

**The contribution of lifestyle factors – smoking, obesity and alcohol – to
 state mortality differences in the United States**

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Abstract

Background: Already in 1980 the American government introduced the *Healthy People* initiative for increasing the healthy lifespan of Americans by the aim to reduce and eventually eliminate health disparities. However, reasons for geographical health disparities across the United States are still not completely understood. By focusing on to what extent all-cause mortality differences are due to lifestyle factors – smoking, obesity and alcohol – in the United States, this thesis contributes to the debate on determinants of mortality and geographical mortality differences.

Data and methods: This study contains a secondary analysis with quantitative data from the Institute of Health Metrics and Evaluation. This data includes deaths by all-causes, smoking, alcohol and obesity of every state in the United States in 2016. With this data age-standardized mortality rates were calculated. Then, (clustered) differences in age-standardized all-cause, smoking-, obesity- and alcohol-attributable mortality rates were mapped. Eventually the variance in all-cause mortality rates was decomposed to calculate the contribution of smoking, obesity and alcohol to all-cause mortality differences.

Results: Both genders showed high all-cause mortality in the South and East North Central, whereas the Northeast, the West and northern states of the West North Central showed the lowest all-cause mortality rates. Smoking- and obesity-attributable mortality differences showed for both genders similar patterns as all-cause mortality. Alcohol-attributable mortality differences for both genders were less comparable. Eventually, it was calculated that smoking has the highest contribution (males 26%; females 18%) to all-cause mortality differences in the United States in 2016, obesity has the second-highest contribution (males 6%; females 8%) and alcohol has the lowest contribution (males 1.9%; females 0.2%).

Conclusion: Smoking and obesity show a high contribution to all-cause mortality differences between states in the United States in 2016, whereas the contribution of alcohol is rather small and marginal. Therefore, the American government is advised to adjust smoking and obesity policy on a low or state level scale, whereas the alcohol policy suits a national approach to reduce and eventually eliminate health disparities as part of the *Healthy People* initiative.

Keywords: Lifestyle, Smoking, Alcohol, Obesity, Mortality, Regional differences, United States

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List of abbreviations

ASCDR	Age-standardized crude death rates
BMI	Body mass index
C	Age-composition
CHD	Coronary heart disease
CSDH	Commission of Social Determinants of Health
GBD	Global Burden of Disease
HHS	United States Department of Health and Human Services
IHME	Institute of Health Metrics and Evaluation
M	Age-specific death rates
PAF	Population attributable fraction
SES	Socioeconomic status
US	United States

1. Introduction

1.1. Background

Health inequalities apply to every geographical scale. It is known that large inequalities in health between countries exist. Sierra Leone for example has a life expectancy of 50 years, whereas this is 83 years in Japan (United Nations, 2017). But even neighboring countries are challenging health inequalities. The life expectancy in Canada is 81 years, whereas the United States (US) has a life expectancy of 79 years (United Nations, 2017).

Within countries, there are large health inequalities as well. According to Murray et al. (1998) the most and least advantaged populations in the US differ twenty years in life expectancy. This makes clear that health inequalities also exist in developed countries (Mackenbach, 2012). Health inequalities are widely present in the developed country of the US, because the country still lags behind other developed countries in handling major issues regarding well-being and health (United States Department of Health and Human Service [HHS], 2018a). This is remarkable because most of the gross domestic product of the US is spent on well-being and health (HHS, 2018a).

Although the US nowadays still experiences health inequalities, already in 1980 the HHS raised a national initiative to prevent diseases and promote health. This initiative was called *Healthy People* and presented a strategy for increasing the lifespan of Americans by aiming to reduce and eventually eliminate health disparities. Since this initiative was launched, states and counties are interested in understanding health equity issues by health monitoring of the population and providing background data. Every decade the health initiative sets objectives. In 2010 *Healthy People 2020* was launched (Singh et al., 2017).

Because *Healthy People 2020* is interested in eliminating health disparities (Singh et al., 2017), the initiative is partly focused on lifestyle (HHS, 2018b). Lifestyle factors are the major preventable mortality determinants (e.g., Lantz et al., 1998), with smoking, obesity and alcohol as the three lifestyle factors with most attributable deaths (Centers for Disease Control & Prevention, 1997; HHS, 2001; McGinnis & Foege, 2013). For these three lifestyle-attributable mortalities, significant geographical disparities exist in the US. For smoking this is caused by disparities among states in their smoking policies, such as differences in tobacco prices or smoke-free protection (HHS, 2018c). Differences in alcohol-attributable deaths occur because the states' own laws influence marketing, prices and availability of alcoholic beverages (Naimi et al., 2014). Geographical differences in obesity-attributable mortality exist because of many reasons as well, with the quality of health care as an important factor (Kelley et al., 2016). This illustrates why the *Healthy People* initiative is partly focused on lifestyle factors when it is aiming to eliminate health disparities.

1.2. Societal relevance

It is a challenge to help the US in reaching its full potential handling major issues regarding health and well-being and to be on a comparable level with other developed countries (HHS, 2018a). Because *Healthy People* is interested in eliminating health disparities (Singh et al., 2017), the initiative is partly focused on lifestyle (HHS, 2018b). Therefore, this thesis focuses on the contribution of lifestyle factors – smoking, alcohol and obesity – to all-cause mortality differences between states within the US. A local-level measurement of mortality is used, which ensures that avoidable disparities will be identified and can be addressed (Dwyer-Lindgren, 2017). This thesis can therefore provide some new information towards the *Healthy People 2020* initiative, so health differences can be eliminated within the country.

Information on the contribution of lifestyle factors to all-cause mortality differences is valuable, because health intervention design and policy can be helped by understanding the underlying causes of disparities in mortality (Tencza et al., 2014). When it is known that a certain lifestyle factor has a high contribution to geographical all-cause mortality differences in the US, it can be concluded that policy for that lifestyle factor has to be adjusted on a low scale. When a lifestyle factor has almost no contribution to geographical all-cause mortality differences in the US, a national approach could be effective.

Additionally, the information about the contribution of lifestyle factors to all-cause mortality differences provides a better understanding of the extent to which population reductions in smoking-, obesity- and alcohol-attributable mortality can be achieved in specific regions in the country (Kelley et al., 2016). The American government can undertake action to lower the deaths in the states or regions that have more lifestyle-attributable deaths. This is possible because lifestyle is a modifiable effect (Djoussé et al., 2009).

Moreover, mapping the geographical differences of lifestyle-attributable and all-cause mortality can result in new topics and issues for further research. This information is useful for ecological analyses to confirm or to reject existing hypotheses (Dwyer-Lindgren, 2017).

1.3. Academic relevance

Already in 1980 the American government introduced the initiative *Healthy People* for increasing the lifespan of Americans by aiming to reduce and eventually eliminate health disparities. However, the reasons for the geographical health disparities across the US are a growing area of research, because these disparities are still not fully understood (Montez et al., 2016). By focusing on the contribution of lifestyle factors – smoking, alcohol and obesity – to state all-cause mortality differences within the US, this thesis contributes to the debate on determinants of mortality and geographical mortality differences.

The research examines the three lifestyle factors with the most attributable deaths, namely smoking, obesity and alcohol (Centers for Disease Control & Prevention, 1997; HHS, 2001; McGinnis & Foege, 2013). No studies have been found which looked at the exact contribution of lifestyle factors to

geographic all-cause mortality differences in the US. However, thorough and recent studies of the contribution of lifestyle factors to geographic all-cause mortality differences have been carried out in other developed countries, such as the Netherlands and Norway (Jenum et al., 2001; Janssen & Spiensma, 2012).

Although no studies looked at the exact contribution of lifestyle factors to geographic all-cause mortality differences in the US, Montez et al. (2016) did find that the tobacco environment – including tobacco consumption – was an important predictor of state disparities in men's mortality. They did not find this result for women though. Additionally, studies which are focused on lifestyle-attributable mortality and their regional variation, are known, such as the study of Fenelon and Preston (2012), which focused on smoking-attributable mortality and state variation in the US. Such a study for alcohol-attributable mortality was carried out by Stahre et al. (2014). But by focusing on the exact contribution of lifestyle factors – smoking, alcohol and obesity – to state all-cause mortality differences within the US, it becomes clear that this thesis contributes to an unresearched area of the debate on determinants of mortality and geographical mortality differences.

1.4. Objective

The aim of this research is to identify to what extent state differences in all-cause mortality in the United States in 2016 could be due to the lifestyle factors smoking, alcohol and obesity.

1.5. Research questions

Main question:

To what extent are state differences in all-cause mortality in the United States in 2016 due to lifestyle factors smoking, alcohol and obesity?

Sub-questions:

1. What are the all-cause mortality differences between states of the United States in 2016 and how are these differences clustered or dispersed?
2. What are the smoking-, obesity- and alcohol-attributable mortality differences between states of the United States in 2016 and how are these differences clustered or dispersed?
3. How comparable are all-cause mortality differences in the United States in 2016 with smoking, obesity- and alcohol-attributable mortality differences?
4. What is the contribution of lifestyle factors – smoking, obesity and alcohol – to state differences in all-cause mortality in the United States in 2016?

1.6. Structure

In *chapter 2* the theories and literature review are discussed, from which a conceptual model is constructed. Additionally, some hypotheses are formulated. *Chapter 3* describes the data that is used and the source from which it was obtained. It also elaborates on the applied methods in this study. In

chapter 4 the results are shown. *Chapter 5* summarizes the findings of this thesis, followed by a discussion, from which conclusions and recommendations are drawn.

2. Theoretical framework

2.1. Theories

2.1.1. Epidemiologic Transition Theory

To what extent state differences in all-cause mortality are due to lifestyle factors smoking, alcohol and obesity, is a question that falls under the category of the Department of Demography. Epidemiology is the demographic study which is focused on the distribution of health, but also on their consequences and determinants (Omran, 2005). The distribution of epidemiology, and therefore mortality, is explained by the *Epidemiologic Transition Theory*, which contains that “the proportion of deaths from infectious diseases in a population will decline over time, while the proportion from degenerative diseases will increase” (Omran, 2005, p. 161). While the epidemiologic transition progresses in three stages, death tends to occur later in life. The transition of a population is generated by improvements in nutrition and sanitation (Omran, 2005). This illustrates how the *Epidemiologic Transition Theory* explains that mortality can vary geographically, because populations differ in their improvements in nutrition and sanitation.

The *Epidemiologic Transition Theory* described the changing patterns of diseases before 1960. Later information suggested that developed societies, such as the US, had entered a new stage in the transition. A few new stages were suggested, such as the hybrid stage (Rogers & Hackenberg, 1987). In this stage the health and mortality of developed populations is increasingly influenced by individual behaviors and lifestyles (Rogers & Hackenberg, 1987). So this new stage of the *Epidemiologic Transition Theory* suggests that mortality can vary geographically in developed populations because these populations differ in their behavior and lifestyles. This applies to this thesis, in which geographical variation of populations with different lifestyle-attributable mortality rates is researched.

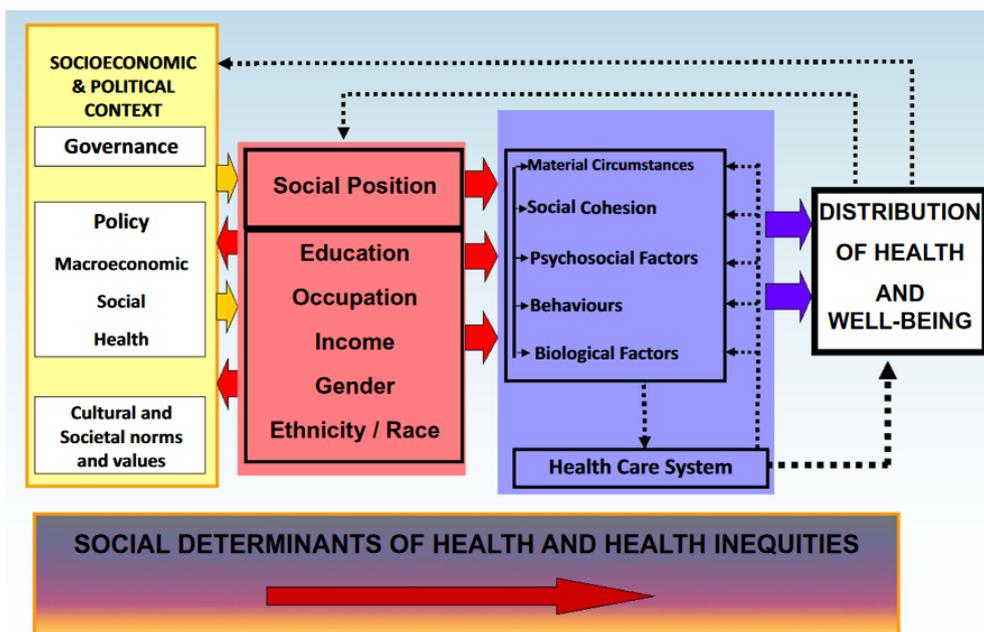
2.1.2. Determinants of health

This thesis examines to what extent state differences in all-cause mortality are due to lifestyle factors smoking, alcohol and obesity. Lifestyle factors are a determinant of health (Health and Welfare Canada, 1974; Dahlgren & Whitehead, 1991; Young, 2005), which are statuses in which people are born and live. These characteristics of statuses of individuals and groups affect mortality outcomes at individual and population levels (Singh et al., 2017).

The health determinants have been categorized by many researchers and studies (Health and Welfare Canada, 1974; Dahlgren & Whitehead, 1991; Young, 2005), which provided different categorizations. However, all these categorizations have in common that personal lifestyle and behavior is one of the health determinants (Health and Welfare Canada, 1974; Dahlgren & Whitehead, 1991; Young, 2005). Among the overlapping health determinant personal lifestyle and behavior the determinants smoking, obesity, alcohol, sexual practices, drugs and safety practices are represented (e.g., Young, 2003).

In the model of causation of social determinants of health (Commission of Social Determinants of Health [CSDH], 2008), all the different health determinants categorizations are represented (Figure 2.1). This model explains the (geographical) distribution of health and well-being, and therefore mortality, by the health determinants. According to the model, lifestyle factors, represented by health determinant behavior, have a direct influence on the (geographical) distribution of health and well-being. This applies to this thesis, which examines to what extent state differences in all-cause mortality are due to lifestyle factors smoking, alcohol and obesity.

Figure 2.1. Model of causation of social determinants of health (CSDH, 2008)



2.1.3. Compositional vs. contextual effects

Shaw et al. (2002) explained variations in health by distinguishing between compositional and contextual effects. These different effects of populations ensure differences in mortality (Boyle et al., 2004). Compositional effects contain differences in health at the individual level. The aggregate of these individual level characteristic differences are the compositional effect differences on population level. Such characteristics are for example sex, age and lifestyle (Shaw et al., 2002).

The contextual effects consist of the environment in which people live their lives, the physical and social environment. The social environment contains for example health policies, the socio-economic situation and the provision and utilization of services, such as healthcare. Examples of the physical environment are air and water quality, pollution and climate (Anthamatten & Hazen, 2011).

Boyle et al. (2004) stressed whether geographical differences in health could be attributed to contextual or compositional effects. A study by Mitchell et al. (2000) showed that the majority of the mortality differences in the United Kingdom could be attributed to compositional effects. However, for some regions mortality differences seemed to be due to contextual factors. Therefore, it was decided to

consider the compositional effects firstly for researching variations in health differences (Boyle et al., 2004). However, all in all, the different composition and contextual effects of populations ensure differences in health and therefore mortality.

2.2. Literature review

2.2.1. Geographical all-cause mortality differences

This thesis examines to what extent state differences in all-cause mortality are due to lifestyle factors smoking, alcohol and obesity. It is known that geographical differences exist in all-cause mortality in the US. Xu et al. (2018) researched the crude death rates per 100,000 of the population for every state in the US in 2016. A pattern can be seen in these crude death rates. Especially the southern region (see Figure S.1 in the Supplementary material for an overview of the regions and divisions in the US) experiences high crude death rates: Alabama (1078.8 per 100,000), Arkansas (1062.7 per 100,000), Kentucky (1077.9 per 100,000), Mississippi (1062.0 per 100,000), Oklahoma (1001.0 per 100,000) and Tennessee (1020.2 per 100,000). To compare, the average crude death rate per 100,000 population in the US in 2016 is 849.3. On the other hand, low death rates are seen in the western region: Alaska (605.7 per 100,000), California (668.1 per 100,000), Colorado (677.4 per 100,000), Utah (587.1 per 100,000) and Washington (751.1 per 100,000). This research of Xu et al. (2018) showed all-cause mortality differences in the US are of a significant proportion and it illustrates the importance of understanding the underlying factors for these all-cause mortality differences.

2.2.2. Health determinants and geographical mortality differences

Differences in health and mortality outcomes across US regions reflect differences in sociodemographic, institutional, environmental and behavioral factors (Murray et al., 2006). However, no thorough or recent studies have been found that looked at the exact contribution of health determinants to geographic all-cause mortality differences in the US. Related research on the US is focused on the relationship between health determinants and geographical differences in health and mortality.

