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Modeling the Economic Cost of Obesity Risk and Its Relation to the Health Insurance Premium in the United States: A State Level Analysis

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Abstract: We propose a new approach for estimating the state-level direct and indirect economic cost of obesity in the United States for the time period 1996 to 2018. Our unique top-down methodology integrates a prevalence-based method with various medical-level costs, economic, demographic, and socio-economic factors. Using this approach, we investigate the relationship between the estimates of the total obesity-related costs and the health insurance premium by state in order to evaluate the state burden of obesity. Our estimate of the total national economic cost attributed to obesity is approximately $422 billion in 2018, representing about 2% of the national GDP for the same year. Using exponential smoothing models, we forecast that the total cost would reach $475 billion in 2021 without accounting for the impact of COVID-19 on obesity. The top states driving the cost estimates are California, Texas, New York, and Florida. A bootstrapping technique is employed to the state-level estimated cost in order to determine the average cost per person. We hope that our study will promote interest in this topic and open discussion for further research in this area.

Keywords: obesity; economic cost; forecasting; health premium; United States

JEL Classification: C53; I13; H51

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1. Introduction

The importance of estimating economic cost of obesity and the obesity-related conditions in the United States is not only important for the insurance providers but also for the policy makers involved in the state and federal health programs. Actuaries showed much interested in estimating the economic cost of obesity in the United States. Two major publications Alves et al. (2021) and Behan and Cox (2010) by the working groups of Society of Actuaries (SOA) are the evidence of these efforts, while these studies focus on the estimation of costs due to obesity based on the publicly available data they lack some considerations. These approaches do not examine possible margin of error related to the estimation of costs. Building a predictive model with the purpose of forecasting the future costs due to obesity is important for life and health actuaries working for insurance and reinsurance companies, government agencies, and regulators. The actuaries in these sectors are expected to recognize if there is any significant gap in the insurance coverage and develop potential solutions as well as mitigation and adaptation strategies to manage risk and profitability of the health insurance providers.

It is estimated that obesity-related medical costs alone account for nearly $150 billion annually (Adult Obesity Facts 2021) in the United States. Those who are obese are seen to take an increased number of sick days, have decreased productivity, and are more likely to develop a mobility disability, all of which add to the overall costs as Wolf and Colditz (1998) noted. From a financial perspective, understanding the trends of obesity provides a way of measuring and addressing this epidemic.

For actuaries working in the healthcare insurance sector, Brown and McDaid (2003) identified obesity as one of the several underwriting risk classification factors that can be used to estimate mortality-driven benefits. Obesity itself is responsible for many diseases and health conditions causing indirect impact on absenteeism and excess mortality in the workforce. In 2018, 42.4% of Americans were considered obese, 9.2% being severely obese, with future statistics projected to be even more severe by the Centers for Disease Control and Prevention (Adult Obesity Facts 2021). Obesity is linked to many serious diseases, namely coronary heart disease (CHD), hypertension, gallbladder disease, breast, endometrial and colon cancer, and osteoarthritis (Wolf and Colditz 1998), which can complicate the visible impact of obesity risk. Moreover, the effects of obesity incur a large cost not only as it relates to money spent on treatment of obesity itself and related diseases, but also costs that impact employment and productivity, while the health insurance premium has doubled in the past ten years, it is unclear how much of this premium is sufficient to cover the financial burden of the obesity pandemic. Any potential gaps would indicate the need for additional expansion of state and federal health programs for managing the obesity pandemic. The evaluation of existing and developing new health coverages related to obesity-related conditions is an important consideration for the profitability of the health insurance providers.

