. These results show a small but significant decrease over time for male *SD(M+)* in the least deprived areas and female *SD(M+)* in the most deprived areas. Figure 6.5 shows the development of *SD(M+)* in men and women without deprivation stratification. Both decile-stratified and Belgian-specific results suggest that while the compression of mortality above the mode is still occurring, it has slowed down in those areas.

A detailed inspection of the *SD(M+)* trends reveals that between 2000 and 2007, the behavior of male *SD(M+)* in the most deprived areas was erratic, showing a small, but steep increase followed by a decrease of similar intensity. Then between 2008 and 2012, the mortality variability above *M* remained more or less the same. Afterward, *SD(M+)* followed a trend of repetitive decreases and increases, fluctuating between 6.50 and 7.50 years. Male *SD(M+)* in the least deprived areas showed a similar but more subdued trend. In women, the *SD(M+)* of the most deprived areas almost perfectly mirrored the trend of the least deprived areas.

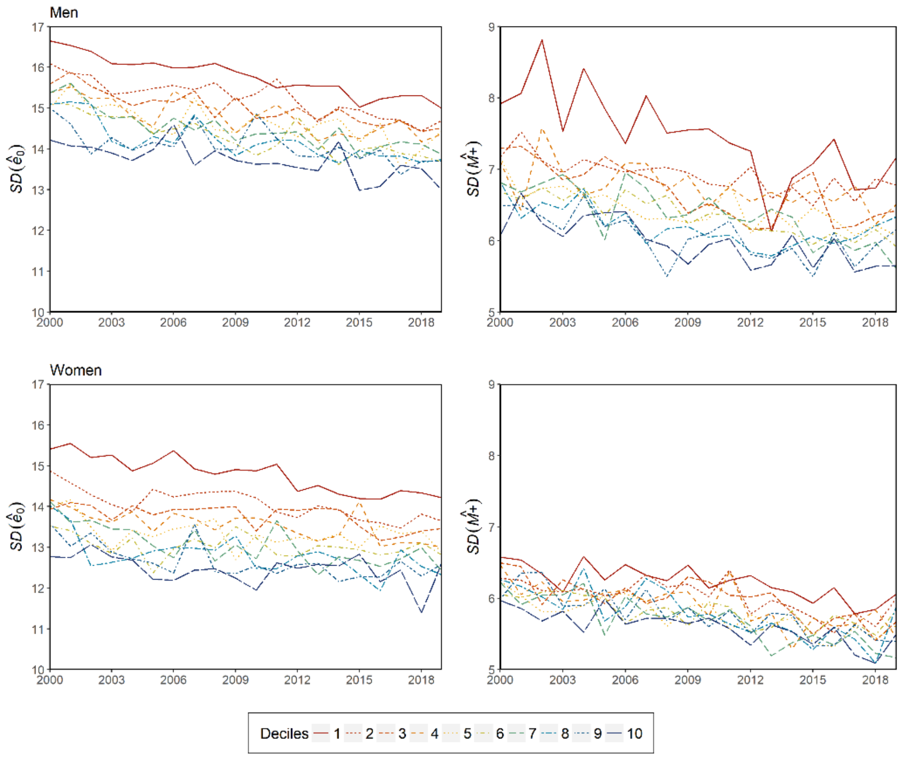


Figure 6.5 Estimated standard deviation of life expectancy at birth and standard deviation above the modal age at death and by sex and deprivation deciles in Belgium, 2000 to 2019.

Trends and levels of cause-specific modal age at death (Mk)

Figure 6.6 depicts trends and levels in the cause-specific modal age at death (M_k) for men and women living in the most and least deprived areas of Belgium between 2000 and 2019. A similar ranking (from lowest to highest values of M_k) was observed in men living in the most and least deprived areas: lung cancer, colorectal cancer, and a tie between cerebrovascular diseases and heart disease. In women living in the most and least deprived areas between 2000-2019, the lowest M_k was observed for lung cancer, followed by breast cancer, colorectal cancer, cerebrovascular, and heart disease.

In 2000, the greatest gap in cause-specific M_k estimates for men living in the most and least deprived areas was observed between lung cancer and prostate cancer, whereas for women, the largest difference was seen between lung cancer and heart disease (the most deprived) and lung cancer and cerebrovascular diseases (the least deprived). The most common age of death from lung cancer in men living in the most deprived areas occurred around the age of 71.79 (95%CI, 70.16-72.63), almost 3 years earlier than for men dying of lung cancer living in the least deprived areas 74.50 (95%CI, 73.43-77.12). These men, however, died about 12 years sooner than men with prostate cancer, living either in the most (83.99, 95%CI 83.22-85.60) or least deprived areas (86.05, 95%CI 85.02-86.51). At the same time in the most and least deprived areas, the most common age of death of women dying by heart disease was 87.47 (95%CI, 87.32-88.17), and 86.81 (95%CI, 86.95-88.06) years, whereas M_k of cerebrovascular diseases was 86.03 (95%CI, 85.67-87.74) and 88.32 (95%CI, 86.54-90.10) years, about 14 and 10 years later than women who died of lung cancer in the most (71.17, 95%CI 70.81-75.73) and least deprived areas (78.52, 95%CI, 76.25-81.09).

During the period studied, the modal age at death has increased for all causes of death. In 2019, men living in the most and least deprived most commonly died at the following ages: lung cancer - 78.35 (95%CI, 76.70-80.01) vs 80.43 (95%CI, 78.14-82.72), colorectal cancer – 82.31 (95%CI, 78.70-82.40) vs 85.35 (95%CI, 83.74-86.94), cerebrovascular diseases – 85.20 (95%CI, 84.00-86.47) vs 89.07 (95%CI, 88.28-89.99), heart diseases – 85.94 (95%CI, 84.27-86.29) vs 89.94 (95%CI, 89.25-90.00), and prostate cancer – 85.47 (95%CI, 84.61-86.34) vs 89.95 (95%CI, 89.12-90.78). Female modal age at death in the most and least deprived areas in 2019 corresponded to: lung cancer – 73.23 (95%CI, 71.99-75.70) vs 79.55 (95%CI, 75.66-83.43), breast cancer – 82.97 (95%CI, 80.77-84.40) vs 85.61 (95%CI, 82.76-86.79), colorectal cancer – 85.91 (95%CI, 84.73-86.82) vs 87.93 (95%CI, 86.88-89.12), cerebrovascular diseases – 88.79 (95%CI, 88.15-89.81) vs 90.60 (95%CI, 89.82-91.34), and heart disease – 90.17 (95%CI, 89.84-90.50) vs 91.89 (95%CI, 91.56-92.22).