Already in 1947 it was argued that race is a health determinant that resulted in geographical mortality differences in the US. The study of Altenderfer (1947) found that regions with more non-whites in their 'color composition' experienced higher total mortality and infant mortality compared to regions with more whites in their 'color composition'.

Gender is another important determinant for geographical mortality differences in the US. Mortality rates, as a result of coronary heart disease (CHD), were highest in the East South Central of the US while the lowest were found in Mountain states. Despite that, CHD rates for both genders seemed to follow a similar pattern but CHD mortality rates showed a more clustered geographical pattern for females (Fabsitz & Feinleib, 1980).

From the article of Brand (1971) it became clear that (non-)metropolitan areas are a determinant for geographical health and mortality differences. Low rates of lung cancer were located in the non-metropolitan East South Central division. The highest rates were almost all found in metropolitan areas in the Northeast. Community air pollution is one of the reasons for the high urban rates according to the article. This study is in line with the study of Wiehl (1948), from which it became clear that urban populations have higher mortality rates compared to rural populations.

The importance of the health determinant economic environment is illustrated by the finding that states with a high median household income tend to have low mortality rates (Morgan & Morgan, 2013), while Osler et al. (2003) found that an area's unemployment level predicts adult mortality. Income inequality in a state seems to matter as well: it is a strong predictor for trends in mortality in the US (Kaplan et al., 1996). According to Kennedy et al. (1996) the lack of access to medical care is the reason why income inequality in a region ensures higher mortality rates.

Social cohesion seems to affect health differences between states as well. One indicator of social cohesion is social capital, which is a predictor of the mortality of a state according to Kawachi et al. (1997). Social capital can affect mortality by norms of reciprocity, solidarity, information flows and collective actions in a community setting (Putnam, 2000), whereas it can predict income inequality (Subramanian et al., 2001) and individual health (Herian et al., 2014) on a state level.

A state's policy or socio-political orientation is another health determinant. States with a high presence of tobacco manufacturers therefore show a higher prevalence of tobacco consumption. Moreover, less restrictive controls were seen in those states, for example for smoking in public places. As a result the population of these states may experience more exposure to second-hand smoke (Montez et al., 2016). Also, with the lifestyle factor alcohol a state's policy seems to influence this, with its own laws on marketing, availability and even prices affecting alcoholic beverages (Naimi et al., 2014). A state's socio-political orientation can also affect mortality by the social expenditures on health (Montez et al., 2016).

Previous mentioned studies show health determinants can explain all-cause mortality differences, but also lifestyle-attributable mortality differences (e.g., a state's policy). This illustrates it is important to examine to what extent state differences in all-cause mortality are due to lifestyle factors smoking, alcohol and obesity. Additionally, it shows it would be interesting to know which lifestyle factor is more influenced by the variation of other health determinants and therefore varies more across the population itself. On the other hand, it would become clear which lifestyle factor is more independent from other health determinants and is therefore more equally divided across the population. For this research it was decided to examine the three lifestyle factors with the most attributable deaths (e.g., Centers for Disease Control & Prevention, 1997; HHS, 2001; McGinnis & Foege, 2013).

2.2.3. Lifestyle factors and geographical mortality differences

2.2.3.1. Smoking

Cigarette smoking is the lifestyle factor with the most attributable deaths in the US and produces therefore significant health-related costs (Centers for Disease Control & Prevention, 1997; Max, 2001). Smoking-attributable mortality is of international importance (Ezzati & Lopez, 2004) and therefore many studies have looked into the contribution of smoking to all-cause mortality differences between countries (Bobak & Marmot, 1996; Spijker, 2003; Janssen et al., 2007; Staetsky, 2009; Rostron & Wilmoth, 2011). However, less research is focused on the existing contribution within a country (Shaw et al., 2000; Vallin et al., 2001; Bonneux et al., 2010). Studies focusing on the exact contribution of smoking to geographical all-cause mortality differences in the US are therefore missing. However, Montez et al. (2016) did find that the tobacco environment – including tobacco consumption – was an important contributor to state mortality differences for males in the US.

There are studies for other countries focusing on the exact contribution of smoking to geographical all-cause mortality disparities. Smoking had a contribution of 39% among males and 30% among females to all-cause mortality disparities in the Netherlands (Janssen & Spiensma, 2012). Additionally, Jenum et al. (2001) studied 25 districts in Oslo between 1991-1995 with Norwegians aged 45-74 and found that smoking contributed for 70% to all-cause mortality disparities between those districts among males and 46% among females. It illustrates how high the contribution of smoking can be to geographical differences in all-cause mortality within a developed country.

What is known about geographical differences within the US regarding the topic of smoking, is that significant differences exist across states in the population that smokes (Datta et al., 2006; Pearce et al., 2008; Chahine et al., 2011). A contemporary study of Dwyer-Lindgren (2017) found high levels of cigarette smoking among males in parts of the Midwest and South. Low levels of cigarette smoking were observed in western states like Washington, California, Colorado, Utah and Wyoming. The highest levels of cigarette smoking by women have been found in the East South Central around Kentucky and Tennessee. The lowest levels were seen in the same states as the males, but also along the Mexico-Texas border.

These results are in line with the study of Fenelon and Preston (2012), who published an article about smoking-attributable mortality for people in the age of 50 to 84 in 2004. The substantive pattern they found was the relative disadvantage of southern smoking-attributable mortality to other regions. Their smoking-related mortality fractions among males were close to 30%, while Mountain states – like Utah, New Mexico and Colorado – had fractions lower than 15%. For females, the highest attributable fractions were spread in Alaska, Kentucky and Nevada (around 22%), whereas western states Utah, New Mexico and Hawaii had the lowest fractions (around 10%). The question arises what the results would be for other age groups when using more contemporary data.

2.2.3.2. Obesity

The US showed a large increase in the prevalence of obesity in the last four decades, which therefore became the main public health crisis next to smoking (HHS, 2001; Ogden et al., 2006). Obesity studies have reported large disparities between American states and population groups (Ogden et al., 2006; Wang & Zhang, 2006). Whereas racial and gender disparities in the prevalence of obesity in the US are frequently studied, geographic disparities are not. This is mainly the result of small geographical scale surveys used in studying disparities in the prevalence of obesity (Singh et al., 2008). Studies focusing on the contribution of obesity to geographical all-cause mortality differences in the US are therefore missing.

What is known are geographical differences in obesity prevalence. Male and female children show similar geographical patterns in obesity in the US. Particularly children in southern states had excess odds of obesity, while the Mountain states showed low obesity prevalence among children (Singh et al., 2008). Wang and Beydoun (2007) did such a study for American adults, and found that states in the East South Central have higher prevalence obesity rates among adults than states in the Northeast, Midwest and along the Pacific.

Obesity-related quality-adjusted life years lost were examined by Jia and Lubetkin (2010), and their results mostly confirmed the other studies. The lowest levels of lost obesity-attributable quality-adjusted life years were found in western states, while the highest levels were seen in and around states in the East South Central such as Alabama. Additionally, they saw disparities between states decrease over time, meaning that less obese states are reaching levels of more obese states. However, the study did not look at gender differences among the states.

2.2.3.3. Alcohol

Approximately 88,600 deaths were attributable to alcohol in the US in 2010, which makes it the third cause of preventable death in the country (McGinnis & Foege, 2013). Alcohol studies have reported disparities between American states and population groups. Naimi et al. (2014) concluded that the alcohol policy environment in a state is an important determinant of drinking behavior at the population level and therefore alcohol-attributable mortality. Differences in alcohol-attributable deaths occur because state laws influence marketing, prices and availability of alcoholic beverages (Naimi et al., 2014).

Mainly national-level surveys collect information on alcohol use in the US. The Behavioural Risk Factor Surveillance System and National Survey on Drug Use and Health generate estimates for states though (Dwyer-Lindgren, 2017). However, thorough studies focusing on the contribution of alcohol to geographical differences in all-cause mortality in the US are still lacking.

What is known about geographical differences in the US regarding the topic of alcohol, is that the prevalence of any, heavy and binge drinking is relatively high in counties in the northern states of the

West and Midwest, but also along the Pacific and in the states of New England. Lower levels of drinking were found in the South and southern states of the West centered around Utah. Alcohol use prevalence is typically higher for males compared to females (Dwyer-Lindgren, 2017).

The study of Gonzales et al. (2014) examined geographical differences in alcohol-attributable mortality in the US, also between genders. They saw the highest level of alcohol-attributable mortality rates in New Mexico for both males (73.4%) and females (29.4%) between 2006 and 2010. The lowest levels were found in Utah for males (31.0%) and Virginia for females (12.7%). The problem is that this study only examined eleven out of fifty states. Stahre et al. (2014) did look at all states when examining alcohol-attributable mortality differences. They found small differences between alcohol-attributable mortality rates of states in the US between 2006 and 2010. But relatively high rates were found in southern and western states, whereas low alcohol-attributable mortality was seen in the Northeast. These results are partly contradicting the study of Dwyer-Lindgren (2017), although Stahre et al. (2014) did not look at gender differences.

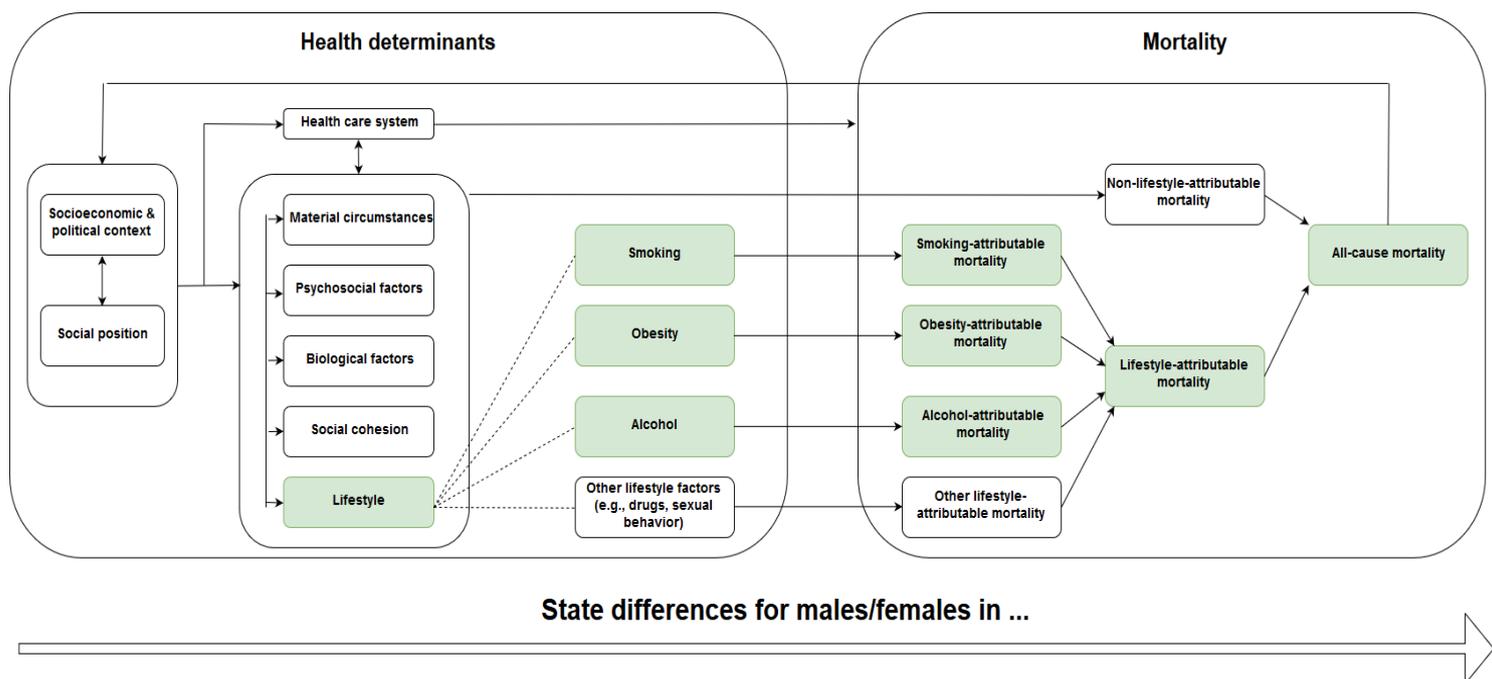
2.3. Conceptual model

From the theories and literature review a conceptual model has been constructed (see Figure 2.2). This model is needed to show the main concepts of this thesis and their interrelations because the aim of this research is to examine to what extent all-cause mortality differences are due to lifestyle factors – smoking, obesity and alcohol – in the US. The conceptual model is therefore based on the model of causation of social determinants of health (CSDH, 2008), which explains the distribution of health via the health determinants. The distribution of health in this thesis is represented by all-cause mortality differences. In the model of causation of social determinants of health (CSDH, 2008) all the different health determinant categorizations are represented. Smoking, obesity and alcohol are health determinants that belong to the overlapping determinant lifestyle and behavior.

The conceptual model should be read from left to right, as shown by the arrow. For every concept in the model, the words “State differences for males/ females in...” can be placed. Because this thesis elaborates on the differences between the sexes (based on theory and the literature review), the conceptual model can be seen separately for the sexes. The arrow from left to right indicates that state differences on the left side of the model result in state differences on the right side of the model. An example: state differences for males in social positions result in state differences for males in lifestyle. State differences for males in lifestyle result in state differences for males in lifestyle-attributable mortality. State differences for males in lifestyle-attributable mortality then result in state differences for males in all-cause mortality.

This thesis focuses on the extent in which all-cause mortality differences are due to lifestyle factors – smoking, obesity and alcohol – in the US. All the concepts in this thesis that have been researched are therefore highlighted in green. The health determinant lifestyle is divided into smoking, obesity, alcohol

Figure 2.2. Conceptual model



and other lifestyle factors (e.g., sexual practices and drugs) (Young, 2003), but this thesis only examines smoking, obesity and alcohol. State differences for males and females in lifestyle are influenced by state differences in other health determinants, such as social position, socioeconomic and political context, material circumstances, psychosocial factors, biological factors, social cohesion and the health care system. In contrast to the model by the CSDH (2008), state differences in socioeconomic and political context directly influence the state differences in other health determinants in this conceptual model. This became clear from the literature review (e.g. Montez et al., 2016).

Besides the health determinants, the two other mentioned theories are indirectly represented in the conceptual model. The *Epidemiologic Transition Theory* of Omran (2005) functions firstly as a background for the indication that the US is at a new stage in the epidemiologic transition, and therefore modifications in lifestyle are of great influence on mortality. Rogers and Hackenberg (1987) designed a new stage for the *Epidemiologic Transition Theory*, the so-called hybridic stage. This new stage suggested that mortality can vary geographically in developed populations because these populations differ in their behavior and lifestyles. This is illustrated in the conceptual model.

Shaw et al. (2002) explained variations in health by distinguishing between compositional and contextual effects. These different effects of populations ensure differences in mortality. The compositional and contextual effects are represented in the health determinants. So are compositional effects for example sex, age and lifestyle, which are represented in the model of causation of social determinants of health (CSDH, 2008) in the health determinants social position, biological factors and behavior. The contextual effects contain the statuses in which people live their lives, the social

environment and the physical environment (Shaw et al., 2002). These environments are also represented in health determinants, such as material circumstances. So populations differ in mortality because of different composition and contextual effects, known as different health determinants. This is what the conceptual model shows.

2.4. Hypotheses

The following hypotheses are formulated:

1. A clustered pattern of high all-cause mortality rates will be found in the southern region, whereas a low cluster of all-cause mortality rates will be found in the western region in the United States in 2016.

The hypothesis is based on the study of Xu et al. (2018), who researched the crude death rates per 100,000 population for every state in the US in 2016. They found that especially the southern region experienced high crude death rates, whereas low crude death rates were seen in the western region. The same pattern is expected with standardized all-cause mortality rates in this thesis.

2. A clustered pattern of high smoking-, obesity- and alcohol-attributable mortality rates will be found in the southern region in the United States in 2016, whereas low clusters of mortality rates will be found in the western region for smoking and obesity and in the Northeast region for alcohol.

This hypothesis is based on most studies in the literature review. Fenelon and Preston (2012) discovered the southern smoking mortality disadvantage relative to other regions (especially the Mountain division). Obesity-related quality-adjusted life years lost were examined by Jia and Lubetkin (2010), who found the lowest lost years in western states, while the highest levels were seen in and around states in the East South Central. Stahre et al. (2014) found high alcohol-attributable mortality in southern and western states between 2006 and 2010, but low alcohol-attributable mortality in the Northeast.

3. The patterns of smoking- and obesity-attributable mortality differences will be similar to all-cause mortality differences, whereas patterns of alcohol-attributable mortality differences will look different compared to all-cause mortality differences in the United States in 2016.

This hypothesis is also based on the literature mentioned at the previous hypothesis, which showed patterns of smoking- and obesity-attributable mortality are expected to be similar to patterns of all-cause mortality. However, Stahre et al. (2014) found high alcohol-attributable mortality in western states, which indicates a different pattern can be expected compared to all-cause mortality.