The analysis of the costs of obesity requires some specificity and precision with the terminology used to describe both the methods and approaches in cost estimation. First, the definition of obesity is typically linked to the Body Mass Index (BMI) defined as person's weight in kilograms divided by the square of height in meters. Despite some criticism (see Romero-Corral et al. (2008), Miljkovic et al. (2017)), the BMI is still widely used in many epidemiological studies and the individuals are categorized into weight groups as underweight (BMI < 18.5), normal weight ($18.5 \leq$ BMI < 25), and overweight ($25 \leq$ BMI < 30). To be consistent with the CDC and the World Health Organization, in this paper we are interested in the obesity category, or those individuals whose BMI is at least 30. Second, we define obesity-related costs in two categories: direct and indirect, as seen in Figure 1. Direct costs are medical costs spent to treat obesity. Indirect costs are those incurred as a result of obesity, other than treatment itself.

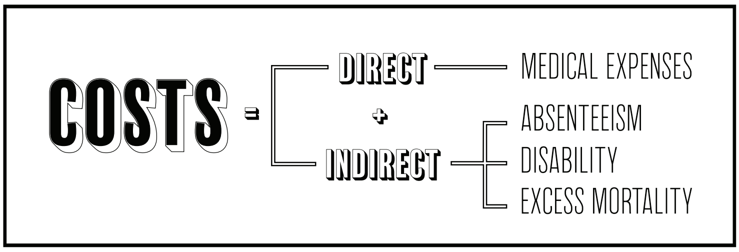

Figure 1. Basic composition of costs for obesity.

When determining direct costs for a particular disease, there are two general approaches: prevalence-based and incidence-based economic evaluations, seen in Figure 2. A prevalence-based economic evaluation analyzes the costs of a disease for an entire population over the duration of a specific timeline, i.e., typically one year (Mauskopf 1998). An incidence-based economic evaluation focuses on the costs incurred by a predetermined group, often called a cohort, for the duration of the disease itself (Mauskopf 1998). Since obesity is a risk factor for so many other conditions, it is necessary to determine the extent to which obesity risk is responsible for these related conditions. This is done by looking at the extent of a condition in a group of obese individuals, and comparing it to that of a group of normal weight individuals, while controlling for various other factors. This process is known as finding the population-attributable risk percent (PAR%) or attributable case percent (Wolf and Colditz 1998).

Figure 2. Main cost estimation procedures.

The objectives of this paper are as follows:

1. Develop a top-down approach for the estimation of the state-level economic costs of obesity risk for the time period 1996 to 2018.
2. Employ the bootstrapping method to estimate the average economic cost of obesity per person, including the 95% confidence intervals.
3. Propose the forecasting models that will estimate the future costs of obesity by state over a 3-year period.
4. Compare the total economic cost of obesity relative to the aggregated health premium and annuity considerations from the Schedule T of the Annual Statement for year 2018.

Previous studies on the topic of the costs of obesity each take different approaches, but the core terminology is universal. In the next subsection, we review several important studies in this area of research.

Literature Review

Several important studies were reviewed in the area of economic cost estimation related to obesity and morbidity. Wolf and Colditz (1998) performed an estimate of the economic cost of obesity in the United States, estimating $99.2 billion in 1995. The authors conducted a prevalence-based approach to examine diseases in which obesity was a noticeable risk factor to derive an estimate for the direct cost of obesity. The PAR% was estimated for these diseases to approximate the proportion of the costs that were attributable to obesity. The indirect costs associated with obesity was estimated based on the data from the National Health Interview Survey, and the results were trended using the Consumer Price Index to report costs in 1995 dollars.

Thorpe et al. (2004) used the data from the 1987 National Medical Expenditure Survey and the 2001 Medical Expenditure Panel Survey, Household Component to create a two part regression model. This model took into account a range of covariates, including but not limited to weight, health insurance status, income, and region. Per capita spending was estimated by producing cost estimates simulating if all people were underweight, normal weight, overweight, or obese. Doing so "nets out the impact of observable individual characteristics (such as age, insurance status, income)" (Thorpe et al. 2004). The analysis was done for 1987 and 2001, utilizing unique models for each year. Additionally, a large part of the contribution of the study was to decompose the spending growth of obesity into what was attributable to changing obesity rates, and what was attributable to increased per capita spending. The finding was that 27% of the increase in costs from 1987 to 2001 were due to the increase in the rate of obesity and spending, while the study does provide a more dynamic perspective by showing a change in costs over time, the length of time between the chosen years is quite large. Therefore, the year-to-year fluctuations of spending due to obesity are not seen, making it difficult to rule out other confounding factors during that time frame.