Figure 6.6 Estimated modal age at death for leading causes of death among Belgian men and women living in the most and least deprived areas, 2000-2019.

Figure 6.7 shows the absolute difference in cause-specific M_k between the least and most deprived areas in the period studied. The greatest absolute difference was observed in M_k of lung cancer in both sexes, oscillating between 2 and 10 years with an average of 5.31 years in men, and fluctuating between -2 and 14 years with an average of 6.12 years in women. An average absolute difference of around 3.60 years (men) and 1 year (women) was observed for the remaining M_k, i.e. colorectal cancer, heart diseases, and cerebrovascular diseases. The average absolute difference in M_k was 2.21 years for prostate cancer and 1.57 years for breast cancer.

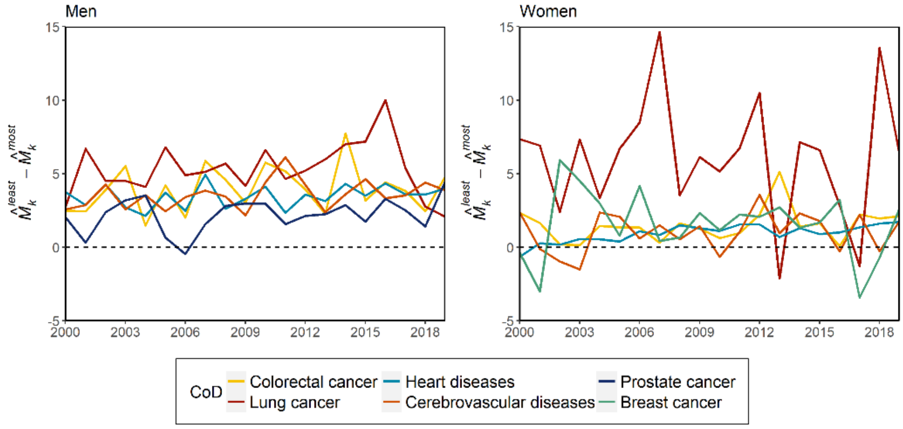


Figure 6.7 Absolute difference between the cause-specific Mk of the least and most deprived areas.

To assess the slopes of the various M_k, we modeled each M_k trend as a linear function of time. The results presented in Figure 6.8 indicate no significantly different increase in the pace of the male M_k. From selected causes of death, heart diseases show the fastest increase in male M_k in the most and least deprived areas, nevertheless without a significant difference. In women, we see a significant difference in M_k increase of heart diseases between the most and least deprived areas. In addition, the M_k of breast cancer has been increasing the fastest, with a significantly greater pace in the most deprived areas compared to the remaining M_k. The results of the linear model reflect the fluctuating trend of M_k of lung cancer in women, by showing a value of 0 and a large uncertainty.

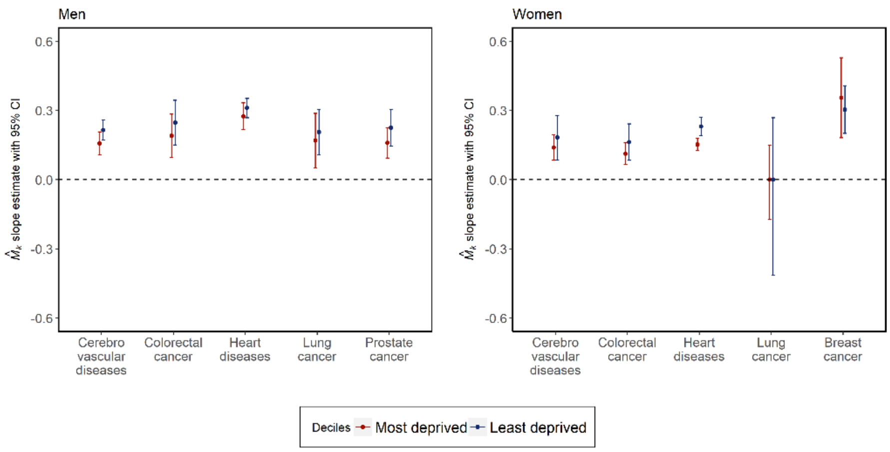


Figure 6.8 Estimated cause-specific M linear slope and 95% CI for men

and women in the most and least deprived deprivation deciles, 2000 to 2019.

Cause-specific standard deviation above the mode

Figure 6.9 shows cause-specific trends in $SD(M_k+)$ in men and women living in the most and least deprived between 2000 and 2019, revealing a few significant reductions, but mainly small, insignificant decreases in $SD(M_k+)$. The greatest dispersion of cause-specific deaths across old ages was observed in men and women living in the most deprived areas compared to the least deprived. In men living in the most and least deprived areas, we observed the greatest $SD(M_k+)$ for lung and colorectal cancer compared to prostate cancer, and heart, and cerebrovascular diseases. Among women, lung and breast cancer displayed the greatest $SD(M_k+)$ in the most deprived areas, whereas in the least deprived areas, $SD(M_k+)$ of selected causes of death were more interwind.

For men in 2000, the cause of death with the greatest dispersion was lung cancer, corresponding to 20.82 years (95%CI, 19.96-22.34) in the most and 18.45 years (95%CI, 15.86-19.52) in the least deprived areas. Nineteen years later, lung cancer still has the greatest dispersion, showing no change in the level of its *SD(M_k+)* in the most deprived areas (20.24, 95%CI 17.45-21.05), but showing a significant reduction for the least deprived areas (13.00, 95%CI 9.15-13.42). A significant decline in the variability of male age at death above *M* was observed for heart diseases – falling from 13.25 (95%CI, 12.31-14.64) to 9.97 (95%CI, 9.66-11.50) years among the most deprived, and from 9.20 (95%CI, 8.67-9.57) to 7.82 (95%CI, 7.44-8.21) among the least deprived. Another significant decrease in dispersion above M was seen in deaths by prostate cancer for men living in the least deprived areas, *SD(M_k+)* fall from 7.48 (95%CI, 6.95-8.44) to 4.70 (95%CI, 4.22-5.43). In 2000, the gap between the most and least deprived was greatest and only significant for deaths by cerebrovascular diseases, heart diseases, and lung cancer, corresponding to 3.59, 3.30, and 2.36 years. In 2019, the same causes of death showed a significant inequality. The gap, however, narrowed by 1.20 years for heart diseases, a positive change run by faster decline among the most deprived compared to the least deprived. On the other hand, the gap widened by 0.50 and almost 5 years for cerebrovascular diseases and lung cancer. In addition, the gap between *SD(M_k+)* of prostate cancer between the most and least deprived increased from 1 to 2.12 years, resulting in greater and significant inequalities between these two deprivation groups. In all three cases (cerebrovascular diseases, lung cancer, and prostate cancer), this increase was linked to a faster decline in $SD(M_k+)$ in the least deprived compared to the most deprived regions.