4. Smoking will have the highest, obesity the second-highest and alcohol the lowest contribution to all-cause mortality differences in the United States in 2016.

This hypothesis is based on a few studies in the literature review. In other studies it was found that smoking has a significant contribution to all-cause mortality disparities for both sexes within a

developed country (Jenum et al., 2001; Janssen & Spriensma, 2012). For alcohol the lowest contribution to all-cause mortality differences is expected, since the study of Stahre et al. (2014) showed small differences between alcohol-attributable mortality rates of states in the US. Therefore, it is expected that obesity-attributable mortality has the second-highest contribution to all-cause mortality differences.

3. Data and methodology

3.1 Study design

To what extent state differences in all-cause mortality in the US are due to lifestyle factors smoking, alcohol and obesity in 2016, is examined by a quantitative analysis. Quantitative research is often cross-sectional. Cross-sectional studies involve observations of a cross section of a population that are made one point in time (Babbie, 2016). Because differences between states are only examined in 2016 in this thesis, this counts as a cross-sectional study.

Babbie (2016) also mentioned that a major purpose of many social science studies is to describe situations and events. Therefore, this thesis mainly has a descriptive purpose, because this research describes and maps all-cause and lifestyle-attributable mortality differences which are observed between the states of the US in 2016.

3.2 Setting

The population in this study consists of all the individual inhabitants of the US in 2016. All ages are therefore included. The US has been chosen to study because literature showed that the contribution of smoking, obesity and alcohol to all-cause mortality differences in the US has not been researched yet. The year 2016 has been chosen because this was the year the most recent data was available for. It is beneficial to work with recent data when the aim of the research is to make some recommendations about health policy in the US.

The research is done on state level. The US consists of fifty states and one federal district (see Figure S.1). In this research the federal district is treated as a state, otherwise the inhabitants of this district could not be incorporated in the research. States are semi-sovereign regions that can determine their own policies and laws. Studies found that states shape mortality by these policies and laws, e.g. through tobacco tax (Montez et al., 2016). The states are divided in regions and divisions according to the United States Census Bureau (2018), which are the most contemporary used regions and divisions. This thesis needs these to find geographical differences within the country. The most recent regions and divisions fit with the data of the Institute of Health Metrics and Evaluation (IHME) which is used in this research.

This thesis elaborates on the two different sexes. From the theories it became clear that differences between sexes in the contributions to all-cause mortality differences could be expected, since sex is a compositional factor (Shaw et al., 2011) and a health determinant (a biological factor) according to the model of causation of social determinants of health (CSDH, 2008). The study by Montez et al. (2016) was one of the studies which showed that lifestyle-attributable mortality disparities in the US differed between the sexes. Additionally, it became clear by the studies of Jennum et al. (2001) and Janssen and Spriensma (2012) that the contribution of a lifestyle factor to all-cause mortality differences within a developed country differs between the sexes. For these reasons this research focuses on the sexes separately.

3.3. Data

The quantitative analysis of the contribution of lifestyle to state all-cause mortality differences in the US is examined using secondary data obtained from the IHME. This data includes deaths by all-causes and lifestyle causes (e.g., smoking, alcohol and obesity) of every state in the US in 2016. Additionally, the data for all ages is separately available.

As secondary data is used in this research, sampling of the population is not done by the researcher, but by the IHME. More than three hundred diseases and injuries are measured by the Global Burden of Disease (GBD) study of the IHME, which produces estimates for causes of death. All this data is not only available for the US as a whole but also for the district of Columbia and each of the fifty states. The data can be downloaded by sex and age group for each cause of death and more than eighty risk factors, from 1990 until 2016 (IHME, 2018a).

3.3.1 Operationalization of concepts

Mortality data is typically expressed as the total number of deaths due to a specific cause during a specific time period. Any condition that causes death is considered to be a "cause of death", such as cancer or cardiovascular diseases (Wang et al., 2016). Therefore, *all-cause mortality* rates in this thesis sum up the deaths of the inhabitants of the US in 2016, which can be obtained from the IHME.

The contribution of lifestyle factors to all-cause mortality differences in this research is represented by data on smoking-attributable, alcohol-attributable and obesity-attributable mortality, which is also retrieved through the IHME. As mentioned, mortality data is expressed as the total number of deaths due to a specific cause during a specific time period. So in this research smoking-attributable, alcohol-attributable and obesity-attributable mortality is the total number of deaths due to smoking, alcohol and a high body mass index (BMI) in 2016. Within the IHME data obesity is namely represented by data of a BMI (IHME, 2018a), which was calculated by data on weight and height as $\text{weight (kg)} / \text{height}^2 (\text{m}^2)$. An individual is obese if his or her BMI is higher than 30 kg/m^2 (Dwyer-Lindgren et al., 2013). Ogden et al. (2008) argued that the BMI is a good representation for measuring weight for height, both for children and for adults.

Estimates of *smoking-attributable mortality* data are generated by analyzing risk-outcome pairs, which are estimations using a comparative risk assessment approach. This approach firstly compared “observed health outcomes to those that would have been observed with a set of exposure where no one is exposed for each age group, sex and year” (Lim et al., 2012, p. 2228). According to Lim et al. (2012) the exposure definition for smoking in GBD studies is “*Smoking impact ratio for cancers and chronic respiratory disease, 10-year lagged tobacco smoking prevalence for all other causes including cardiovascular diseases*” (p. 2228). Additionally, second-hand smoking is added, with as exposure definition: “*Proportion of children and non-smoking adults reporting exposure to second-hand smoking*” (p. 2228). The theoretical minimum-risk exposure distributions are “*no tobacco smoking*” and

“no second-hand smoking exposure” (Lim et al., 2012, p. 2228). In other words, “the contribution of smoking to mortality is estimated by comparing the population risk of diseases under the current exposure distribution, to a theoretical counterfactual distribution, where no one is exposed” (Agardh et al., 2016, p. 1808); also called the population attributable fraction (PAF). Every risk-cause pair (e.g., smoking - chronic obstructive pulmonary disease) has such a PAF. To get the number of cause-specific deaths due to a risk factor, the estimated PAF is multiplied by the total cause-specific deaths. The resulting number is then divided by 100,000 to make it a rate. This process happens for each individual cause of the risk smoking and second-hand smoking, which is cumulative the *smoking-attributable mortality* (Forounzafar et al., 2015; Agardh et al., 2016).

Estimates of *obesity-attributable mortality* data are similar generated as smoking-attributable mortality, which are estimations using a comparative risk assessment approach (Lim et al., 2012; Agardh et al. 2016). The exposure definition for obesity in GBD studies is: “body mass index, measured in kg/m^2 ” (Lim et al., 2012, p. 2229). The theoretical minimum-risk exposure distribution is: “mean 21.0 – 23.0 kg/m^2 ” (Lim et al., 2012, p. 2229). Also here every risk-cause pair (e.g., obesity – pancreatic cancer) has a PAF. To get the number of cause-specific deaths due to a risk factor, the estimated PAF is multiplied by the total cause-specific deaths. The resulting number is then divided by 100,000 to make it a rate. This process happens for each individual cause of the risk obesity, which is cumulative the *obesity-attributable mortality* (Forounzafar et al. 2015; Agardh et al. 2016).

Estimates of *alcohol-attributable mortality* data are similar generated as smoking- and obesity-attributable mortality, which are estimations using a comparative risk assessment approach (Lim et al., 2012; Agardh et al. 2016). The exposure definition for alcohol in GBD studies is: “Average consumption of pure alcohol (measure in g/day) and proportion of the population reporting binge consumption of 0.06 kg or more of pure alcohol on a single occasion” (Lim et al., 2012, p. 2229). The theoretical minimum-risk exposure distribution is: “no alcohol consumption” (Lim et al., 2012, p. 2229). Also here every risk-cause pair (e.g., alcohol – tuberculosis) has a PAF. To get the number of cause-specific deaths due to a risk factor, the estimated PAF is multiplied by the total cause-specific deaths. The resulting number is then divided by 100,000 to make it a rate. This process happens for each individual cause of the risk alcohol, which is cumulative the *alcohol-attributable mortality* (Forounzafar et al. 2015; Agardh et al. 2016).

3.3.2. Ethical considerations

All data was secondary and the anonymity of the participants was guaranteed as this data was already displayed anonymously by the IHME. No patients were involved in the design and implementation of the study, because the data was collected by the IHME. Therefore, no contact was made with the participants of this study.

While there might be no ethical considerations regarding gathering the data, there are a few considerations handling the data. A researcher is not allowed to share the data collected by the IHME. All available data can be downloaded or requested directly at the website of the IHME¹. Additionally, it is important that the required data is not adjusted. The data is original and should be reproduced as it is by the IHME.

Ethical considerations regarding drawing conclusions from the data were mentioned by Babbie (2016). He argues to keep in mind with cross-sectional studies that conclusions are based on observations at only one time, so the researcher has to be careful drawing conclusions from processes that occur over time. In this research it has to be taken into account that the results are only based on 2016, but those results are affected by developments in earlier years which are not examined in the research.

3.4. Methods

The aim of this research is to identify to what extent state differences in all-cause mortality in the US could be due to the lifestyle factors smoking, alcohol and obesity. This aim is reached by using demographic, statistical and geographical techniques.

3.4.1. Age-standardization

First, age-standardized crude death rates (ASCDR) are made. Age-standardization is a demographic technique to compare populations with different age structures. Therefore, the composition of the populations is statistically transformed to a reference population (Naing, 2000), which in this thesis is the total population of the US by age and sex in 2016. Age-standardization is done because comparisons of age-dependent mortality across states can be masked by relative over- or under-representation of different age groups (IHME, 2018b). The ASCDR is formed via the direct standardization formula (Curtin & Klein, 1995):

$$ASCDR^j = \sum_{i=1}^{\infty} M_i^j \cdot C_i^s$$

First, age-specific mortality rates (M) are created. Age specific mortality rates are the total number of deaths of an age (group) in a state divided by the total population of the same age (group) in the same state (in 2016) and multiplied by 100,000. The direct standardization method means that the observed age-specific mortality rates (M) of a state are multiplied by the age-structure of the US (C) and taking its sum to get the ASCDR of a state (Curtin & Klein, 1995).

¹ Downloading or requesting the data, collected by the IHME, can be done via: <http://ghdx.healthdata.org/gbd-2016>

3.4.2. Mapping state differences

When the ASCDR's are made, age-standardized all-cause and smoking-, obesity- and alcohol-attributable mortality rates by sex are mapped with ArcGIS. The rates are categorized into five equally large intervals. This geographical analysis is to show geographical patterns of all-cause mortality and lifestyle mortality separately in ArcGIS. These maps are compared to observe similarities and differences.

Additionally in the same maps, which show age-standardized mortality rates per state, significant differences between states and the national level are viewed. In order to find out if the mortality in a state is significantly different from the average of the US, the equation of the differences between proportions is assessed, by assuming a normal distribution (Janssen & Spriensma, 2012). The equation of the differences between proportions is (Stattrek, 2018):

$$\sigma_{p1 - p2} = \text{sqrt} \{ [P_1 * (1 - P_1) / n_1] + [P_2 * (1 - P_2) / n_2] \}$$

where P_1 and P_2 are the standardized mortality rates for the US and a specific state and n_1 and n_2 the populations of the US and a specific state (Stattrek, 2018). To find out if there are significant differences between the rates of a state and the American average, a standard score, or Z-score had to be calculated. This score shows how many standard deviations a specific state is below or above the American average and is calculated by dividing the differences in the ASCDR of a state and the American average by the differences between proportions of this state and the American average (Thompson et al., 2004).

3.4.3. Cluster analysis

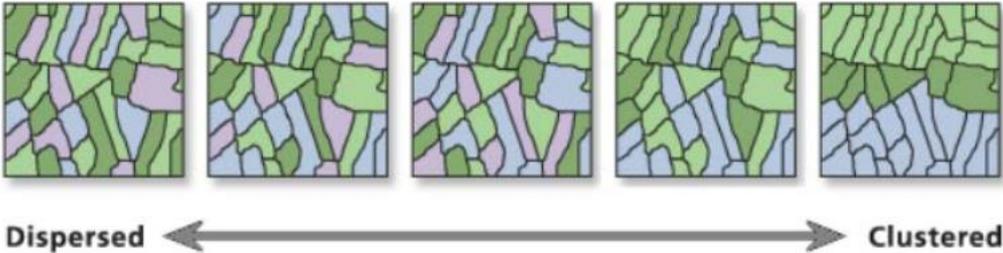
The third step in the analysis is to show how all-cause and lifestyle-attributable mortality differences between states of the US in 2016 are dispersed or clustered. This is examined by spatial autocorrelation, by the Global Moran's I in ArcGIS, to determine whether geographical patterns that were shown are significantly clustered within a region. A cluster is a region that has states with unusual high or low values; a local concentration of high or low rates (Cromley & McLafferty, 2002). The differences between state-specific ASCDR's and the average of all states combined are taken into account by the Global Moran's I. Because the Global Moran's I only allows features (in this case: states) that have at least one neighbor, the states Alaska and Hawaii are not integrated in the cluster analysis (ESRI, 2017). This analysis is represented in ArcGIS by the spatial statistics toolbox (Gatrell, 2002; Mitchell, 2005).

The Global Moran's I tests whether the observed patterns are randomly distributed, dispersed or clustered (see Figure 3.1). The outcome of this test can vary between -1 and 1. A value above zero indicates positive spatial autocorrelation and below zero indicates negative spatial autocorrelation. A value of 0 indicates that the pattern is random. The closer the value reaches -1 or 1, the more the patterns are dispersed or clustered in the country (Mitchell, 2005).

When the Global Moran's I presents positive spatial autocorrelation, an output shows where the clusters are located in the area of study. Specifically, the output shows where clusters of low values (LL), clusters of high values (HH), outliers in which low values are surrounded by high values (LH) and outliers where high values are surrounded by low values are located (HL) (ESRI, 2017).

The output of the Global Moran's I also shows a P-value. This P-value is used to determine whether the outcomes of the test are significant. The outcomes are significant if the null-hypothesis of the Global Moran's I is rejected, which contains that observed patterns are randomly distributed in the study area (Gatrell, 2002; Mitchell, 2005).

Figure 3.1. Outcomes of the spatial autocorrelation test (ESRI, 2017)



3.4.4. Decomposition of all-cause mortality variance

To determine the contribution of smoking-, obesity- and alcohol-attributable mortality to state variance in all-cause mortality, the latter is decomposed. Therefore, age-standardized death rates are used (Janssen & Spriensma, 2012). The state variance in all-cause mortality is separated into the state variance in smoking-, obesity- and alcohol-attributable mortality, the variance in non-smoking-, non-obesity- and non-alcohol-attributable mortality and twice the covariance between smoking-, obesity- and alcohol-attributable mortality and non-smoking-, non-obesity- or non-alcohol-attributable mortality (Janssen & Spriensma, 2012).

4. Results

4.1. All-cause mortality differences

In the US, all-cause mortality was represented by 5.44 deaths for males and 4.87 for females per 1000 population in 2016. The ASCDR for males ranged from 7.75 (Mississippi) to 4.30 (Utah), and for females from 6.46 (Mississippi) to 3.29 (Hawaii), also in deaths per 1000 population (see Figure 4.1). Both genders showed that the South and East North Central regions experience the highest all-cause mortality in general, whereas the Northeast, the West and northern states of the West North Central show the lowest ASCDR.

The all-cause ASCDR differs significantly for many states compared to the American average. For males, just 4 states did not significantly differ from the American average, 20 states and the District of Columbia had significantly higher ASCDR than average and 26 states had significantly lower ASCDR than average. For females, 10 states did not significantly differ from the American average, 17 states and the District of Columbia had significantly higher ASCDR than average and 23 states had significantly lower ASCDR than average.

The Global Moran's I (see Table 4.1) shows ASCDR of all-cause mortality are significantly clustered for both males and females at the 99% confidence interval. Clusters of high all-cause mortality for males are located in the South and southern states of the Midwest (see Figure 4.2). Therefore, a few surrounding states (Texas, Florida, Illinois and Virginia) are significant low-high outliers, which means these four states with low ASCDR are surrounded by a cluster of states with high ASCDR. Clusters of low all-cause mortality for males are predominantly located in the West and New England, with Nevada as the only significant high-low outlier.

Clusters of high all-cause mortality for females show a comparable pattern with males (see Figure 4.2). But now only Texas and Illinois are significant low-high outliers. Clusters of low all-cause mortality for females are predominantly located in the Mountain states and some states of the West North Central and New England divisions, with again Nevada as the only significant high-low outlier.