Behan and Cox (2010) reviewed a larger body of work, looking at obesity and its connection to diseases as well as its relevance to mortality and morbidity, ending with an analysis of the cost of obesity. Upon reviewing nearly 500 articles on the topic, their study concluded that the overall cost in the United States and Canada was approximately $300 billion per year for medical costs, disability, and excess mortality caused by obesity.

The study used a weighted approach to get a general risk value for each of the respective diseases that obesity is linked to, then combined that with the expenditures listed on the Medical Expenditure Panel Survey to get a cost estimate. The breadth of the study is substantial, but lacks deeper actuarial analysis where statistical models can be employed to assess the error in estimation for their produced cost estimates.

Hammond and Levine (2010) identified four main categories of economic impact due to obesity: direct medical costs, productivity costs, transportation costs, and human capital costs. All are sizeable, but the largest of these categories are direct medical costs and productivity costs, while the estimates given from the different studies vary, the authors agreed with a similar conclusion: the cost of obesity is substantial and impacts a wide array of areas. The discussion about the direct medical costs and productivity costs, specifically absenteeism, presenteeism, and disability costs, clearly have an impact on the overall cost of obesity. Transportation costs and human capital accumulation are also discussed, and while it may be argued that obesity has an effect on these costs, the connection of obesity is tangential at best. It is not completely discernible whether obesity is a driving factor in the costs, or if there is merely a correlation in its presence.

A time series model by Revels et al. (2017) forecasted the change in prevalence of those considered overweight, obese, and morbidly obese, as well as the overall healthcare costs in the United States. The 2019 forecast for healthcare costs was \$3.6 trillion, and encompasses all healthcare costs, not just those related to obesity. The obesity healthcare costs in the study, however, were estimated as 10% of total healthcare costs, which is a generalization from varying predictions without considering the state variation in the cost estimates. When looking at the costs of obesity over a longer period, it may not be realistic to assume that obesity-related costs remain a set fraction of the overall healthcare costs. It is especially important to make distinctions of costs related to obesity between years when there is a rapidly evolving landscape such as it is now. The proportion of people who are obese is rising steadily, so the amount spent on obesity is likely to rise as well; however it is not clear whether the increase will be directly proportional. Additionally, social media ploys have saturated outlets to promote experimental treatments and "quick fixes", which indicates that there is a sizeable increase in expenses toward new weight loss strategies. Thus, it is prudent to recognize these changes as study limitations in the estimation procedure.

The most recent study by Alves et al. (2021) builds on the previous study by Behan and Cox (2010) with a focus on examining the latest trends in obesity and developing an estimate of obesity's impact on morbidity, productivity loss from disability and productivity loss from premature mortality in the United States and Canada. Alves et al. (2021) estimated the total morbidity cost of \$177.9 billion in 2019 for the United States and Canada with the United States bearing \$172.0 billion of that total cost. Morbidity costs are examined by age band and sex across different classes of obesity prevalence. The authors considered state-level, by-age, per-capita estimates for lost income, lost earnings, supplemental security income payments, and absenteeism costs in 2019 dollars, but these are also merely point estimates.

The following outlines the order of the paper. Section 2 summarizes the methodology for building the state-level obesity-related cost data as well as the exponential smoothing models for the cost estimation and forecasting by state. Section 3 includes the data validation and comparisons of our results to those reported by the existing studies. Section 4 provides the analysis of the data including the cost estimation and forecasts by state. Section 5 discusses limitations of this study. Section 6 provides the concluding remarks.