Substantial differences between $SD(M_k+)$ of selected causes of death were also noticed in women. In 2000, the variability of age at death among the elderly was greatest for lung cancer (20.07, 95%CI 18.41-23.29) and breast cancer (15.70, 95%CI 12.10-18.39) in the most deprived areas. The $SD(M_k+)$ of these two causes of death stayed greatest across the whole period studied, oscillating between 16 and 27; and 11 and 22 years. Figure 6.9 shows that for women living in the least deprived areas, breast cancer and lung cancer competed for the first place in the greatest variability of age at death at higher ages during the period studied. In the first and last year, breast cancer won this competition with $SD(M_k+)$ of 16.23 (95%CI, 12.10-18.40) and 11.40 (95%CI, 8.64-12.63), suggesting no significant reduction in variability over time. No significant $SD(M_k+)$ decrease was observed among women in the least and most deprived areas. The gap between the most and least deprived was greatest and significant for $SD(M_k+)$ of lung cancer, cerebrovascular diseases, and heart diseases in 2000 and 2019. The gap between the female $SD(M_k+)$ of lung cancer in the most and least deprived areas decreased from 10.67 to 8.25 years. This reduction was caused by two events - a decrease in $SD(M_k+)$ among the most deprived by 0.92 and a rise in $SD(M_k+)$ among the least deprived by 1.52 years. Inequality in female $SD(M_k+)$ has also decreased for cerebrovascular diseases – the gap narrowed from 5.18 to 3.51 years. In this case, $SD(M_k+)$ was reduced in both opposite deprivation deciles, but this reduction was greater for the most deprived (by 2.24 years) compared to the least deprived (0.57 years). On the contrary, the gap between female $SD(M_k+)$ of heart disease increased from 1.02 to 1.34 years due to a much greater reduction of $SD(M_k+)$ in the least deprived (by 1.30 years) compared to the least deprived (by 0.90 years).

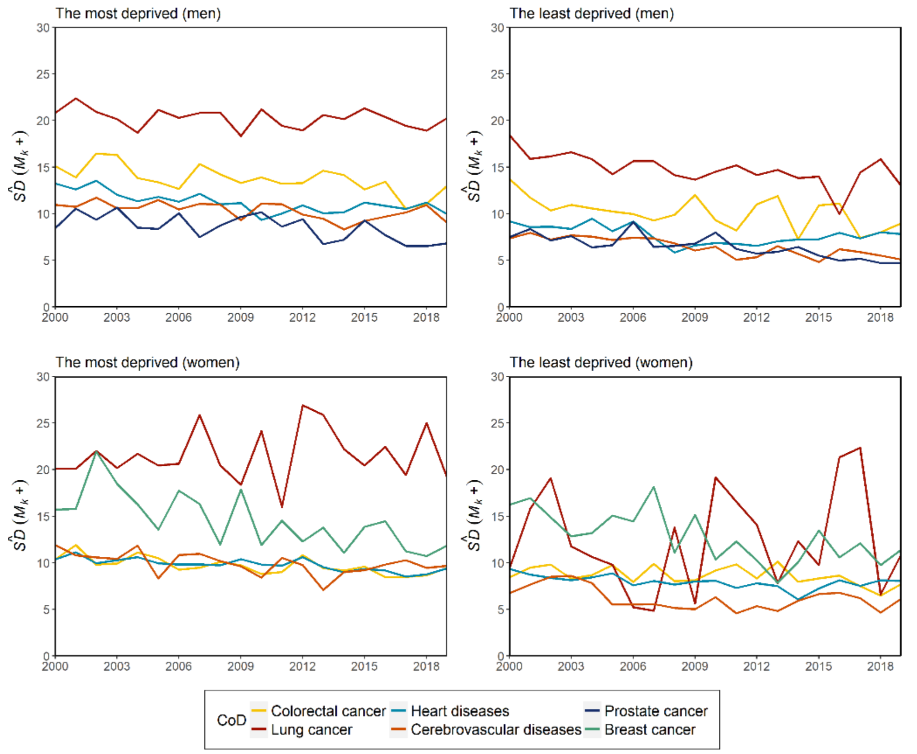


Figure 6.9 The standard deviation above the modal age at death for the most relevant causes of death.

6.4 Discussion

Our study compares levels and trends in sex-, all-cause, and cause-specific lifespan indicators and their dispersion measures between different socioeconomic deprivation groups in Belgium from 2000 to 2019. Our results show that the most common age of death has been significantly higher than life expectancy at birth for men and women across the whole study period and the most and least deprived deprivation levels. Both lifespan indicators have increased for men and women in the most and least deprived areas, with a faster pace of improvement in the least deprived areas leading to an increase in lifespan disparities.

Time trend results show differences between life expectancy at birth and modal age at death, revealing a lack of survival advantage in modal age at death among women in the least deprived areas in the early 2000s. While a significant disparity in life expectancy at birth between women in the most and least deprived areas was evident throughout the whole study period, a notable convergence in the modal age at death of women from these areas was observed between 2000 and 2004. Our cause-specific analysis of modal age at death shows that women in the most deprived areas had M of breast cancer, cerebrovascular diseases, and heart disease either similar or significantly higher than women in the least deprived areas. Since no methods currently exist that would decompose M by cause of death, our cause-specific results can only give a broad idea of what causes of death might contribute to the unexpected pattern of all-cause M.

Existing studies from abroad as well as from Belgium on socioeconomic inequalities in breast cancer have already reported greater all-age and premature mortality rates in the higher socioeconomic groups (Faggiano et al., 1997; Heck & Pamuk, 1997; Otavova et al., 2024; Renard et al., 2015). Similarities in *M* of cerebrovascular diseases and heart diseases have not been explained in the Belgian context and need further investigation.