4.2. Smoking-attributable mortality differences

In the US, the smoking-attributable mortality rates in 2016 showed 165.89 deaths for males and 133.55 for females per 100,000 population. The ASCDR ranged from 86.97 (Utah) to 282.59 (Mississippi) deaths per 100,000 for males. Males showed that the South and East North Central regions experience the highest mortality in general, whereas the Northeast, the West and northern states of the West North Central show the lowest ASCDR (see Figure 4.3). For females, the age-standardized crude death rates range from 73.77 (Utah) to 211.37 (Kentucky) deaths per 100,000. Females show a slightly different

pattern compared to males. Particularly states in the Northeast and northern states in the West do not have significant lower ASCDR than average compared to males.

In many states, the ASCDR for smoking-attributable mortality differs significantly from the American average. For males, 7 states and the District of Columbia did not significantly differ from the American average, 21 states had significantly higher ASCDR than average and 22 states had significantly lower ASCDR than average. For females, 9 states did not significantly differ from the American average, 23 states had significantly higher ASCDR than average and 18 states and the District of Columbia had significantly lower ASCDR than average.

The Global Moran's I (see Table 4.1) shows ASCDR for both males and females are significantly clustered at the 99% confidence interval. Clusters of significant high smoking-attributable mortality for males are centered around the East South Central division (see Figure 4.2). Therefore, a few surrounding states (Texas, Florida and Illinois) are significant low-high outliers. Clusters of low smoking-attributable mortality for males are located predominantly in the Mountain states and New England, with Maine and Nevada as the significant high-low outlier.

Clusters of significant high smoking-attributable mortality for females are also centered around the East South Central division (see Figure 4.2). Only Illinois is a significant low-high outlier. Clusters of low smoking-attributable mortality for females are located in Rhode Island and the Mountain states Arizona and Colorado. Nevada, Wyoming and Delaware are significant high-low outliers.

4.3. Obesity-attributable mortality differences

In the US, obesity-attributable mortality rates in 2016 showed 122.44 deaths for males and 116.54 for females per 100,000 population. The ASCDR ranges from 85.12 (Colorado) to 170.99 (Louisiana) deaths per 100,000 for males (see Figure 4.4). The ASCDR for females ranges from 78.03 (Hawaii) to 166.89 (Mississippi) deaths per 100,000. Both genders showed that the South and East North Central experience the highest mortality in general, whereas the Northeast, the West and northern states of the West North Central show the lowest ASCDR.

The ASCDR differs significantly for many states compared to the American average. For males, 8 states did not significantly differ from the American average, 17 states and the District of Columbia had significantly higher ASCDR than average and 25 states had significantly lower ASCDR than average. For females, 10 states did not significantly differ from the American average, 17 states and the District of Columbia had significantly higher ASCDR than average and 23 states had significantly lower ASCDR than average.

The Global Moran's I (see Table 4.1) shows ASCDR among both males and females are significantly clustered at the 99% confidence interval. Clusters of significant high obesity-attributable mortality for

males are centered around the South and southern states of the Midwest (see Figure 4.2). Therefore, a few surrounding states (Florida and Virginia) are significant low-high outliers. Clusters of low obesity-attributable mortality for males are predominantly located in the West and New England, with Nevada as the only significant high-low outlier. Clusters of significant high obesity-attributable mortality for females are centered around the South and southern states of the Midwest (see Figure 4.2). Therefore, a few surrounding states (Florida and Virginia) are significant low-high outliers. Clusters of low obesity-attributable mortality for females are predominantly located in the whole West and New England, with not even a high-low outlier.

4.4. Alcohol-attributable mortality differences

In the US, alcohol-attributable mortality rates in 2016 showed 44.74 deaths for males and 16.00 for females per 100,000 population. The ASCDR ranged from 32.52 (Iowa) to 78.01 (Mississippi) deaths per 100,000 for males. High alcohol-attributable mortality rates are seen in the South, which is also partly the case for the western region. Low alcohol-attributable mortality rates are seen in the Midwest and Northeast regions for males. For females, the ASCDR ranged from 11.78 (Hawaii) to 25.87 (Alaska) deaths per 100,000. The pattern of high alcohol-attributable mortality rates for females is similar compared to males. Low alcohol-attributable mortality rates for females are different compared to males. Only a few neighboring states in the Northeast and Midwest have lower alcohol-attributable mortality rates than average, the rest is spread across the country.

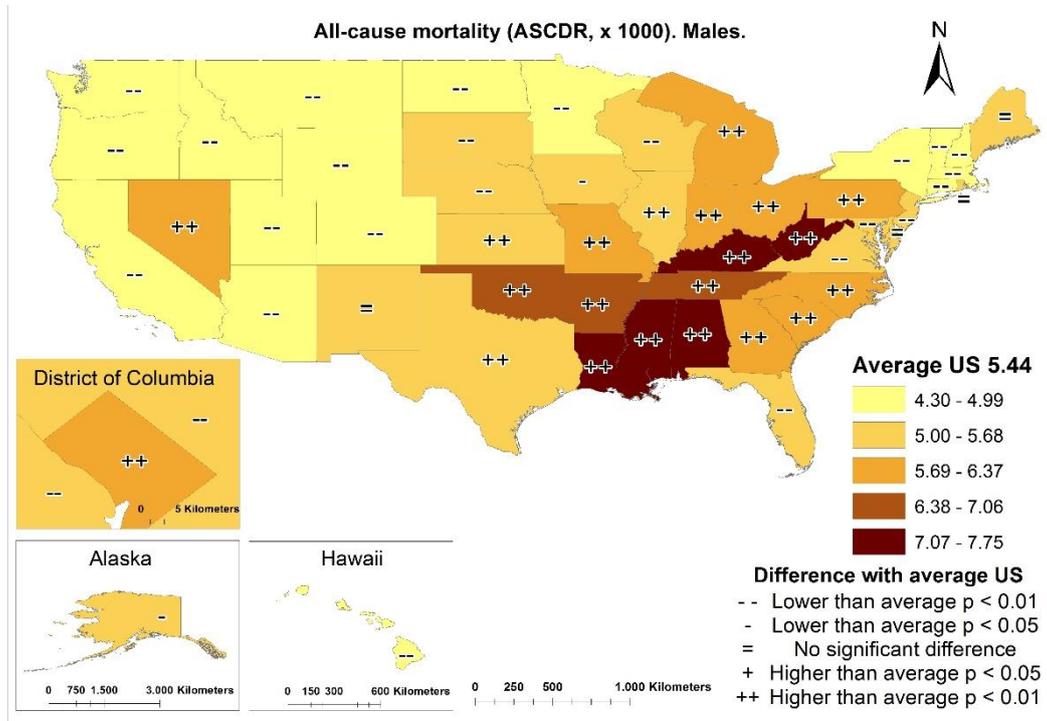
The ASCDR differs significantly from the American average for many states. For males, 12 states did not significantly differ from the American average, 18 states and the District of Columbia had significantly higher ASCDR than average and twenty states had significantly lower ASCDR than average. For females, 22 states did not significantly differ from the American average, 18 states and the District of Columbia had significantly higher ASCDR than average and just 10 states had significantly lower ASCDR than average.

The Global Moran's I (see Table 4.1) shows ASCDR among both males and females are significant clustered at the 99% confidence interval. Clusters of significant high alcohol-attributable mortality for males are centered around the divisions East South Central and South Atlantic (see Figure 4.2). Only Texas is a significant low-high outlier. Clusters of low alcohol-attributable mortality are predominantly located in the Northeast and Midwest, with no high-low outliers.

A cluster of significant high alcohol-attributable mortality for females is only centered in three states in the divisions East South Central and South Atlantic (see Figure 4.2). Clusters of low alcohol-attributable mortality for females are located in Illinois and the Northeast. No significant outliers have been found for females.

Figure 4.1. Age-standardized all-cause mortality rates (per 1000) in the United States, by sex and state or district, 2016

Males



Females

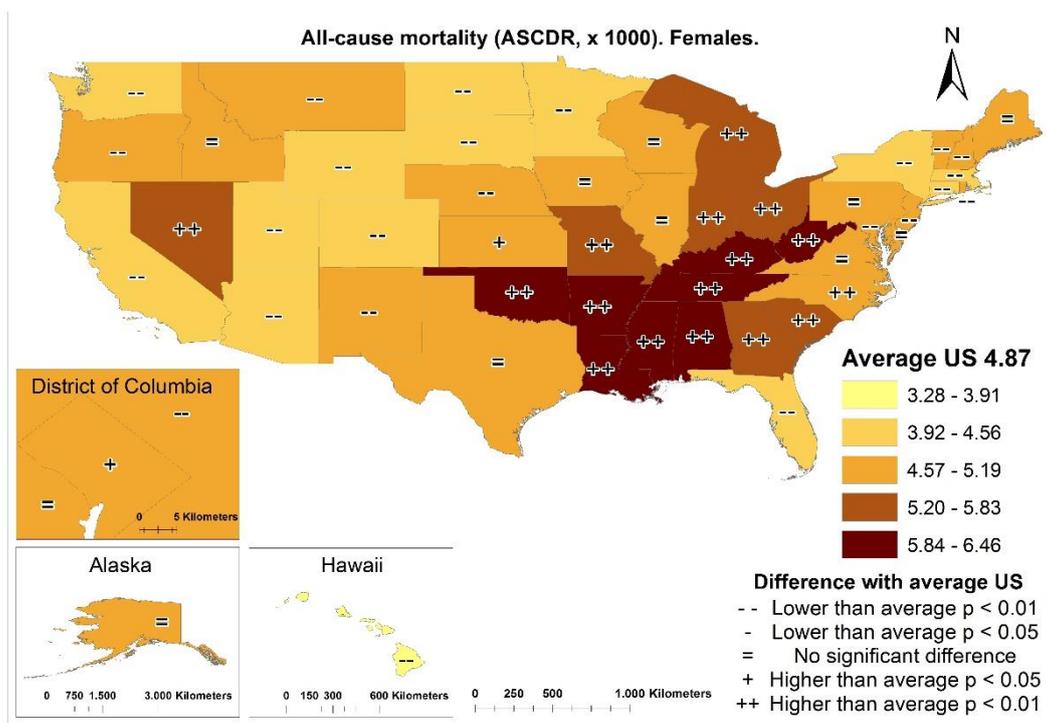


Figure 4.2. Clusters and outliers in age-standardized mortality rates in the United States, by sex and state or district, 2016

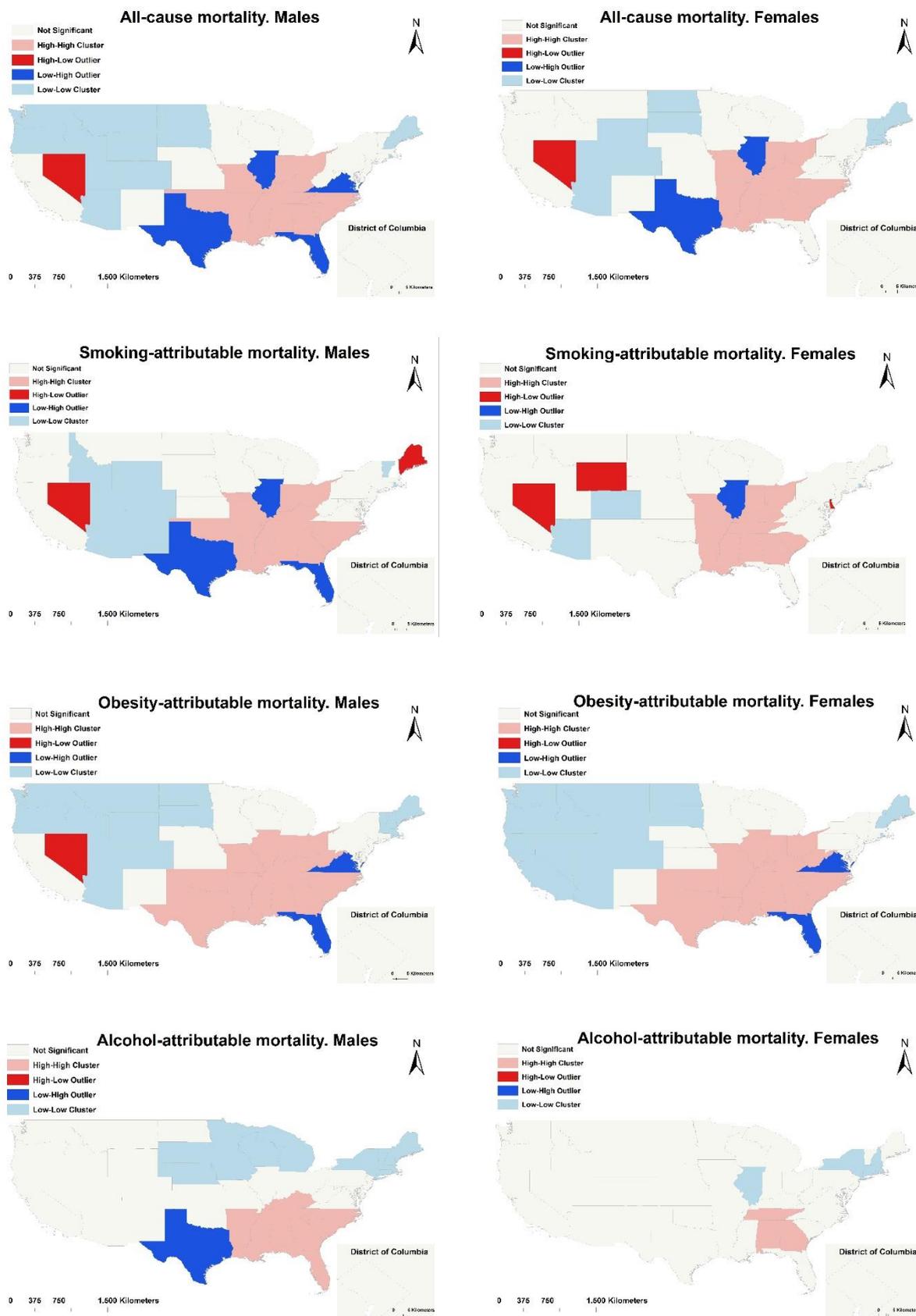
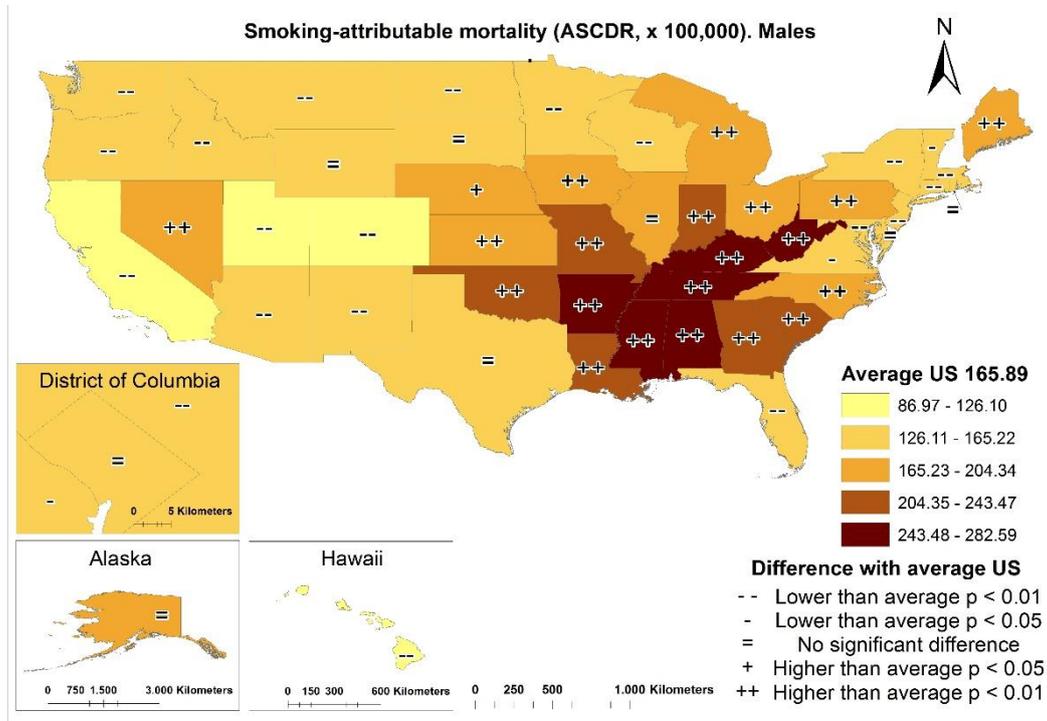


Figure 4.3. Age-standardized smoking-attributable mortality rates (per 100,000) in the United States, by sex and state or district, 2016