Since 2005, all-cause female *M* started diverging, demonstrating an almost twice as high relative increase in the least deprived compared to the most deprived areas. Studies on cause-specific mortality show that mortality rates of breast cancer, cerebrovascular, and heart diseases have been significantly reduced since the 2000s (Otavova et al., 2024; Vanthomme & Gadeyne, 2019). Their reduction has been linked to curative and preventive medicine improvements, behavioral patterns and lifestyle changes, and ongoing medical progress. Women living in the most deprived areas of Belgium may have had more restricted access to advanced screening procedures or effective therapeutic interventions compared to those women living in the least deprived areas. The ability of individuals to optimize their potential for a longer life has been associated with gains in education attainment (Brown et al., 2012), and it has been shown that educational levels are low in the most deprived areas.

The findings of our study also show the downward trends in all-cause standard deviation above the modal age at death in the most and least deprived areas. The compression of deaths into a shorter age span suggests narrower inequalities in the number of years lived by men and women in their respective deciles. The greatest variability in the spread of deaths above *M* has been observed in men and women in the most deprived areas and the gap between these two deprivation groups has slightly reduced for both sexes. The cause-specific standard deviation above the modal age at death varied greatly by cause of death. The largest variability was observed in age at death of lung cancer, followed by colorectal cancer, among men in the most and least deprived areas. In women living in the most deprived areas, the largest *SD(Mk+)* was observed for lung cancer, followed by breast cancer, while in women in the least deprived areas, *SD(Mk+)* of lung cancer competed with *SD(Mk+)* of breast cancer throughout the study period. Between 2000 and 2019, the gap between the most and least deprived cause-specific *SD(Mk+)* was seen for lung cancer.

Strengths and limitations

Our study has three key strengths. The main strength of our study is the use of the Belgian Indices of Multiple Deprivation 2011 for classifying the smallest geographical units of Belgium, statistical sectors, into deprivation deciles. The BIMD2011 integrates data on income, education, employment, housing, and crime to shed light on disparities linked to socioeconomic factors. In addition to encompassing a broad spectrum of disadvantageous circumstances, a key strength of the BIMD2011 is its replicability. This feature allows for future updates with the most recent data, enabling follow-up studies to track developments in lifespan inequalities in Belgium since 2019.

Another key strength of our study is the use of a flexible nonparametric smoothing method based on P-splines proposed by Ouellette and Bourbeau (2011) for estimating the modal age at death (Ouellette & Bourbeau, 2011). Instead of smoothing the age distribution of life table deaths, the P-spline approach for Poisson death counts uses data on observed deaths and person-years lived to obtain a smoothed force of mortality, from which the corresponding smoothed age at death distribution is derived.

An additional notable strength of our study is the use of all-cause and cause-specific mortality data from the whole population of Belgium to obtain population-level estimates of lifespan indicators. All-cause mortality data from death registrations are exhaustive and highly reliable in Belgium (Mikkelsen et al., 2015). Our data can be broken down by geographical area to pinpoint the areas with the greatest lifespan inequalities and variability.

Our research also has several methodological limitations. The modal age at death only reflects changes in mortality at ages above the mode. Canudas-Romo (2010) proved that when mortality at ages below the modal age at death decreases, the modal age at death remains unchanged (Canudas-Romo, 2010). Thus, the evolution of the modal age at death by cause since 2000 does not illustrate the progress made in reducing premature mortality below the modal age. Furthermore, modal age at death, like all demographic indicators obtained from period data (such as life expectancy at birth), represents the most frequent age at death of persons of a fictitious population that is exposed to the same mortality regime throughout their lives as observed during the calendar year in question. This limitation could be solved by conducting a cohort analysis, i.e. estimating the modal age at death within generations. However, the type of data we have at our disposal, i.e. data by calendar year and over a relatively long time, makes it difficult to estimate the modal age at death by cohort.

One potential limitation of our study is the lack of access to all-cause and cause-specific mortality data by a single year of age before 2000. International studies indicate that the most significant increases in the modal age at death and the largest reductions in standard deviation above the mode occurred before the 1990s (Diaconu et al., 2020; Diaconu et al., 2016; Ouellette et al., 2012). A study by Janssen et al. (2019) showed that the mortality delay of women in Northern and Western Europe started very early - between 1955 and 1970 (Janssen & de Beer, 2019). Our data also does not allow us to identify the year of the onset of the increase in modal age at death for cerebrovascular diseases and heart diseases, because the cardiovascular revolution was already in full swing in 2000.

6.5 Conclusion

Our research shed light on changes in the distribution of all-cause and cause-specific most frequent age at death and its variability by sex and deprivation level in Belgium. Our findings indicate that mortality compression in old age persists in both the most and least deprived areas of Belgium.

Chapter 7 General discussion

7.1 Introduction

This thesis aims to study the trends and patterns of socioeconomic inequalities in different health indicators in Belgium since the 2000s. *Chapter 2* describes the development of the first Belgian Indices of Multiple Deprivation (BIMDs). *Chapter 3* investigates the association between housing inequality and increased mortality in Belgium. *Chapter 4* studies the socioeconomic disparities in cause-specific premature mortality, population-attributable fraction, and potential years of life lost due to inequality. *Chapter 5* addresses the spatial variation in cause-specific premature mortality and its association with socioeconomic deprivation. *Chapter 6* uncovers socioeconomic disparities in modal age at death.

7.2 Summary of main findings

The first empirical contribution of this dissertation, introduced in *Chapter 2,* focuses on developing the first Belgian Indices of Multiple Deprivation (BIMD2001 and BIMD2011). More specifically, it presents a major methodological shift from using a simple measure of deprivation, such as income or education, at the individual level, to a more sophisticated composite measure of deprivation at the aggregate level of the smallest geographical unit in Belgium, the statistical sector. The BIMDs are built on six domains of deprivation (income, employment, education, housing, health, and crime), which means that each statistical sector receives a global deprivation score or a domain-specific score that can be ranked and assigned to global or domain-specific deprivation deciles. Such methodology allows scientists to explore either global or domain-specific deprivation.

The results from *Chapter 2* show that in 2001 and 2011, almost 80% of the most deprived statistical sectors were located in Wallonia, while about 90% of the least deprived statistical sectors were in Flanders. The most deprived statistical sectors were more spatially concentrated and clustered, whereas the least deprived areas showed greater spatial variations. In 2001 and 2011, the greatest concentration of the most deprived statistical sectors (measured by global BIMDs) was in the municipality of Charleroi, which was also identified as having the greatest concentration of most deprived sectors in terms of income, employment, education, housing, and crime. Across all six domains, no evidence was found suggesting a higher concentration of the least deprived statistical sectors in one municipality. Overall, the majority of the least deprived sectors in terms of deprivation domains were located in Flanders, fluctuating between 60% in terms of housing deprivation and 95% in terms of employment. The indices and their domains are publicly available at https://github.com/bimd-project/bimd.