Males



Females

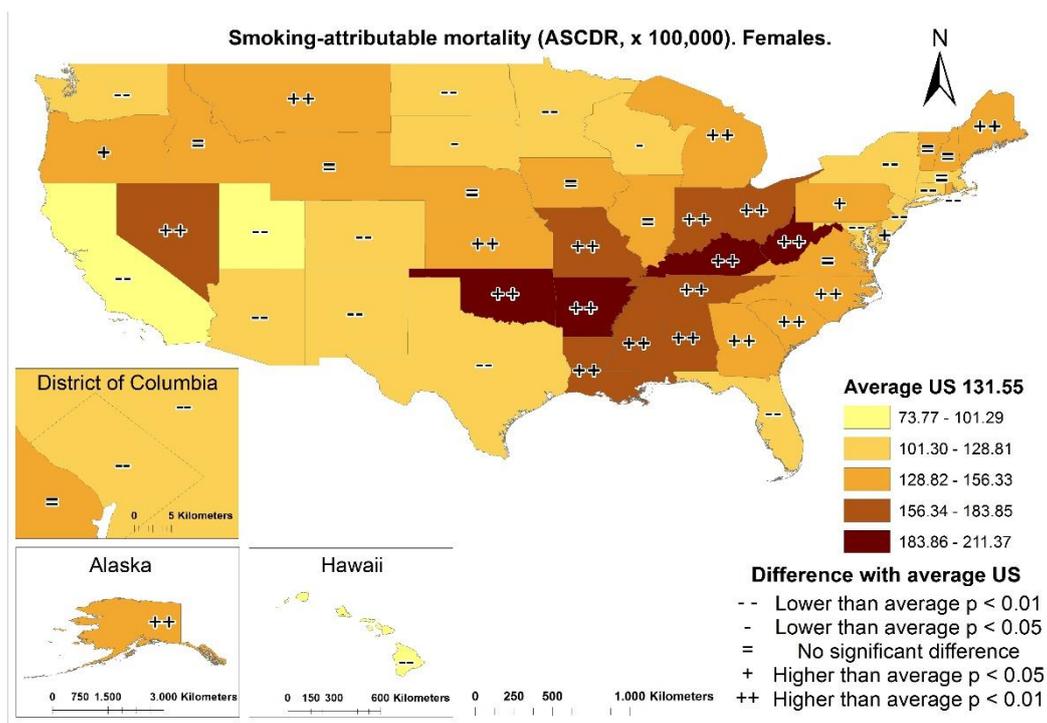
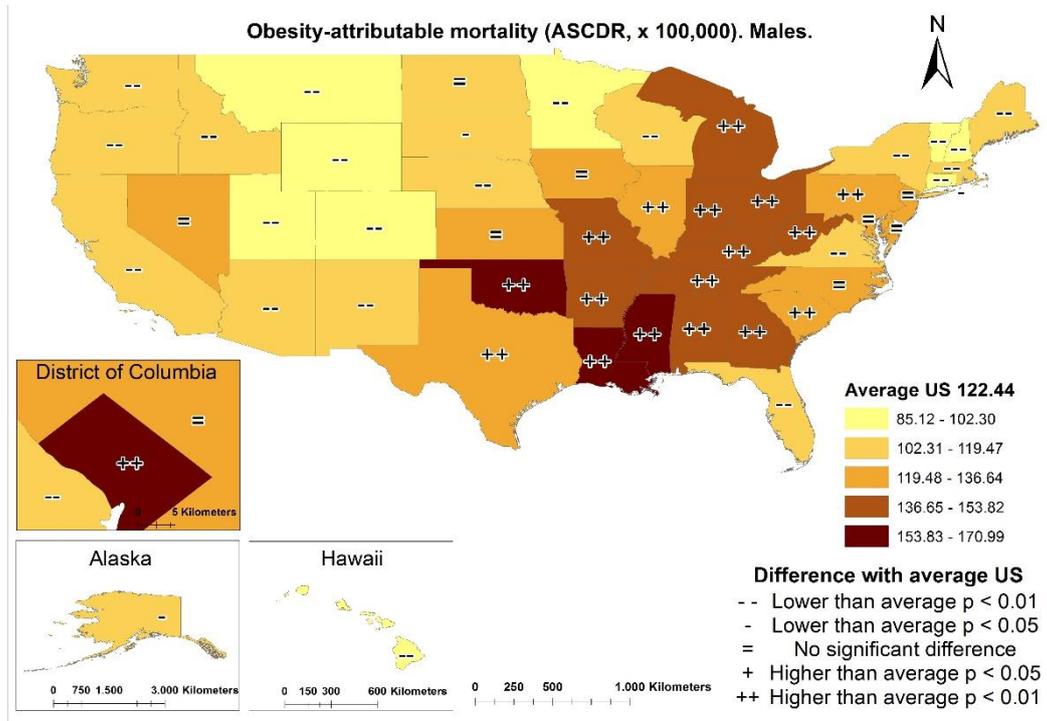


Figure 4.4. Age-standardized obesity-attributable mortality rates (per 100,000) in the United States, by sex and state or district, 2016

Males



Females

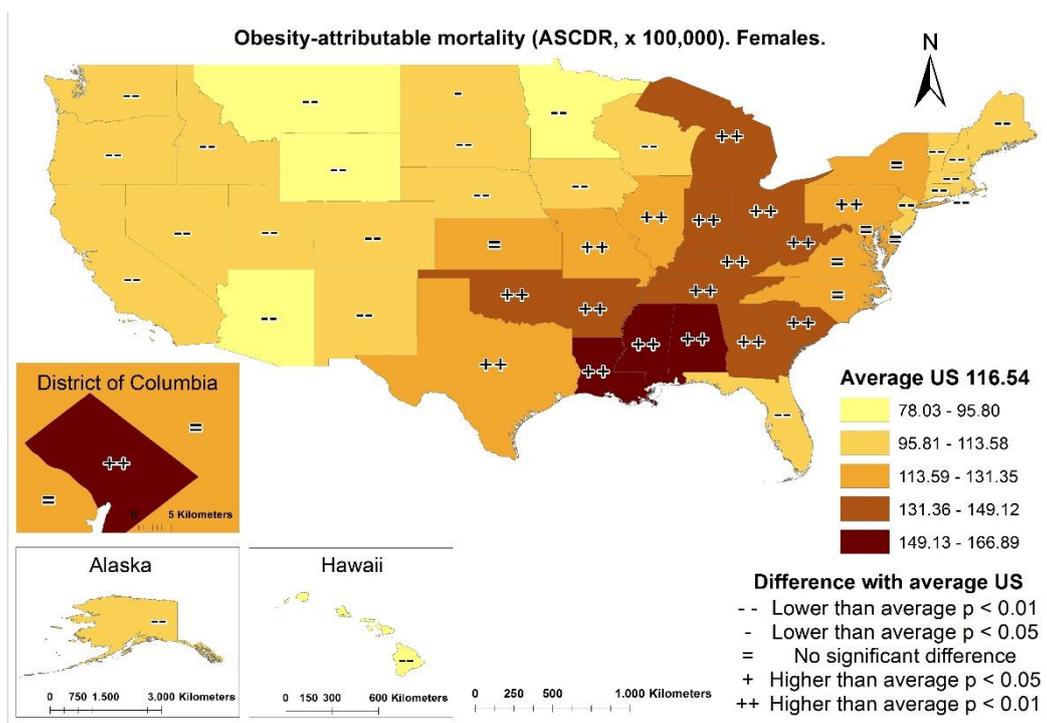
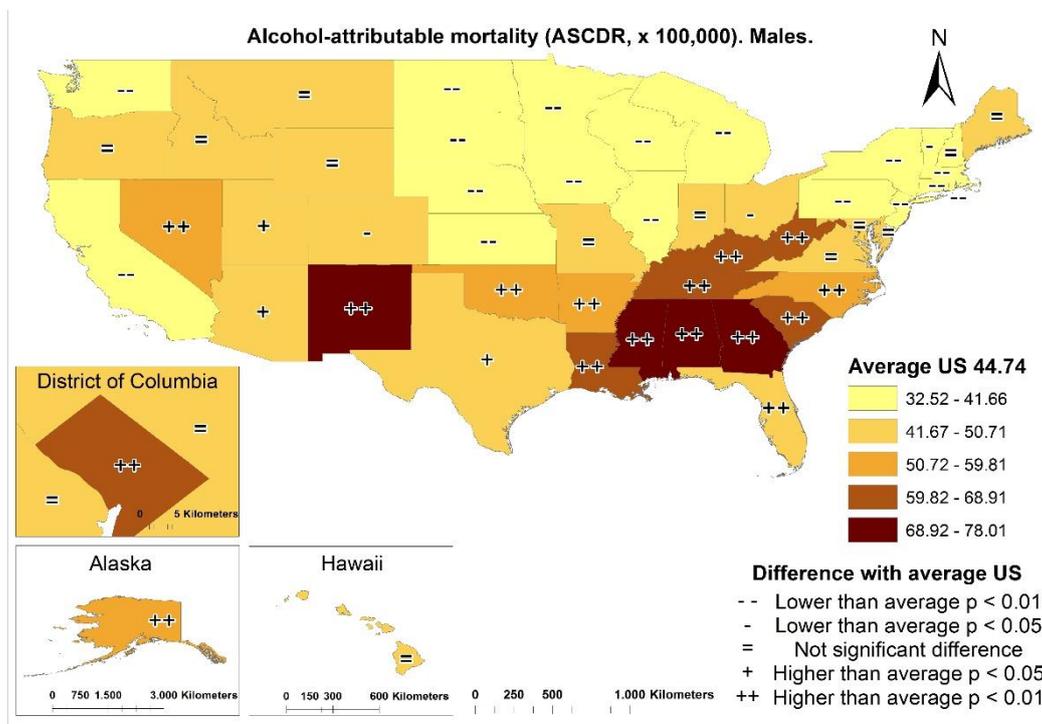


Figure 4.5. Age-standardized alcohol-attributable mortality rates (per 100,000) in the United States, by sex and state or district, 2016

Males



Females

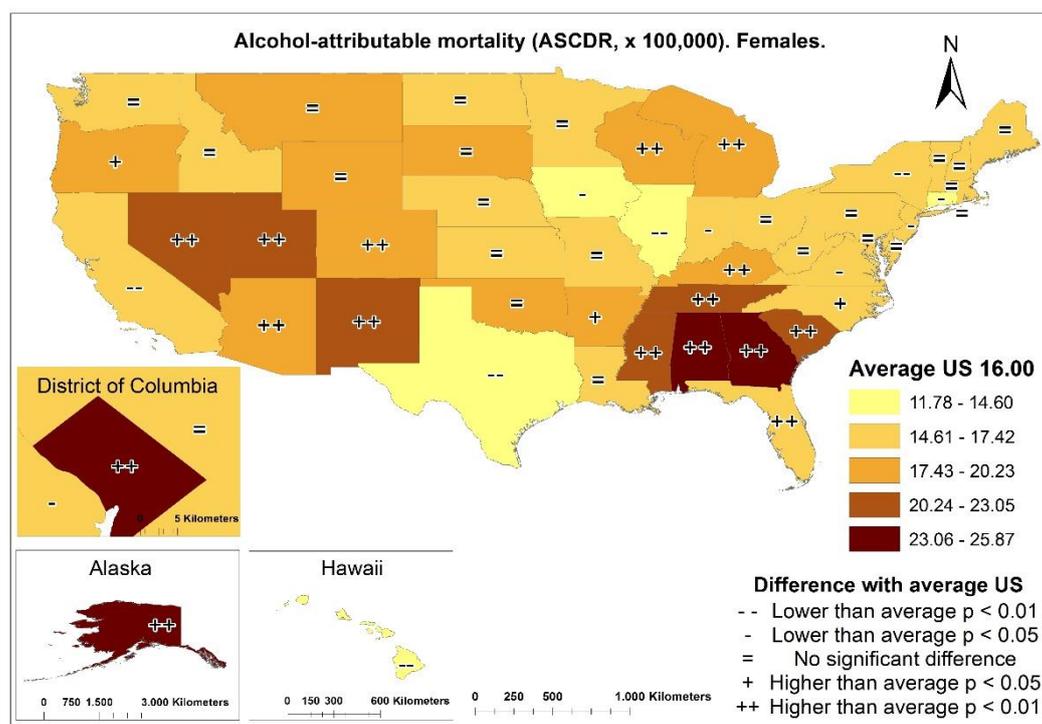


Table 4.1. Spatial clustering of all-cause mortality and smoking-, obesity- and alcohol-attributable mortality in the United States, across sexes and fifty states and one district, 2016

	<i>Males</i>		<i>Females</i>	
	Global Moran's I*	P-value	Global Moran's I*	P-value
Age-standardized all-cause mortality rate	0.48	0.000000	0.50	0.000000
Age-standardized smoking-attributable mortality rate	0.58	0.000000	0.32	0.000002
Age-standardized obesity-attributable mortality rate	0.51	0.000000	0.47	0.000000
Age-standardized alcohol-attributable mortality rate	0.48	0.000000	0.33	0.009437

* The Global Moran's I indicates spatial autocorrelation and has a range from -1 to 1. The further the value reaches -1 or 1, the more the value is dispersed or clustered. A value of 0 indicates a totally random pattern.

4.5. Comparison all-cause mortality differences with smoking-, obesity- and alcohol-attributable mortality differences

4.5.1. Smoking

For males, the South and East North Central experienced the highest smoking-attributable mortality in general, whereas states in the Northeast, the West and northern states of the West North Central show the lowest ASCDR. These regions were quite the same as those that experienced the lowest and highest all-cause mortality. Cluster analysis showed a higher value of clustering for smoking-attributable mortality compared to all-cause mortality. Clusters of significant high smoking-attributable mortality for males are centered around the East South Central division. This is comparable with the figure of all-cause mortality. Clusters of low smoking-attributable mortality for males are located predominantly in the Mountain states and New England. This is also in line with the figure of all-cause mortality. All in all, smoking-attributable mortality differences, clusters and outliers are comparable with all-cause mortality.

For females, both smoking-attributable mortality as all-cause mortality showed high ASCDR in the southern region. However, low ASCDR patterns were slightly different. Particularly states in the Northeast and northern states in the West did not have significant lower ASCDR than average regarding smoking-attributable mortality, while they have obvious significant lower ASCDR than average with all-cause mortality. Cluster analysis showed a lower value of clustering for smoking-attributable mortality compared to all-cause mortality. Clusters of significant high smoking-attributable mortality for females are centered around the East South Central division. This is comparable with the figure of females in all-cause mortality. Clusters of low smoking-attributable mortality for females were slightly different from all-cause mortality. Less clustering was shown in the Mountain states and New England compared to all-cause mortality, which led to more high-low outliers in those divisions. All in all,

smoking-attributable mortality differences, clusters and outliers are comparable with all-cause mortality for females.

4.5.2. Obesity

For males, the South and East North Central experienced the highest obesity-attributable mortality in general, whereas states in the Northeast, the West and northern states of the West North Central showed the lowest ASCDR. These regions were quite the same as those that experienced the lowest and highest all-cause mortality. However, cluster analysis showed obesity-attributable mortality is more clustered than all-cause mortality. Clusters of significant high obesity-attributable mortality for males are centered around the South and southern states of the Midwest, which is comparable with the figure of all-cause mortality. Clusters of low obesity-attributable mortality for males are totally comparable with the figure of all-cause mortality, with low clusters in the West and Northeast. All in all, obesity-attributable mortality differences for males are comparable with all-cause mortality.

For females, a comparable pattern was found with that of all-cause mortality as well. This is illustrated by various states in the South and East North Central division showing significant higher ASCDR than average, whereas states in the Northeast and western region show lower ASCDR than average. Cluster analysis shows less clustering for obesity-attributable mortality than all-cause mortality. Clusters of significant high obesity-attributable mortality for females are centered around the South and southern states of the Midwest. This is in line with the pattern of all-cause mortality. Clusters of low obesity-attributable mortality for females are predominantly located in the whole West and New England. This is mostly comparable with the figure of all-cause mortality rates. Yet more states in the West are now part of the significant low cluster compared to all-cause mortality. All in all, obesity-attributable mortality differences for females are comparable with all-cause mortality differences, but more states are included in the high and low clusters compared to the figure of all-cause mortality rates.

4.5.3. Alcohol

For males, the pattern of alcohol-attributable mortality differs from the pattern of all-cause mortality. States predominantly in the West did not show significantly lower rates than average, whereas this was the case with all-cause mortality. Additionally, East North Central states show significantly lower alcohol-attributable mortality rates than average, whereas these states have significantly higher all-cause mortality rates than average. However, high alcohol-attributable mortality rates were found in the southern region, which is line with all-cause mortality. Cluster analysis showed that the clustering of alcohol-attributable mortality is just as high as all-cause mortality. Clusters of significant high alcohol-attributable mortality for males are centered around the divisions East South Central and South Atlantic. This is comparable with the figure of all-cause mortality rates, but now southern Midwest states are not included in the high cluster. Clusters of low alcohol-attributable mortality are predominantly located in the Northeast and Midwest. This is partly incomparable with the figure of all-cause mortality rates,

which showed a low cluster in the West instead of the Midwest. All in all, especially low alcohol-attributable mortality rates show patterns compared to all-cause mortality.