Chapter 3 aims to assess whether housing inequality is associated with increased mortality and to estimate the number of deaths that could be prevented if the entire country's population faced the mortality rates experienced in the areas classified as the least deprived in terms of housing. Housing inequality is measured by the 1991, 2001, and 2011 housing deprivation domains at the level of statistical sectors, grouped by the housing deprivation deciles. The 1991, 2001, and 2011 Belgian National census data were utilized to create the housing deprivation domains. Individual-level mortality data, extracted from the Civil Registry in Belgium and pertaining to deaths that occurred between January 1, 1991, and December 31, 2020, were used for health indicator estimates, such as age-standardized mortality (ASMR), potential years of life lost due to inequality (PYLL), and life expectancy at birth (e_0). The study time was split into three periods (1991-2000, 2000-2010, and 2011-2020).

Results from this chapter show that one in five deaths occurring in Belgium between 1991 and 2020 could be associated with inequalities in housing measured by the housing deprivation domains. It means that up to 18.5% (95%CI, 17.7-19.3) or 584,875 of all deaths could be prevented if the whole of Belgium had the mortality rates of the least deprived areas. These findings are in sync with the results of a study by Damiens (2020) who concluded that low-quality housing may increase mortality rates by 25% after controlling for educational attainment, professional status, and income.

During the study period, the age-standardized mortality rates declined in both sexes across all deprivation deciles, with the greatest relative decrease observed in men and women living in the least deprived areas. The gap between the most and least deprived narrowed for men but widened for women. Consequently, male mortality associated with housing inequality decreased over time by 8%, while female mortality associated with housing inequality increased by 23%, comparing 1991-2000 vs 2011-2020, respectively. On the other hand, the mean number of potential years of life lost associated with housing inequality decreased in both men and women by 39% and 25%. The observed increase in life expectancy at birth in men and women across all housing deprivation deciles was mostly driven by declines in mortality at higher ages. The disparities in life expectancy at birth between the most and least deprived deciles decreased in men but increased in women.

These results indicate that residing in inadequate housing is associated with adverse health outcomes, and thus, housing should be ranked a priority health determinant in regional and national policies and surveillance systems.

In *Chapter 4* the products of *Chapter 2*, the Belgian Indices of Multiple Deprivation (BIMD2001 and BIMD2011), created without the health domain, are used to investigate the association between area deprivation and detailed cause-specific premature mortality (i.e. deaths before the age of 75) between 1998 and 2019 (split into four periods: 1998-2003, 2004-2008, 2009-2013, and 2014-2019). The causes of death were grouped using a three-level hierarchy: ICD-10 chapters (such as I00-I99: circulatory diseases); subcategories (e.g. I20-925: ischaemic heart disease), and diagnosis responsible for more than 1,000 deaths in each study period (e.g. I20: acute myocardial infarction). Age-standardized premature mortality rates, population attributable fraction, and potential years of life lost due to socioeconomic inequality were estimated by sex, year, deprivation decile, and cause of death.

Results from this chapter show that men and women living in the most deprived areas were 1.96 and 1.78 times more likely to die prematurely compared to those living in the least deprived areas over the study period. About 28% of all premature deaths could be attributed to socioeconomic inequalities (measured by BIMDs), corresponding to 1 person dying prematurely every hour in Belgium between 1998 and 2019). About 30% of potential years of life lost would be averted if the whole population of Belgium faced the premature mortality rates of the least deprived areas.

Results from *Chapter 4* are in line with findings from previous studies that reported a decrease in premature mortality rates and an increase in health inequality in Belgium over time (Damiens, 2020; Eggerickx et al., 2018; Renard, Gadeyne, et al., 2017; Renard et al., 2014, 2015). Standardized premature mortality rates decreased in men and women across all deprivation deciles, with a greater decrease observed in those living in the least deprived areas. Previous findings can therefore be extended by the newest insight that the inequality between the most and least deprived areas has increased due to a faster pace of decrease in the least deprived areas compared to the most deprived. The greatest inequality in cause-specific premature mortality was observed for diseases of the respiratory, mental, behavioral, and digestive systems. The greatest inequality measured by the population attributable fraction (or premature mortality attributable to inequality) and potential years of life lost due to inequality was seen in premature deaths due to psychoactive substance use, chronic lung and liver disease, obesity, and diabetes mellitus – causes of death linked to increased use of opiates, alcohol, and tobacco, and poor diet.

Results published in *Chapter 4* emphasize the importance of a more in-depth evaluation of health and social policies, highlighting the need for new, subnational interventions to protect individuals with lower socioeconomic status more effectively from health-deteriorating lifestyles and environments.

Chapter 5 examines spatial variation in cause-specific premature mortality and its association with socioeconomic deprivation in Belgium from 2000 to 2019. In doing so, socioeconomic deprivation is not measured by BIMD's deciles at the level of statistical sectors, but by global and domain-specific average deprivation scores at the municipal level. These scores are population-weighted measures, based on BIMD2011 global deprivation score and domain-specific scores.

The health outcome of interest is the relative risk of all-cause or cause-specific premature mortality (i.e. cardiovascular diseases; cerebrovascular diseases; lung cancer; cancer of the lip, oral cavity, pharynx, larynx, and oesophageal cancer; breast cancer; colorectal cancer; diabetes mellitus; mental and neurological diseases excluding alcohol-related deaths; COPD; alcohol-related deaths; road accidents; non-transport accidents; and suicide). This study employs an innovative approach – a spatio-temporal model fitted within the Integrated Nested Laplace Approximation (INLA).