For females, the patterns are also different compared to all-cause mortality. Remarkable is that the Mountain division has significant higher alcohol-attributable mortality rates than average, while this division had significant lower all-cause mortality rates than average. Additionally, predominantly the Northeast region did not differ significantly from the American average, whereas this region showed mostly significant lower all-cause mortality rates than average. However, high alcohol-attributable mortality rates were found in the southern region, which is in line with all-cause mortality. Cluster analysis showed less clustering for alcohol-attributable mortality than all-cause mortality. The cluster of significant high alcohol-attributable mortality rates for females is only centered in three states in the divisions East South Central and South Atlantic. This cluster is slightly smaller compared to the cluster of all-cause mortality in that area. Clusters of low alcohol-attributable mortality for females are located in Illinois and the Northeast. This is partly not comparable with the figure of all-cause mortality, which showed a low cluster in the West instead of the Midwest. All in all, especially the clusters of low alcohol-attributable mortality rates for females show a different pattern compared to all-cause mortality.

4.6. Contribution of smoking, obesity and alcohol in all-cause mortality differences

State variance in all-cause mortality was decomposed to determine the contribution of smoking, obesity and alcohol to state variance in all-cause mortality. The results showed that the variance in smoking-attributable mortality has a contribution of 26% for males and 18% for females to all-cause mortality differences (Table 4.2), the variance in obesity-attributable mortality has a contribution of 6% for males and 8% for females to all-cause mortality differences and the variance in alcohol-attributable mortality has a contribution of 1.9% for males and 0.2% for females to all-cause mortality differences.

Table 4.2. The variances of age-standardized mortality rates by all-causes, smoking, obesity and alcohol. Additionally the variance in all-cause mortality rates in the United States is decomposed, across sexes and fifty states and one district, 2016

	<i>Males</i>	<i>Females</i>
Variance all-cause ASCDR (x 1000)	0.765	0.476
Variance smoking-attributable ASCDR (x 1000)	0.200	0.085
Variance obesity-attributable ASCDR (x 1000)	0.045	0.038
Variance alcohol-attributable ASCDR (x 1000)	0.014	0.009
Variance smoking-attributable ASCDR divided by variance all-cause ASCDR	0.261	0.179
Variance obesity-attributable ASCDR divided by variance all- cause ASCDR	0.059	0.079
Variance alcohol-attributable ASCDR divided by variance all- cause ASCDR	0.019	0.002

5. Conclusion

5.1. Summary of the findings

The aim of this study was to examine to what extent state differences in all-cause mortality in the US could be due to smoking, alcohol and obesity. From this objective, the following research question was formulated: “To what extent are state differences in all-cause mortality in the United States due to lifestyle factors smoking, alcohol and obesity?”.

In order to answer this main question some sub-questions had been formulated:

1. What are the all-cause mortality differences between states of the United States in 2016 and how are these differences clustered or dispersed?

The South and East North Central experience the highest all-cause mortality in general, whereas the Northeast, the West and northern states of the West North Central show the lowest ASCDR. Both genders showed a significant clustered pattern for all-cause mortality differences, in which the mentioned differences are represented in clusters of states with high or low all-cause mortality rates.

2. What are the smoking-, obesity- and alcohol-attributable mortality differences between states of the United States in 2016 and how are these differences clustered or dispersed?

Smoking- and obesity-attributable mortality showed mostly the same pattern. The South and East North Central experience the highest mortality rates in general, whereas the Northeast, West and northern states of the West North Central show the lowest ASCDR. Both genders showed a significant clustered pattern for smoking- and obesity-attributable mortality differences, in which the mentioned differences were represented in clusters of states with high or low smoking- and obesity-attributable mortality rates.

With alcohol-attributable mortality, both genders showed moderate to high ASCDR in the southern and western region. For males, low alcohol-attributable mortality rates were seen in the Midwest and Northeast. For females, only a few neighboring states in the Northeast and Midwest had low alcohol-attributable mortality rates, the rest was spread across the country. Both genders showed a significant clustered pattern for smoking-attributable mortality differences, but only for males differences are slightly shown in clusters of states with high or low alcohol-attributable mortality rates.

3. How comparable are all-cause mortality differences in the United States in 2016 with smoking, obesity- and alcohol-attributable mortality differences?

Smoking- and obesity-attributable mortality differences for males and females showed similar mortality patterns and clusters to those that experienced the lowest and highest all-cause mortality. Alcohol-attributable mortality differences were less comparable with all-cause mortality, particularly because moderate to high alcohol-attributable mortality rates were found in the West, whereas this region showed low all-cause mortality.

4. What is the contribution of lifestyle factors – smoking, obesity and alcohol – to state differences in all-cause mortality in the United States in 2016?

Smoking has the highest contribution to state differences in all-cause mortality in the US in 2016, with 26% for males and 18% for females. Obesity comes second with 6% for males and 8% for females. Alcohol has the lowest contribution to state differences in all-cause mortality in the US in 2016, with 1.9% for males and 0.2% for females.

5.2. Reflecting on main results

5.2.1. Reflecting on the hypotheses

The following hypotheses were expected to be confirmed:

1. A clustered pattern of high all-cause mortality rates will be found in the southern region, whereas a low cluster of all-cause mortality rates will be found in the western region in the United States in 2016.

This hypothesis is confirmed. What should be added is that next to high all-cause mortality rates in the South, the East North Central division also experienced high all-cause mortality. Additionally to the West, the Northeast and northern states of the West North Central division showed low ASCDR.

The hypothesis was based on the study of Xu et al. (2018), who researched the crude death rates per 100,000 population for every state in the US in 2016. They found that especially the southern region experienced high crude death rates, whereas low death rates were seen in the western region. The results of the current thesis are in line with the study of Xu et al. (2018). However, it is remarkable that especially states in the Northeast had moderate to high crude death rates (Xu et al., 2018), but these states have low ASCDR according to this thesis. It becomes clear that standardizing for age plays a significant role when looking at mortality differences.

2. A clustered pattern of high smoking-, obesity- and alcohol-attributable mortality rates will be found in the southern region in the United States in 2016, whereas low clusters of mortality rates will be found in the western region for smoking and obesity and in the Northeast region for alcohol.

This hypothesis is confirmed. What should be added is that next to high mortality rates in the South, southern states in the East North Central division also experienced high smoking- and obesity-attributable mortality. Additionally to the West, the Northeast and northern states of the West North Central division showed low ASCDR for smoking- and obesity-attributable mortality. For alcohol-attributable mortality it should be added that high alcohol-attributable mortality rates were also seen in the West, whereas low rates were also seen in the Midwest next to the Northeast.

This hypothesis was based on most studies in the literature review, from a study such as the one from Fenelon and Preston (2012), who published an article about smoking-attributable mortality for people of ages between 50 and 84 in 2004. The substantive pattern they found was the relative disadvantage of southern mortality to other regions: southern states had higher smoking-attributable mortality rates compared to other regions in the country (especially the Mountain division). These results of Fenelon and Preston (2012) were also found in the current thesis. Jia and Lubetkin (2010) examined geographical differences in the US with obesity-attributable quality-adjusted life years lost. The lowest levels of lost obesity-attributable quality-adjusted life years were found in western states, while the highest levels were seen in and around states in the East South Central. These results are also comparable with the current study. For alcohol such a study was provided by Stahre et al. (2014), who found high alcohol-attributable mortality in western and southern states between 2006 and 2010. However, they did not look at gender differences. This was mostly in line with the current study, which found high alcohol-attributable mortality rates in the South and moderate to high alcohol-attributable mortality in western states.

3. The patterns of smoking- and obesity-attributable mortality differences will be similar to all-cause mortality differences, whereas patterns of alcohol-attributable mortality differences will look different compared to all-cause mortality differences in the United States in 2016.

This hypothesis is confirmed. The results of this thesis showed that smoking- and obesity-attributable mortality differences for both genders were quite comparable with all-cause mortality differences. However, alcohol-attributable mortality differences did not look totally different compared to all-cause mortality differences, but just a bit less comparable than smoking- and obesity-attributable mortality for both men as women.

This hypothesis was based on the same literature as mentioned at the previous hypothesis.

4. Smoking will have the highest, obesity the second-highest and alcohol the lowest contribution to all-cause mortality differences in the United States in 2016.

This hypothesis is confirmed: smoking has the highest contribution for males (26%) and females (18%) to all-cause mortality differences. Obesity comes second with 6% for males and 8% for females. The lowest contribution is from alcohol with 1.9% for males and 0.2% for females.

This hypothesis was based on a few studies in the literature review. Montez et al. (2016) found that the tobacco environment – including tobacco consumption – was an important contributor to state mortality disparities in the US for males. Additionally, it was found that smoking has a significant contribution to all-cause mortality differences within developed countries for both males and females (Jenum et al., 2001; Janssen & Spiensma, 2012). The current thesis confirmed that smoking is a big contributor to all-cause mortality differences in another developed country, for both females and males. Although the contribution of smoking to all-cause mortality differences was 26% for males and 18% for females in

the US, in other developed countries like the Netherlands and Norway higher contributions were found. Their findings of a higher contribution of smoking to all-cause mortality differences between regions than the current research is likely because they used other countries than the US. The small geographical scales in these studies are not comparable with the geographical scale of the current study, which used states in the US. For this reason it could be possible that the contribution of lifestyle to all-cause mortality differences within states is even higher than between states. This is confirmed by Dwyer-Lindgren (2017), who said that previous studies at the county level found an even smaller degree of variation among states than among counties.

The lowest contribution to all-cause mortality differences was expected for alcohol, since the study of Stahre et al. (2014) showed small differences of alcohol-attributable mortality between states in the US between 2006 and 2010. This was also seen in the current thesis and confirms the low contribution of alcohol to all-cause mortality differences. As was expected, obesity therefore is the second-highest contributing factor to all-cause mortality differences.

5.2.2. Explaining differences between contributions to all-cause mortality differences

It can be concluded that differences between the contributions of lifestyle factors to all-cause mortality differences exist. Additionally, differences exist between the contribution of lifestyle factors between the genders. How can these differences be explained?

5.2.2.1. Differences between contributions of lifestyle factors to all-cause mortality differences

The differences between the contributions of lifestyle factors to all-cause mortality differences is firstly explained by the used method. The contribution of lifestyle factors to all-cause mortality differences is mainly based on the variance of lifestyle-attributable mortality rates between states. Because the smoking-attributable mortality rates were by far the highest, the variance is high as well. The opposite applies to alcohol-attributable mortality, where the rates were really low and therefore the variance is lower. Because the variance is higher with smoking-attributable mortality, it contributes more to the all-cause mortality differences. The other way around applies for alcohol-attributable mortality.

In theory it is possible that when the mortality rates are really high, a low variance appears. In this situation mortality rates are quite equal across the country. However, the results of this thesis showed a high variance for smoking-attributable mortality and therefore a high contribution. This high variance for smoking-attributable mortality can be explained by the conceptual model. State differences in smoking-attributable mortality are explained by state differences in the population that smokes which are influenced by state differences in other health determinants. According to the literature review, such an important health determinant is a state's policy or socio-political orientation (Montez et al., 2016). Most states within the South and southern states in the East North Central (where high smoking-attributable mortality rates were found) indeed operate differently with regard to smoking than the average US state. Cigarette packs, on average, are 19 percent cheaper in most of these states (\$5.48)

than in the rest of the US (\$6.72) (Truth Initiative, 2017). It can be concluded that state differences in health determinants (such as the smoking socio-political orientation) vary, which ensure that state differences in the population that smokes vary. The high variations in the share of population that smokes result in a high variance in smoking-attributable mortality.

In theory it is possible that when the mortality rates are low, a high variance appears. In this situation mortality rates are not equal across the country. However, alcohol-attributable mortality has a low variance (especially for women) and therefore a low contribution to all-cause mortality. This low variance for alcohol-attributable mortality can also be explained by the conceptual model. State differences in alcohol-attributable mortality are explained by state differences in the population that consumes alcohol which are influenced by the state differences in other health determinants. According to the literature review such an important health determinant is a state's policy or socio-political orientation (Montez et al., 2016). Differences in alcohol-attributable deaths occur because the states' own laws influence marketing, prices and availability of alcoholic beverages (Naimi et al., 2014). Although Naimi et al. (2014) concluded that the alcohol policy environment is an important determinant of drinking behaviors at the population level and therefore alcohol-attributable mortality, from this thesis it can be concluded that state differences in health determinants (such as the alcohol socio-political orientation) have a relatively low variance. This ensures that state differences in the alcohol consuming population show a low variance. The low variation in the share of the population that consumes alcohol thus results in a low variance in alcohol-attributable mortality. Another explanation can be that the share of the alcohol consuming population is more or less independent from other health determinants, and therefore has a low variation which in turn results in a low variation of alcohol-attributable mortality. But this last explanation is not showed in the literature (Naimi et al., 2014).

5.2.2.2. Differences between genders of one lifestyle factor to all-cause mortality differences

Differences between the contributions of one lifestyle factor between the genders exist. Smoking and alcohol-attributable mortality differences are higher for males compared to females. On the contrary, obesity-attributable mortality differences are higher for females compared to males.

These differences between the genders can be explained by the conceptual model. For example the obesity-attributable mortality differences are bigger for females compared to males. The obesity-attributable mortality differences occur by differences in the share of the people that are obese. These differences are affected by differences in other health determinants. It is generally known that high-SES groups (SES being socioeconomic status) have a higher likelihood to be obese than low-SES groups in industrialized countries (Wang & Zhang, 2006). Sobal and Stunkard (1989) already argued that the negative SES-obesity relationship is stronger for women than men in developed countries, which could explain why obesity has a higher variance among states for females compared to males. It can be concluded that state differences in health determinants (such as the SES) vary more for females than for

males, therefore state differences in the population being obese are bigger for females than males. This causes the higher variance in obesity-attributable mortality for females compared to males.

5.2.3. Explaining mortality differences

5.2.3.1 Explaining lifestyle-attributable mortality differences

For smoking- and obesity-attributable mortality the southern region and North East Central division showed high ASCDR. Low smoking- and obesity-attributable mortality differences were mostly found in the West, North East and northern states of the Midwest. Alcohol-attributable mortality showed particularly high ASCDR in the West and South, whereas low ASCDR was mostly found in the Midwest and North East. But how can these mortality differences be explained?

In the US, lifestyle-attributable mortality can be explained by past lifestyle behavior. Rehm et al. (2001) argued that past drinking problems cause higher alcohol-attributable mortality, whereas Must et al. (1992) found that obese adolescents show a higher likelihood of experiencing multiple comorbidities later in life during adulthood, even when those adolescents were not obese anymore. Therefore, observed geographical patterns in lifestyle-attributable mortality in the US can be explained by data on regional differences in past lifestyle behavior. For example, for the lifestyle factor smoking a lag time of thirty to forty years has to be taken into account (Lopez et al., 1994). The smoking prevalence in 1987 was high in southern and East North Central states (e.g., Kentucky 32%, Michigan 32%, Indiana 29%, Missouri 29%, Tennessee 28%), whereas western states had a low prevalence (e.g., Montana 22%, Idaho 22%, California 21%, New Mexico 21%, Utah 15%) (Burns et al., 1997). This is in line with high and low smoking-attributable mortality patterns found in the current study. It illustrates that geographical patterns in lifestyle-attributable mortality in the US can be explained by data on regional differences in past lifestyle behavior.

As already mentioned earlier, geographical differences in other health determinants influence the geographical differences in the share of people that smoke, consume alcohol and are obese which in turn influence the geographical differences in smoking-, obesity- and alcohol-attributable mortality. Among those health determinants is the SES. Lifestyle choices may result in part from SES, and bad lifestyle choices have become increasingly concentrated among low socioeconomic status groups (Pampel & Rogers, 2004). Less wealthy states can be found in the southern region, whereas Northeast states are most wealthy (Statista, 2018). This is mostly in line with the patterns of low and high lifestyle-attributable mortality. However, SES is not the only determinant that affects lifestyle-attributable mortality. This can be concluded by the fact that not all regions experiencing low SES, show high lifestyle-attributable mortality and the other way around.

Already in 1947 it was argued that race is a health determinant that resulted in geographical mortality differences in the US (Altenderfer, 1947). Wallace Jr. and Bachman (1991) argued that bad lifestyle behavior differed along race or ethnic group membership. The current study was conducted with data

from 2016. In 2016 high levels of the race 'black' were found in the South and East North Central. Lower levels were found in the Mountain states and New England (Census Bureau's March Current Population Survey, 2017). Exactly in states where high rates of the race 'blacks' were found, also high levels of smoking- and obesity-attributable mortality were found in the current study. This applies as well for the states with low levels of the race 'blacks' and low levels of smoking- and obesity-attributable mortality. Race also seems to play an important role in contributing to state differences in lifestyle-attributable mortality.

Earlier it was mentioned that a state's policy or socio-political orientation (Naimi et al., 2014; Montez et al., 2016) is a factor in causing lifestyle-attributable mortality differences. Moreover, it became clear from the literature review that social cohesion seems to affect health differences between states. One indicator of cohesion, social capital, is a predictor of the mortality of a state (Kawachi et al., 1997). Social capital can affect mortality by norms of reciprocity, solidarity, information flows and collective actions in a community setting (Putnam, 2000). The higher the social capital in an area, the lower the risk of bad lifestyle behavior (Chuang & Chuang, 2008). Social capital is high in the New England and West North Central divisions of the US, whereas social capital is low in southern states and Southwestern states (Joint Economic Committee, 2018). This is mostly in line with the high and low lifestyle-attributable mortality patterns that were found in the current study, which illustrates social cohesion is probably a factor in causing lifestyle-attributable mortality differences.