Findings in *Chapter 5* suggest 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, and a positive association between overall and domain-specific deprivation and premature mortality. Most spatial patterns show a strong North-South gradient between Flanders and Wallonia, with higher RRs spatially concentrated, and clustered together, forming a belt that starts by the French border and ends at the German borders with the district of Verviers. In men and women, the greatest increase in heterogeneity in relative risks at the municipal level was observed for causes of death linked to unhealthy lifestyle behavior, such as alcohol consumption, tobacco use, or poor diet. These causes of death have been already identified in Belgium (Otavova et al., 2024) and other countries (Mackenbach, 2012; Mackenbach et al., 2003; Mackenbach et al., 2016) as those driving the increase in inequalities, which also means that a possible reduction in their inequalities would have the maximal impact on Belgian all-cause premature mortality. *Chapter 5* also reports findings revealing a positive correlation between the average deprivation scores and all-cause and most cause-specific relative risk of premature death, with the greatest impact on RRs of premature death due to COPD, alcohol consumption, and diabetes mellitus. A rare negative association is observed between deprivation and the RR of premature deaths due to road accidents. This trend can be explained by the fact that road traffic mortality is associated with distance traveled and higher speed – two elements we see in Belgian municipalities with a higher proportion of rural areas.

The final empirical chapter, *Chapter 6*, returns to the investigation of health inequalities at the statistical sector level. These sectors are grouped into deprivation deciles based on their levels of deprivation as determined by the BIMD2011. This chapter also shifts the focus from premature and all-age mortality to mortality at higher ages, specifically examining the modal age at death, or the most frequent age of death, in men and women across deprivation deciles annually, from 2000 to 2019. The analysis includes multiple metrics: the modal age at death (*M*), estimated using a P-spline approach—a flexible nonparametric smoothing method introduced by Ouellette and

Bourbeau (2011) (Ouellette & Bourbeau, 2011); the dispersion of deaths at older ages is assessed using the standard deviation above the modal age at death (*SD(M+)*); life expectancy at birth (e_0) and its standard deviation (*SD*(e_0)) are also estimated. Furthermore, *M* and *SD*(*M+*) are calculated not only for all-cause mortality but also for the leading causes of death, which include cerebrovascular diseases, heart diseases, lung cancer, prostate cancer, breast cancer, and colorectal cancer.

Findings in *Chapter 6* show that *M* and e_0 have increased since the 2000s and *M* has been significantly higher than e_0 across all deprivation deciles and studied years. Disparities were observed for male and female e_0 and male *M* between the most and least deprived during the whole study period. While a significant difference in male e_0 and *M* between the most and least deprived was observed during the whole study period, a lack of survival advantage was revealed in *M* among women in the least deprived areas between 2000 and 2004. Although currently, no methods exist that would decompose *M* by cause of death, our cause-specific analysis showed that women in the most deprived areas had *M* of breast cancer, cerebrovascular diseases, and heart disease either similar or significantly higher than women in the least deprived areas. These causes of death might contribute to the unexpected pattern of all-cause *M*. This female survival disadvantage in *M* of the least deprived areas disappears in 2005 when a clear divergence between the most and least deprived is observed for the first time. Results in *Chapter 6* also show a downward trend in all-cause and cause-specific *SD(M+)* across all deprivation deciles. The decreasing trend in *SD(M+)* indicates a compression of deaths into a shorter age span suggesting narrower inequalities in the number of years lived by men and women in their respective deciles. The levels of cause-specific *SD(M+)* varied significantly by cause. Among men in the most and least deprived areas, lung cancer had the greatest *SD(M+)* values showing the greatest variability, followed by colorectal cancer. Among women from the most deprived areas, lung cancer had the largest *SD(M+)*, followed by breast cancer, while in the least deprived areas, lung and breast cancer *SD(M+)* were comparable.

7.3 The contribution to existing research on inequality in Belgium

This dissertation aims to provide a more in-depth picture of socioeconomic health inequalities in Belgium in the first twenty years of the 21st century.

The primary and most significant contribution of this dissertation to existing research on socioeconomic inequality in Belgium is the creation of the first Belgian Indices of Multiple Deprivation (BIMDs) – the multidimensional instruments for measuring levels of socioeconomic deprivation at the smallest geographical unit in Belgium, the statistical sector. The development of BIMDs represents a shift a) from simple measures of SES to a modern and powerful tool encompassing multiple dimensions of deprivation, and b) from individual to area-level measures. Although the BIMDs currently exist for 2001 and 2011, they can be updated using the latest available datasets, for example, once data from the census are released. Despite the complexity of their methodology, the BIMDs are designed to be user-friendly, and their outcomes are easily interpretable and useful for both academic and non-academic audiences alike. The indices are publicly available on GitHub (https://github.com/bimd-project/bimd), and the general public can use the BIMD interactive tool (https://bimd.sciensano.be/tool/) to assess the deprivation level of any Belgian address.

When released in 2024, the BIMD tool received a great deal of attention in the national and local press (Trends-Tendances[6], le Soir[7], RTBF[8], etc.). It was also the subject of a question in the Walloon parliament to the Minister of Health and Social Action, who pointed out that his tool could be particularly useful in the development of 'territory diagnosis' for future local and regional healthcare organizations[9].

Although several studies have already investigated the socioeconomic inequalities in health in the Belgian context, none of them used an area-level measure of multiple socioeconomic deprivation similar to the BIMDs. Thus, another relevant contribution of this dissertation to the existing research is a detailed cause-specific analysis of health inequalities between different levels of socioeconomic deprivation, measured either by global BIMDs or individual deprivation domains (i.e. income, education, employment, housing, and crime).

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[6] https://trends.levif.be/a-la-une/social/les-personnes-vivant-dans-un-quartier-defavorise-ont-deux-fois-plus-de-risques-de-deceder-prematurement/

[7] https://www.lesoir.be/560818/article/2024-01-11/vivre-dans-la-pauvrete-cest-risquer-deux-fois-plus-de-deceder-avant-75-ans

[8] https://www.rtbf.be/article/ou-les-inegalites-de-sante-sont-elles-les-plus-elevees-le-nouvel-outil-de-sciensano-et-luclouvain-les-devoile-dans-une-cartographie-11311215

[9] https://www.parlement-wallonie.be/pwpages?p=interp-questions-voir&type=30&iddoc=126206

Measuring the size of health inequality does not only greatly depend on selected measures of socioeconomic inequality, but also on selected health indicators. In this dissertation, first, the association between housing inequality and all-age mortality, population-attributable fractions (PAF or mortality attributable to housing inequality), and potential years of life lost (PYLL) due to housing inequality is investigated (*Chapter 3*), followed by research on the association between global socioeconomic deprivation and premature mortality, PAF, and PYLL (*Chapter 4*). These four health indicators represent four different perspectives – all-age mortality provides a complete picture of the health status and mortality patterns within all populations across deprivation deciles, premature mortality highlights the disparities before the age of 75 across deprivation deciles, PAF measures the impact of the inequality of the whole population and offers an estimate of the potential reduction in premature mortality if socioeconomic inequalities were eliminated, and PYLL completes the picture by weighting the burden of each condition with the loss of quantity of life. In addition, the findings from *Chapter 4* represent a valuable extension of the findings in *Chapter 3*. The greater magnitude of inequality reported in *Chapter 4* might suggest that housing indices only partially capture inequalities and the role of other factors, such as education and income must be considered to have a more comprehensive picture.