5.2.3.2. Explaining all-cause mortality differences

By focusing on the contribution of lifestyle – smoking, alcohol and obesity – to state all-cause mortality differences within the US, this thesis contributed to the debate on determinants of mortality and geographical mortality differences. No studies had been found which looked at the contribution of lifestyle factors to geographic all-cause mortality differences in the US. The reasons for these geographical differences across the US are a growing area of research because the differences are still not fully understood (Montez et al., 2016).

This thesis showed that smoking, obesity and alcohol contribute 33.9% for males and 26.2% for females to all-cause mortality differences between states in the US in 2016. The used data in this research ensured multimorbidity was not incorporated, because every risk-cause pair had its own PAF (Forounzafar et al., 2015; Agardh et al., 2016). Therefore, it is possible to sum up the contributions of the three lifestyle factors.

The other contribution of 66.1% for males and 73.8% for females into the variance of all-cause mortality differences between states of the US, can be explained by geographical differences in other health determinants. This is shown by the conceptual model. Among those other health determinants are lifestyle factors apart from smoking, obesity and alcohol. Young (2003) mentions a few of them: sexual practices, drug use and safety practices. Other health determinants that contribute to all-cause mortality

differences are not lifestyle related. From the conceptual model it became clear that state differences in biological factors, psychosocial factors, social cohesion, material circumstances and the health care system directly influence state differences in all-cause mortality. Indirectly the state differences in the social position and socioeconomic and political context influence the state differences in all-cause mortality differences.

One of those non-lifestyle related health determinants which seems to have a high contribution to all-cause mortality differences is the rural/ urban living situation of a state (Wiehl, 1948; Brand, 1971). High all-cause mortality in this thesis was shown in the South, whereas low all-cause mortality was viewed in the West. Especially in southern states the urban percentage of the population is low (e.g., Alabama 59.0%, Arkansas 56.2%, Kentucky 58.4%, Mississippi 49.4%), whereas the urban percentage of the population is high in the West (e.g., Utah 90.6%, California 95.0%, Nevada 94.2%) (US Census Bureau, 2019). It can be concluded that rural states have higher all-cause mortality than urban states. It illustrates that geographical differences in the urban/ rural living situation of a state probably ensure geographical all-cause mortality differences.

The importance of the health determinant economic environment to all-cause mortality differences was illustrated by the finding that states with a high median household income tend to have low mortality rates (Morgan & Morgan, 2013). In 2016, low median household incomes were found in the southern region, whereas the Northeast has high median household incomes (US Census Bureau, 2017). This is in line with the high all-cause mortality rates in the South and low all-cause mortality rates in the Northeast. This shows that geographical differences in the economic environment of states probably ensure geographical all-cause mortality differences.

5.3. Reflecting on data and methods

This study used data that was collected from the IHME, an institute that provides data for many studies and researches. The data used for the GBD studies is known for their many publications (IHME, 2018c). Therefore, the data that was used as input for this study is considered to be of high quality.

With this data spatial clustering methods were conducted. These methods can help understanding public health questions at local levels to identify high incidence events and describe state patterns (Cromley & McLafferty, 2002). This can help the public health policy decision making process, which makes the chosen methods valuable.

Yet some points should be taken into account. Firstly, the geographical scale in which the study was conducted. The chosen geographical scale can hide patterns at other scales. The state's average might result from counties with unusual low rates and others with unusual high rates (Cromley & McLafferty, 2002). It becomes clear that the difference in rates might be lost due to the aggregate level at which the study is conducted. This is confirmed by Dwyer-Lindgren (2017), who already said that previous

research at the county level has consistently found an even smaller degree of variation among states than among counties.

Additionally, it is known that regional mortality research is disrupted by migration (Kibele et al., 2015), which could have distorted the research. So is it possible that someone who died in Alabama at the first of January in 2016, moved to the state on the 31st of December in 2015. Because this has not been taken into account in the research and the research only used data of one particular year, the outcomes could have been different when the research was conducted for multiple years surrounding 2016.

Moreover, the smoking-, obesity- and alcohol-attributable data is just based on calculations and estimations, so the used methods are therefore questionable. In regard to the data of the IHME, some limitations that reflect aspects of specific causes have to be elaborated on. It has to be taken into account that inconsistencies between prevalence data for select causes and causes of death can occur. The developed data by the IHME namely does “incorporate the extent of redistribution for miscoded causes of death or other sources of error that might affect the accuracy of estimation based on those data” (Naghavi et al., 2017, p. 1201).

Finally, vital registration data sources (such as in the US) are based on how underlying causes are assigned to deaths by doctors. This process of assigning is more complex with multimorbidity. The IHME tried to correct for under-registration to increase the comparability of the results, but systematic problems can still occur (Naghavi et al., 2017). So whereas the IHME tried to control for multimorbidity, it cannot be guaranteed that multimorbidity is treated correctly in handling the data of the IHME. However, that multimorbidity is treated correctly in the data, is especially important in the current study. When this is not the case, it could be that a death was caused by alcohol and smoking, but in the data is only attributed to one lifestyle factor. This would influence the results of this research.

5.4. Recommendations

5.4.1. Recommendations for further research

Further research on the contributions of lifestyle factors to all-cause mortality differences should be applied on a smaller geographical scale. Results showed southern states were most frequently observed in the cluster analysis with experiencing high lifestyle-attributable mortality. Therefore, these states can be regarded as high-risk states with high mortality due to lung cancer or cardiovascular diseases for instance. It would be interesting to see what a cluster analysis will look like within these states.

From earlier research it could also be concluded that further research on the contribution of lifestyle factors to all-cause mortality differences should be applied on a smaller geographical scale. Dwyer-Lindgren (2017) argued that previous research at the county level has found an even greater degree of variation among counties than among states. Dwyer-Lindgren (2017) herself researched the cigarette

smoking prevalence and drinking patterns on county level. However, she did not look at the contribution of lifestyle factors to all-cause mortality differences on smaller scales.

Moreover, further research should be focused on trends of the contribution of smoking, obesity and alcohol to all-cause mortality in the US. In this thesis only data of 2016 was used, but it would be interesting to see how the contribution of lifestyle to all-cause mortality differences in the US has developed in the last decennia. Do the contributions show a more convergent or divergent trend towards each other in the last decennia? From this knowledge, future patterns and trends could be projected as well.

Additionally, further research should be focused on other lifestyle factors to examine the full contribution of lifestyle to all-cause mortality differences in the US. Current research was only focused on the lifestyle factors smoking, obesity and alcohol, whereas literature suggests other factors as well, such as sexual and safety practices (Young, 2003) or drugs (Kumar et al., 2009).

Looking at the contribution of non-lifestyle related health determinants to all-cause mortality differences would be useful research as well. Important health determinants to study in future research according to the literature are race (Altenderfer, 1947), the rural/ urban living situation (Wiehl, 1948; Brand, 1971), the economic environment (Morgan & Morgan, 2013) and income inequality (Kaplan et al., 1996).

5.4.2. Recommendations for policy makers

It is a challenge to help the US reaching its full potential in handling major issues regarding health and well-being, to be on a comparable level among other developed countries (HHS, 2018a). Because the *Healthy People* initiative is interested in eliminating health disparities (Singh et al., 2017), the initiative partly focused on lifestyle (HHS, 2018b). Health intervention design and policy can be helped by understanding the underlying causes of disparities in mortality (Tencza et al., 2014). Therefore, the focus of this thesis was on the contribution of lifestyle factors – smoking, alcohol and obesity – to all-cause mortality differences within the US. This thesis provided information towards the *Healthy People 2020* initiative, so they can eliminate health differences within the country.

The state-level measurement of mortality in this thesis identified problem areas (southern states) and varying risk factors (smoking and obesity), which can be addressed by policymakers (Dwyer-Lindgren, 2017). Moreover, this information provides a better understanding of the extent to which population reductions in smoking-, obesity- and alcohol-attributable mortality can be achieved (Kelley et al., 2016).

Information of this thesis towards the *Healthy People 2020* initiative which can help eliminate health differences within the country, is based on the contribution of a lifestyle factor to all-cause mortality differences. It is known that smoking and obesity have a high contribution to geographical all-cause mortality differences in the US. Therefore, I advise the American government that policy for these lifestyle factors should be adjusted on a low or state level scale. Alcohol, on the contrary, has a small

contribution to geographical all-cause mortality differences. Therefore, I advise a national approach for alcohol policy in the US.

5.5. Overall conclusion

State differences in all-cause mortality in the US in 2016 are largely due to lifestyle factors smoking (males 26%; females 18%) and obesity (males 6%; females 8%), but less to alcohol (males 1.9%; females 0.2%). Therefore, the American government is advised to adjust smoking and obesity policy on a low or state level scale, whereas the alcohol policy suits a national approach to reduce and eventually eliminate health disparities as part of the *Healthy People* initiative.

Reference list

- Agardh, E. E., Danielsson, A. K., Ramstedt, M., Ledgaard Holm, A., Diderichsen, F., Juel, K., ... & Skirbekk, V. (2016). Alcohol-attributed disease burden in four Nordic countries: a comparison using the Global Burden of Disease, Injuries and Risk Factors 2013 study. *Addiction*, *111*(10), 1806-1813.
- Altenderfer, M. E. (1947). Relationship between per capita income and mortality in the cities of 100,000 or more population. *Public Health Reports*, *62*(48), 1681-91.
- Anthamatten, P. & Hazen, H. (2011). *An introduction to the geography of health*. Abingdon, United Kingdom: Routledge.
- Babbie, E. R. (2015). *The practice of social research*. Toronto, Canada: Nelson Education.
- Bobak, M. & Marmot, M. (1996). East-West mortality divide and its potential explanations: Proposed research agenda. *British Medical Journal*, *312*(7028), 421-425
- Bonneux, L. G., Huisman, C. C. & de Beer, J. A. (2010). Mortality in 272 European countries, 2002-2004: An update. *European Journal of Epidemiology*, *25*(2), 77-85.
- Boyle, P., Curtis, S., Graham, E., Moore, E. (2004) *The Geography of Health Inequalities in the Developed World. Views from Britain and North America*. Burlington, VT: Ashgate Publishing Limited.
- Brand, F. (1971). Geographic patterns in the risk of dying. In H. L. Cannon & H. C. Hopps *Environmental Geochemistry in Health and Disease* (pp. 131-151). Boulder, CO: The Geological Society of America, Inc.
- Burns, D. M., Lee, L., Shen, L. Z., Gilpin, E., Tolley, H. D., Vaughn, J., & Shanks, T. G. (1997). Cigarette smoking behavior in the United States. In D. Burns, L. Garfinkel & J. Samet *Changes in cigarette-related disease risks and their implication for prevention and control* (pp. 13-42). Atlanta, Georgia: National tobacco control program.
- Census Bureau's March Current Population Survey (2017). *Population distribution by race/ethnicity, 2016*. Retrieved from <https://www.kff.org/other/state-indicator/distribution-by-raceethnicity/?activeTab=map¤tTimeframe=0&selectedDistributions=black&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D>.
- Centers for Disease Control & Prevention. (1997). Smoking-attributable mortality and years of potential life lost - United States, 1984. *Morbidity and Mortality weekly report*, *46*(20), 444-451.

- Chahine, T., Subramanian, S. V. & Levy, J. I. (2011). Sociodemographic and geographic variability in smoking in the US: A multilevel analysis of the 2006–2007 Current Population Survey, Tobacco Use Supplement. *Social science & medicine*, 73(5), 752-758.
- Chuang, Y. C., & Chuang, K. Y. (2008). Gender differences in relationships between social capital and individual smoking and drinking behavior in Taiwan. *Social Science & Medicine*, 67(8), 1321-1330.
- Commission on Social Determinants of Health. (2008). *Final reports and additional documents from the knowledge networks*. Geneva, Switzerland: World Health Organization. Retrieved from: http://www.who.int/social_determinants/knowledge_networks/final_reports/en/index.html
- Cromley, E. K., & McLafferty, S. L. (2002). *GIS and public health*. New York, NY: The Guildford Press.
- Curtin, L. R., & Klein, R. J. (1995). *Direct standardization (age-adjusted death rates)* (Health People Statistical Note No. 6). Hyattsville, MD: National Center for Health Statistics. Retrieved from: <https://www.cdc.gov/nchs/data/statnt/statnt06rv.pdf>
- Dahlgren, G., & Whitehead, M. (1991). *Policies and strategies to promote social equity in health* (Strategy working paper for Europe). Stockholm, Sweden: Institute for future studies. Retrieved from: https://www.researchgate.net/profile/Goeran_Dahlgren/publication/5095964_Policies_and_strategies_to_promote_social_equity_in_health_Background_document_to_WHO_-_Strategy_paper_for_Europe/links/569540f808aeab58a9a4d946.pdf
- Datta, G. D., Subramanian, S. V., Colditz, G. A., Kawachi, I., Palmer, J. R. & Rosenberg, L. (2006). Individual, neighborhood, and state-level predictors of smoking among US Black women: a multilevel analysis. *Social science & medicine*, 63(4), 1034-1044.
- Djoussé, L., Driver, J. A., & Gaziano, J. M. (2009). Relation between modifiable lifestyle factors and lifetime risk of heart failure. *Jama*, 302(4), 394-400.
- Dwyer-Lindgren, L. (2017). *Geographic Patterns and Disparities in Health-related Behaviors and Outcomes in the United States* (Doctoral dissertation, Erasmus University Rotterdam). Retrieved from: <https://repub.eur.nl/pub/101851/>
- Dwyer-Lindgren, L., Freedman, G., Engell, R. E., Fleming, T. D., Lim, S. S., Murray, C. J., & Mokdad, A. H. (2013). Prevalence of physical activity and obesity in US counties, 2001–2011: a road map for action. *Population health metrics*, 11(7), 1-11.
- ESRI. (2017). *How cluster and outlier analysis: Anselin Local Moran's I works*. Retrieved from: http://resources.esri.com/help/9.3/arcgisengine/java/gp_toolref/spatial_statistics_tools/how_cluster_and_outlier_analysis_colon_anselin_local_moran_s_i_spatial_statistics_works.htm.

- Ezzati, M. & Lopez, A. D. (2004). Regional, disease specific patterns of smoking-attributable mortality in 2000. *Tobacco Control*, 13(4), 388-395.
- Fabsitz, R., & Feinleib, M. (1980). Geographic patterns in county mortality rates from cardiovascular diseases. *American journal of epidemiology*, 111(3), 315-328.
- Fenelon, A., & Preston, S. H. (2012). Estimating smoking-attributable mortality in the United States. *Demography*, 49(3), 797-818.
- Forouzanfar, M. H., Alexander, L., Anderson, H. R., Bachman, V. F., Biryukov, S., Brauer, M., ... & Delwiche, K. (2015). Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks in 188 countries, 1990–2013: a systematic analysis for the Global Burden of Disease Study 2013. *The Lancet*, 386(10010), 2287-2323.
- Gatrell, A. C. (2002). *Geographies of Health: An Introduction*. Oxford, United Kingdom: Blackwell Publishers Ltd.
- Gonzales, K., Roeber, J., Kanny, D., Tran, A., Saiki, C., Johnson, H., ... & Miller, T. (2014). Alcohol-attributable deaths and years of potential life lost—11 states, 2006–2010. *Morbidity and Mortality Weekly Report*, 63(10), 213-216.
- Health and Welfare Canada. (1974). *A New Perspectives on the Health of Canadians*. Ottawa, Canada: Minister of Supply and Services Canada. Retrieved from: <http://www.phac-aspc.gc.ca/ph-sp/pdf/perspect-eng.pdf>
- Herian, M. N., Tay, L., Hamm, J. A., & Diener, E. (2014). Social capital, ideology, and health in the United States. *Social Science & Medicine*, 105(1), 30-37.
- Institute for Health Metrics and Evaluation. (2018a). *US Health*. Retrieved from: <http://www.healthdata.org/us-health>.
- Institute for Health Metrics and Evaluation. (2018b). *Terms defined*. Retrieved from: <http://www.healthdata.org/terms-defined>.
- Institute for Health Metrics and Evaluation. (2018c). *Publications*. Retrieved from: <http://www.healthdata.org/gbd/publications>
- Janssen, F., Kunst, A. & Mackenbach, J. (2007). Variations in the pace of old-age mortality decline in seven European countries, 1950–1999: The role of smoking and other factors earlier in life. *European Journal of Population*, 23(2), 171-188.
- Janssen, F. & Spiensma, A. S. (2012). The contribution of smoking to regional mortality differences in the Netherlands. *Demographic Research*, 27(9), 233-260.