In addition to the sex- and age-specific analysis of socioeconomic inequalities in health, another key contribution of this dissertation is the investigation of the spatial variability of cause-specific relative risk of premature mortality in *Chapter 5*. Through spatio-temporal analysis, this research illustrates the levels and trends of spatial patterns across Belgian municipalities since 2000, highlighting the variability of these patterns over time. The relative risk estimates provide a direct comparison between the risk of premature mortality occurring in municipalities versus the whole of Belgium in a given period. Additionally, it quantifies the strength of the association between socioeconomic deprivation—both global and domain-specific—and premature mortality, potentially guiding health interventions and prevention strategies.

Lastly, this dissertation expands the research on lifespan inequalities by investigating socioeconomic disparities in modal age at death in *Chapter 6*. The most frequent age at death has been long omitted in the Belgian scientific literature, and this is the first study examining differences in modal age at death across different deprivation groups and providing critical insights into old age mortality and longevity. Studying the most frequent age at death complements other lifespan measures like life expectancy at birth, providing a fuller picture of longevity and survival patterns in the Belgian population. Our decile-specific analysis reveals that all-age and cause-specific mortality are not compressed around the same age, indicating significant inequalities. These disparities may stem from differences in access to healthcare, living conditions, and disease prevention measures.

7.4 Methodological considerations

This section outlines the strengths and limitations shared by all empirical chapters presented in this dissertation. More detailed strengths and limitations are discussed within each empirical chapter.

Strengths

The main strength of the research introduced in this dissertation is that it relies on highly reliable individual-level pseudonymized datasets. The Belgian Indices of Multiple Deprivation (*Chapter 2*) and Housing Deprivation Indices (*Chapter 3*) were mainly built on the 1991, 2001, and 2011 population censuses. The individual-level all-cause and cause-specific mortality data were extracted from the Civil Register in Belgium (*Chapters 3, 4, 5, and 6*), and mid-year population estimates were obtained from the National Register data (all chapters). Working with administrative and exhaustive data led to minimizing selection bias and reducing the risk of ecological fallacy. Coupling the census data and national register allowed an imputation of missing information for some indicators, such as in the case of the housing domains (*Chapters 2 and 3*).

Another strength of this research is the decision to build the Belgian Indices of Multiple Deprivation and measure health inequality at the aggregate level, though this decision has raised some questions. The main benefit of the BIMD use is the wider range of disadvantageous circumstances covered. The BIMD2001 and BIMD2011 are constructed using 24 and 19 indicators, respectively. Including such a large number of indicators requires a) outsourcing more databases and b) addressing privacy, security, and confidentiality concerns associated with these data sources. These issues can be more effectively managed at the level of the statistical sector. Another reason for developing the BIMDs at the aggregate level was to encompass all three dimensions of area deprivation: compositional, collective, and environmental (Sally Macintyre, 1997). The compositional meaning of area deprivation is that an area is considered deprived if it contains a large proportion of deprived individuals. In contrast, the collective and environmental meanings refer to the additional deprivation in an area beyond what is attributable to the concentration of deprived individuals, often described as the "neighborhood effect.". Neighborhood effects have been increasingly researched, particularly in health and housing. Studies have shown that neighborhoods influence their inhabitants even after accounting for individual risk factors (Cubbin et al., 2000; Duncan et al., 1999; Dunn & Hayes, 2000; Pickett & Pearl, 2001; Shaw, 2004). Evidence has been accumulating that the area where a person lives can influence various aspects of their lives, including employment, child outcomes, criminal behavior, and other socioeconomic phenomena (Dietz, 2002). By creating the indices at the level of the statistical sector, all three dimensions of area deprivation - compositional, collective, and environmental - were effectively included.

Another notable strength of this dissertation is the selection of the smallest administrative unit, the statistical sector, as the unit of analysis. These statistical sectors represent the smallest workable spatial units that are relatively homogeneous, accurately reflecting actual communities or neighborhoods. Moreover, the boundaries of these sectors change minimally over time and are typically large enough to provide statistically robust estimates of socio-economic or health indicators with minimal smoothing required.

Limitations

The limitations are closely tied to the strengths mentioned above. The Belgian Indices of Multiple Deprivation (BIMDs) rely heavily on national census data, which means updates are only possible once a new census is conducted, processed by the national statistical office, and made publicly available. This dependency explains why BIMD2011 has not been updated yet, and why BIMD2024 is not currently available.

Additionally, the census and National Register data include only legal residents of Belgium, excluding illegal migrants and asylum seekers from this research. The migrant status might be a confounder for diseases with a strong genetic or migration-related risk (Bhopal et al., 2018; Smith et al., 2010) and including only the legal residence of Belgium might have resulted in an underestimation.

The Civil Registry records infant deaths only if the infant survives until January 1st of the following year; as a result, health indicators are calculated for individuals aged 1 year and older. However, in Belgium, infant mortality rates have decreased by 46% since 1998, reaching 2.9 per thousand live births in 2021 (Sciensano, 2024b).

Another limitation of using the Civil Registry is its inability to capture morbidity or quality of life aspects. Additionally, there is a risk of misclassification since mortality data rely on death certificate information, the quality of which is questionable for certain periods (Aelvoet et al., 2005). By restricting the analysis to data from 1998 onwards, periods with higher reporting errors in causes of death are avoided.

Internal mobility was also not considered as the deprivation deciles could only be assigned once to the deceived, i.e. at the time of death. The place of death was identified as the deceased's official place of registration, which may not correspond to the location where they were exposed to specific risk factors throughout their life.

Another limitation concerns our selection of health indicators. Some may consider it a shortcoming that we did not include traditional measures for assessing socioeconomic inequality, such as the Slope Index of Inequality (SII) and the Relative Index of Inequality (RII). Instead, we focused on more direct and intuitive health indicators, such as premature mortality rates and the population-attributable fraction. These indicators are often easier for stakeholders and policymakers outside the scientific community to interpret, whereas SII and RII can be more complex and may require additional explanation to be fully understood by non-scientific audiences.