- Jenum, A.K., Stensvold, I., & Thelle, D.S. (2001). Differences in cardiovascular disease mortality and major risk factors between districts in Oslo. An ecological analysis. *International Journal of Epidemiology*, 30(1), 59-65.
- Jia, H. & Lubetkin, E. I. (2010). Obesity-related quality-adjusted life years lost in the US from 1993 to 2008. *American journal of preventive medicine*, 39(3), 220-227.
- Joint Economic Committee. (2018). *The geography of social capital in America* [SCP report no 1, 2018]. Washington, DC: Social Capital Project. Retrieved from: https://www.lee.senate.gov/public/_cache/files/da64fdb7-3b2e-40d4-b9e3-07001b81ec31/the-geography-of-social-capital.pdf.
- Kaplan, G. A., Pamuk, E. R., Lynch, J. W., Cohen, R. D., & Balfour, J. L. (1996). Inequality in income and mortality in the United States: analysis of mortality and potential pathways. *Bmj*, 312(7037), 999-1003.
- Kawachi, I., Kennedy, B. P., Lochner, K., & Prothrow-Stith, D. (1997). Social capital, income inequality, and mortality. *American journal of public health*, 87(9), 1491-1498.
- Kelley, E. A., Bowie, J. V., Griffith, D. M., Bruce, M., Hill, S., & Thorpe Jr, R. J. (2016). Geography, race/ethnicity, and obesity among men in the United States. *American journal of men's health*, 10(3), 228-236.
- Kennedy, B. P., Kawachi, I., & Prothrow-Stith, D. (1996). Income distribution and mortality: cross sectional ecological study of the Robin Hood index in the United States. *British medical journal*, 312(7037), 1004-1007.
- Kibele, E. U. B., Klüsener, S. & Scholz. (2015). Regional Mortality Disparities in Germany Long-Term Dynamics and Possible Determinants. *Kolner Zeitschrift Fur Soziologie Und Sozialpsychologie*, 67(1), 241–270.
- Kumar, S., Kumari, A., & Murarka, S. (2009). Lifestyle factors in deteriorating male reproductive health. *Niscair Online Periodicals Repository*, 47(8), 615-624.
- Lantz, P. M., House, J. S., Lepkowski, J. M., Williams, D. R., Mero, R. P., & Chen, J. (1998). Socioeconomic factors, health behaviors, and mortality: results from a nationally representative prospective study of US adults. *Jama*, 279(21), 1703-1708.
- Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., Shibuya, K., Adair-Rohani, H., ... & Aryee, M. (2012). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010. *The Lancet*, 380(9859), 2224-2260.

- Lopez, A. D., Collishaw, N. E., & Piha, T. (1994). A descriptive model of the cigarette epidemic in developed countries. *Tobacco Control*, 3(3), 242-247.
- Mackenbach, J. P. (2012) The persistence of health inequalities in modern welfare states: The explanation of a paradox. *Social science & medicine*, 75(4), 761-76
- Max, W. (2001). The financial impact of smoking on health-related costs: a review of the literature. *American journal of Health Promotion*, 15(5), 321-331.
- McGinnis, J. M. & Foege, W. H. (1993). Actual causes of death in the United States. *JAMA*, 270(18), 2207–2212.
- Mitchell, A. (2005). *The ESRI guide to GIS analysis: Volume 2: Spatial measurements and statistics*. Redlands, CA: ESRI Press. Retrieved from: <http://agris.fao.org/agris-search/search.do?recordID=SO2007100043>
- Mitchell, R., Dorling, D. & Shaw, M. (2000). *Inequalities in life and death: what if Britain were more equal?* Bristol, United Kingdom: The Policy Press.
- Montez, J. K., Zajacova, A., & Hayward, M. D. (2016). Explaining inequalities in women's mortality between US States. *SSM-population health*, 2(1), 561-571.
- Morgan, K. O. L., & Morgan, S. (2016). *State Rankings 2016: A Statistical View of America*. Washington, DC: CQ Press.
- Murray, C. J., Kulkarni, S. C., Michaud, C., Tomijima, N., Bulzacchelli, M. T., Iandiorio, T. J., & Ezzati, M. (2006). Eight Americas: investigating mortality disparities across races, counties, and race-counties in the United States. *PLoS medicine*, 3(9), e260.
- Murray, C. J., Michaud, C. M., McKenna, M. T., & Marks, J. S. (1998). *US patterns of mortality by county and race: 1965-1994*. Cambridge, United Kingdom: Harvard Center for Population and Development Studies.
- Must, A., Jacques, P. F., Dallal, G. E., Bajema, C. J., & Dietz, W. H. (1992). Long-term morbidity and mortality of overweight adolescents: a follow-up of the Harvard Growth Study of 1922 to 1935. *New England journal of medicine*, 327(19), 1350-1355.
- Naghavi, M., Abajobir, A. A., Abbafati, C., Abbas, K. M., Abd-Allah, F., Abera, S. F., ... & Ahmadi, A. (2017). Global, regional, and national age-sex specific mortality for 264 causes of death, 1980–2016: a systematic analysis for the Global Burden of Disease Study 2016. *The Lancet*, 390(10100), 1151-1210.
- Naimi, T. S., Blanchette, J., Nelson, T. F., Nguyen, T., Oussayef, N., Heeren, T. C., ... & Xuan, Z. (2014). A new scale of the US alcohol policy environment and its relationship to binge drinking. *American journal of preventive medicine*, 46(1), 10-16.

- Naing, N. N. (2000). Easy way to learn standardization: direct and indirect methods. *The Malaysian journal of medical sciences: MJMS*, 7(1), 10-15.
- Ogden, C. L., Carroll, M. D., Curtin, L. R., McDowell, M. A., Tabak, C. J., & Flegal, K. M. (2006). Prevalence of overweight and obesity in the United States, 1999–2004. *JAMA*, 295(13), 1549–55.
- Ogden, C. L., Carroll, M. D. & Flegal, K. M. (2008). High body mass index for age among US children and adolescents, 2003-2006. *JAMA*, 299(20), 2401-2405.
- Omran, A. R. (2005). The epidemiologic transition: a theory of the epidemiology of population change. *The Milbank Quarterly*, 83(4), 731-757.
- Osler, M., Christensen, U., Lund, R., Gamborg, M., Godtfredsen, N., & Prescott, E. (2003). High local unemployment and increased mortality in Danish adults; results from a prospective multilevel study. *Occupational and Environmental Medicine*, 60(11), 1-5.
- Pampel, F. C., & Rogers, R. G. (2004). Socioeconomic status, smoking, and health: a test of competing theories of cumulative advantage. *Journal of health and social behavior*, 45(3), 306-321.
- Pearce, J., Hiscock, R., Moon, G. & Barnett, R. (2008). The neighbourhood effects of geographical access to tobacco retailers on individual smoking behaviour. *Journal of Epidemiology & Community Health*, 63(1), 69-77.
- Putnam, R. (2000). *Bowling Alone the Collapse and Revival of American Community*. New York, NY: Simon and Schuster Paperbacks.
- Rehm, J., Greenfield, T. K., & Rogers, J. D. (2001). Average volume of alcohol consumption, patterns of drinking, and all-cause mortality: results from the US National Alcohol Survey. *American Journal of Epidemiology*, 153(1), 64-71.
- Rogers, R. G., & Hackenberg, R. (1987). Extending epidemiologic transition theory: a new stage. *Social biology*, 34(3-4), 234-243.
- Rostron, B. L. & Wilmoth, J. R. (2011). Estimating the effect of smoking on slowdowns in mortality declines in developed countries. *Demography*, 48(2), 461-479.
- Shaw, M., Dorling, D. & Mitchell, R. (2002). Health Inequalities: Composition or Context? In M. Shaw, D. Dorling & R. Mitchell *Health, Place and Society* (pp. 126-154). London, United Kingdom: Pearson.
- Shaw, M., Orford, S., Brimblecombe, N. & Dorling, D. (2000). Widening inequality in mortality, between 160 regions of 15 European countries in the early 1990s. *Social Science & Medicine*, 50(7), 1047-1058.

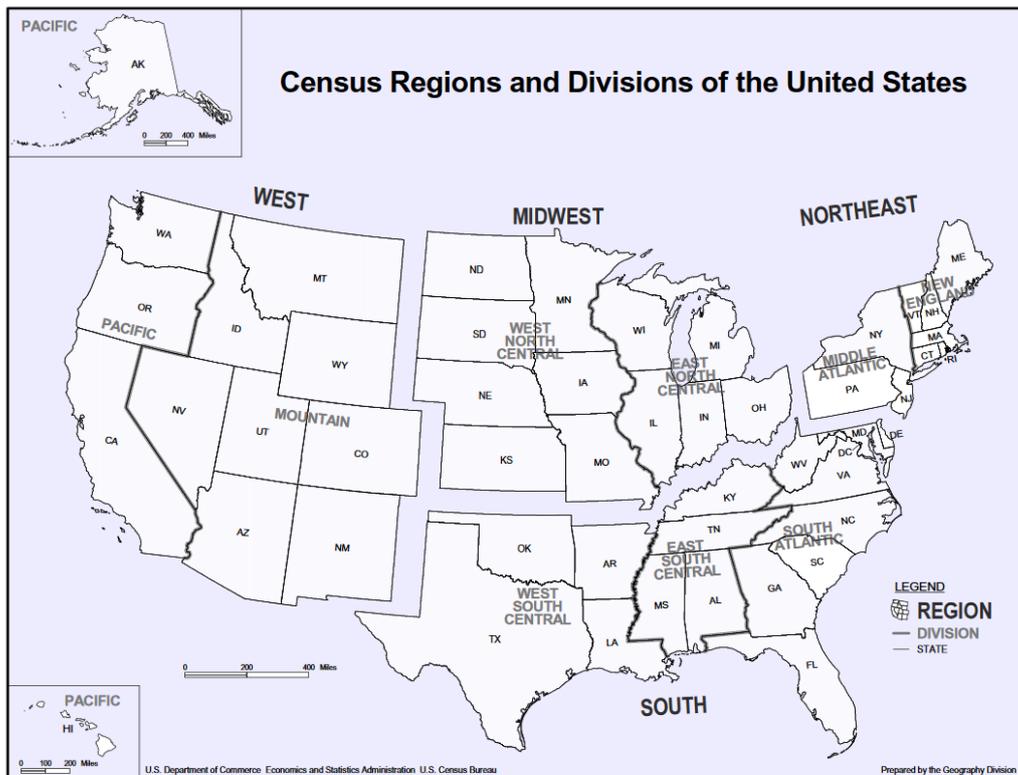
- Singh, G. K., Daus, G. P., Allender, M., Ramey, C. T., Martin, E. K., Perry, C., ... & Vedamuthu, I. P. (2017). Social determinants of health in the United States: addressing major health inequality trends for the nation, 1935-2016. *International journal of MCH and AIDS*, 6(2), 139-164.
- Singh, G. K., Kogan, M. D., & van Dyck, P. C. (2008). A multilevel analysis of state and regional disparities in childhood and adolescent obesity in the United States. *Journal of community health*, 33(2), 90-102.
- Sobal, J., & Stunkard, A. J. (1989). Socioeconomic status and obesity: a review of the literature. *Psychological bulletin*, 105(2), 260-275.
- Spijker, J. (2003). *Socioeconomic and other determinants of mortality differences in Europe: A pooled, cross-country, time-series analysis*. Barcelona, Spain: Centre d'Estudis Demogràfics.
- Staetsky, L. (2009). Divergent trends in female old-age mortality: A reappraisal. *Demographic Research*, 21(30), 885-914.
- Stahre, M., Roeber, J., Kanny, D., Brewer, R. D., & Zhang, X. (2014). Peer reviewed: contribution of excessive alcohol consumption to deaths and years of potential life lost in the United States. *Preventing chronic disease*, 11(1), E119.
- Statista. (2018). *Median household income in the United State by state*. Retrieved from: <https://www.statista.com/statistics/233170/median-household-income-in-the-united-states-by-state/>
- Stattrek. (2018). *Differences in proportions*. Retrieved from: <https://stattrek.com/estimation/difference-in-proportions.aspx>
- Subramanian, S. V., Kawachi, I., & Kennedy, B. P. (2001). Does the state you live in make a difference? Multilevel analysis of self-rated health in the US. *Social science & medicine*, 53(1), 9-19.
- Tencza, C., Stokes, A., & Preston, S. (2014). Factors responsible for mortality variation in the United States: a latent variable analysis. *Demographic research*, 21(2), 27-70.
- Thompson, O. M., Ballew, C., Resnicow, K., Must, A., Bandini, L. G., Cyr, H. D. W. H., & Dietz, W. H. (2004). Food purchased away from home as a predictor of change in BMI z-score among girls. *International journal of obesity*, 28(2), 282-289.
- Truth Initiative. (2017). *Tobacco nation*. Retrieved from: <https://truthinitiative.org/sites/default/files/Tobacco-Nation-FINAL.pdf>
- United Nations. (2017). *World Population Prospects: The 2017 Revision*. Retrieved from: <https://population.un.org/wpp/DataQuery/>

- United States Census Bureau. (2017). *Median household income*. Retrieved from <https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk>
- United States Census Bureau. (2018). *Geographic Terms and Divisions – Census Divisions and Census Regions*. Retrieved from https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf.
- United States Census Bureau. (2019). *Urban percentage of the population for states*. Retrieved from <https://www.icip.iastate.edu/tables/population/urban-pct-states>
- United States Department of Health and Human Services. (2001). *The Surgeon General's call to action to prevent and decrease overweight and obesity*. Retrieved from: <https://www.ncbi.nlm.nih.gov/books/NBK44206/>
- United States Department of Health and Human Services. (2018a). *Healthy People 2030 Framework*. Retrieved from: <https://www.healthypeople.gov/2020/About-Healthy-People/Development-Healthy-People-2030/Framework>
- United States Department of Health and Human Services. (2018b). *2020 Topics and Objectives*. Retrieved from: <https://www.healthypeople.gov/2020/topics-objectives>
- United States Department of Health and Human Services. (2018c). *Tobacco use*. Retrieved from: <https://www.healthypeople.gov/2020/topics-objectives/topic/tobacco-use>
- Vallin, J., Meslé, F. & Valkonen, T. (2001). Trends in mortality and differential mortality. *Population Studies*, 36(1), 1-33.
- Wallace Jr, J. M., & Bachman, J. G. (1991). Explaining racial/ethnic differences in adolescent drug use: The impact of background and lifestyle. *Social problems*, 38(3), 333-357.
- Wang, Y. & Beydoun, M. A. (2007). The obesity epidemic in the United States—gender, age, socioeconomic, racial/ethnic, and geographic characteristics: a systematic review and meta-regression analysis. *Epidemiologic reviews*, 29(1), 6-28.
- Wang, H., Naghavi, M., Allen, C., Barber, R. M., Bhutta, Z. A., Carter, A., ... & Coggeshall, M. (2016). Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980–2015: a systematic analysis for the Global Burden of Disease Study 2015. *The Lancet*, 388(10053), 1459-1544.
- Wang, Y. & Zhang, Q. (2006). Are American children and adolescents of low socioeconomic status at increased risk of obesity? Changes in the association between overweight and family income between 1971 and 2002. *American Journal of Clinical Nutrition*, 84(4), 707–16.
- Wiehl, D. G. (1948). Mortality and socio-environmental factors. *The Milbank Memorial Fund Quarterly*, 26(4), 335-365.

- Xu, J., Murphy, S. L., Kochanek, K. D., Bastian, B., & Arias, E. (2018). Deaths: final data for 2016. *National vital statistics reports*, 67(5), 1-76.
- Young, T. K. (2003). Review of research on aboriginal populations in Canada: relevance to their health needs. *Bmj*, 327(7412), 419-422.
- Young, T. K. (2005). *Population health: concepts and methods*. New York, NY: Oxford University Press.

Supplementary material

Figure S.1. Map with the regions and divisions of the United States (United States Census Bureau, 2018)



Region	Division	Abbreviation	State
West	Pacific	AK	Alaska
		CA	California
		HI	Hawaii
		OR	Oregon
		WA	Washington
	Mountain	AZ	Arizona
		CO	Colorado
		ID	Idaho
		NM	New Mexico
		MT	Montana
MidWest	West North Central	IA	Iowa
		KS	Kansas
		MN	Minnesota

		MO	Missouri
		NE	Nebraska
		ND	North Dakota
		SD	South Dakota
	East North Central	IN	Indiana
		IL	Illinois
		MI	Michigan
		OH	Ohio
		WI	Wisconsin
NorthEast	Middle Atlantic	NJ	New Jersey
		NY	New York
		PA	Pennsylvania
	New England	CT	Connecticut
		ME	Maine
		MA	Massachusetts
		NH	New Hampshire
		RI	Rhode Island
		VT	Vermont
South	South Atlantic	DE	Delaware
		DC	District of Columbia
		FL	Florida
		GA	Georgia
		MD	Maryland
		NC	North Carolina
		SC	South Carolina
		VA	Virginia
		WV	West Virginia
	East South Central	AL	Alabama
		KY	Kentucky
		MS	Mississippi
		TE	Tennessee
	West South Central	AR	Arkansas
		LA	Louisiana
		OK	Oklahoma
		TX	Texas