All empirical chapters present ecological studies, which must be considered when interpreting the results. Ecological bias is unavoidable when assessing deprivation using aggregate indices, even when the smallest geographical unit is used (Sedgwick, 2015). Thus, inferences about individuals cannot be drawn from this analysis, as it focuses on group-level characteristics rather than individual experiences. It would be incorrect to assume that all individuals residing in highly deprived areas are themselves highly deprived, or that those living in less deprived areas are uniformly less deprived. The analysis examines the broader patterns and effects of area-level deprivation, not the specific deprivation status of each individual.

7.5 Suggestions and recommendations

When the Belgian Indices of Multiple Deprivation (BIMDs) for 2001 and 2011 were created, one of the main criteria was ensuring comparability over time. To maintain this comparability, similar indicators building the same domains were used. However, I have come to understand that this approach is no longer sustainable. While the conceptual framework of the indices should remain consistent for continuity, it is necessary to consider expanding the indices by including indicators or domains that reflect current experiences and circumstances as much as possible and practical. Thus, I advise the responsible parties for the BIMDs' update to consider several changes.

First, I suggest incorporating an outdoor living environment deprivation domain. This domain could account for environmental aspects such as air quality, the number of road accidents involving injury to pedestrians or cyclists, or access to green spaces. Environmental factors play a crucial role in shaping health, well-being, and socioeconomic outcomes, and including these indicators in the indices would enhance their reliability and comprehensiveness.

My second suggestion is inspired by the English Indices of Multiple Deprivation and its two supplementary indices – the Income Deprivation Affecting Children Index (IDACI) and the Income Deprivation Affecting Older People Index (IDAOPI). These indices are sub-sets of the Income Deprivation Domain, focusing on the two most vulnerable subpopulations: children and the elderly. The IDACI measures the proportion of all children aged 0 to 15 living in income-deprived families, while the IDAOPI measures the proportion of all individuals aged 60 or over experiencing income deprivation (McLennan et al., 2019).

I also recommend including discrimination-related indicators by using both direct and indirect measures to capture its social and economic impacts. Direct indicators could document reported experiences of discrimination, such as racial discrimination based on race, nationality, or ethnic origin, as well as discrimination related to religious beliefs or sexual orientation. Indirect indicators could reflect disparities often resulting from discriminatory practices, such as higher unemployment rates among non-Belgian-born residents or their disproportionate representation in lower-status jobs. To access relevant data, I suggest reaching out to Belgium's statistical office, Statbel, to review available datasets in advance. Additionally, consulting independent organizations like UNIA, the Brussels-based public organization dedicated to promoting equality and combating discrimination, could provide further data on inequality and discrimination across Belgium.

My last suggestion regarding the update of the BIMD is to validate and measure uncertainty. When building the BIMD2001 and BIMD2011, we used the shrinkage estimation to reduce uncertainty by borrowing strength from nearby areas - a technique used in the indices of multiple deprivation across the UK countries (Scottish Government, 2020; Smith et al., 2015). Only a few research articles discuss uncertainty in deprivation measures or provide any confidence interval

(Allik et al., 2020). Most often, a categorical deprivation measure is used without applying alternative methods. Given the range of techniques available for handling uncertainty, I strongly recommend that researchers working on the BIMD update place greater emphasis on this important aspect.

I believe that only by evolving and implementing these changes, the BIMD can remain a relevant and robust tool for measuring multiple deprivation in Belgium.

The fact that the indices are computed at the aggregated rather than the individual level has received substantial criticism. Therefore, my next suggestion is to assess the ecological bias induced by using the BIMDs at the aggregate level. The BIMD, likely in a reduced form, could be computed for individuals living in a smaller geographical area of Belgium, such as the Brussels-Capital Region, using individual-level socioeconomic characteristics. Limiting the study to a smaller area would be necessary due to data availability and the otherwise high computational demand.

To assess ecological bias, I recommend the following approaches - Receiver Operating Characteristics (ROC) analysis and distribution analysis. In the ROC analysis, the ROC curves for the global BIMDs and their deprivation domains would be assessed against each individual-level counterpart. This will help determine the accuracy and predictive power of the aggregate indices in identifying individual-level deprivation. In order to assess how well the indices can distinguish between the most and least deprived, the Area Under the Curves (AUC) could be calculated. The AUC can range between 0 to 1, with values close to 1 suggesting that the aggregate index perfectly distinguish individual deprivation, and values close to 0.5 means the contrary. The distribution analysis is more a complimentary approach, when the distribution of individuals considered most and least deprived at the individual level according to the decile version of the aggregate BIMDs is analyzed. This approach will provide insights into the degree of misclassification and the extent of ecological bias.

By implementing these assessments, we can better understand the limitations of using aggregated data and make necessary adjustments to improve the accuracy and relevance of the BIMDs.

About the author

Martina Otavova was born in 1982 in Považská Bystrica, Slovakia. In 2006, after completing her studies in Translation (Czech-German-English) at the University of Applied Sciences in Zittau, Germany, Martina moved to the United States. In 2012, Martina decided to return to school - a decision she has not regretted even after 12 years of academic pursuit.

In 2014, Martina earned an Associate in Arts degree from the College of the Florida Keys and then relocated to Orlando to continue her studies at the University of Central Florida. She graduated summa cum laude in 2016 with a Bachelor of Science in Interdisciplinary Studies, with minors in psychology and health sciences. Martina then moved to Belgium to pursue a master's degree, and in 2018, she graduated with distinction with a Master of Science in Statistics, specializing in Epidemiology & Public Health Methodology, from Hasselt University. Her master's project focused on the potential impact of reduced tobacco use on life and health expectancies in Belgium.

Following her master's degree, Martina received a full one-year fellowship from the Max Planck Institute of Demography at the European Doctoral School of Demography. She spent 11 months studying demographic methods at the University of Southern Denmark in Odense. After completing the program in 2019, she worked as a research assistant in the epidemiology unit at the Interdisciplinary Centre on Population Dynamics at the University of Southern Denmark.

In October 2020, Martina began a joint PhD program in Demography at the Catholic University of Louvain, Louvain-la-Neuve, and in Statistics at Hasselt University, Hasselt. In December 2022, she was awarded the Mitacs Globalink Research Award, enabling her to conduct a three-month research stay at the Department of Demography at the University of Montreal, Canada. During the winter of 2023, Martina interned at the Unit of Sensory Functions, Disability, and Rehabilitation at the World Health Organization in Geneva.

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