2. Methodology

In this section, we present the proposed methodology for the estimation and forecasting of direct and indirect state-level costs in the United States related to obesity. Due to unavailability of the state-level medical cost data, we utilize national medical cost data, as well as various demographic and socio-economic variables to develop a robust framework for building a database with the state-level cost estimates. The state level-cost estimates include direct and indirect costs. Using these estimates from 1996 to 2018, we consider forecasting models to predict the future obesity-related cost by state for 3 years ahead, the approach that is significantly different from the work done by Wolf and Colditz (1998), Behan and Cox (2010), and Alves et al. (2021). Additionally, we compare our state-level estimates to the state-level health premium to evaluate the impact of the obesity-related costs on the insurance industry.

2.1. Input Variables and Notations

The notation defined below associated with the input variables will have the same interpretation throughout this section unless otherwise stated.

- p—the population count. Source: State Population Totals (2020), United States Census Bureau; URL: www.census.gov (accessed on 20 July 2021).
- m—the median income for a specified population. Source: Current Population Survey Annual Social and Economic Supplements (2020), United States Census Bureau; URL: www.census.gov (accessed on 20 July 2021).
- d—the prevalence of those reporting a work-impacting disability. Source: Disability Characteristics (2020), United States Census Bureau; URL: www.census.gov (accessed on 20 July 2021).
- e—the employment average ratio: the proportion of the population that is employed. Source: Characteristics of the Employed (2020), United States Census Bureau; URL: www.census.gov (accessed on 20 July 2021).
- b—the proportion of employment benefit for a given population: the average increase from salary that a worker's position is worth. Source: Employer Costs for Employee Compensation (2021), The Bureau of Labor Statistics; URL: www.bls.gov (accessed on 20 July 2021).
- π—the proportion of obese people in the United States population by state. Source: Table of Overweight and Obesity (BMI) (2020) (BRFSS), The Centers for Disease Control and Prevention; URL: www.cdc.gov (accessed on 21 July 2021). Refer to the papers by Daawin et al. (2019) and Miljkovic and Wang (2021) for additional information about the data processing and calculations.
- π^k for $k = I, II, III$ - the proportion of obese people in each obesity class k. Class I ($30 < \text{BMI} \leq 35$), Class II ($35 < \text{BMI} \leq 40$), and Class III ($\text{BMI} > 40$). Source: Table of Overweight and Obesity (BMI) (2020) (BRFSS), The Centers for Disease Control and Prevention; URL: www.cdc.gov (accessed on 21 July 2021).
- ψ—the cost of disease group for a given population. These costs include any direct costs toward care or treatment of the disease group. Source: MEPS (2021), The Agency for Healthcare Research and Quality; URL: www.ahrq.gov (accessed on 21 July 2021).
- φ—health insurance premium. Source: Premium and Considerations (2020), The U.S. Life Statutory Information, aggregated by the Life Industry, Annual Statements, Schedule T Premium and Other Considerations. S&P Capital IQ; URL: www.spglobal.com (accessed on 29 October 2021).
- RR—the relative risk of a disease group on obesity. Source: Murray et al. (2020).
- r—Consumer Price Index (CPI) ratio. Ratio of CPI in year of interest to CPI in 2018. Source for CPI: Consumer Price Index (2021). URL: www.bls.gov (accessed on 21 July 2021).
- r'—Medical Consumer Price Index (MCPI) ratio. Ratio of MCPI in year of interest to MCPI in 2018. Source for MCPI: Consumer Price Index (2021) URL: www.bls.gov (accessed on 21 July 2021).

2.2. Calculations of the Obesity-Related Costs

2.2.1. Cost Trending

In effort to isolate the impact of cost changes with respect to obesity, it is necessary to examine costs on a uniform basis. As such, we trend the indirect cost within this study to the value of the dollar in 2018 ($2018) using the CPI. For ease of use and interpretation, the trending is done by taking the ratio of the CPI in year t, denoted θ_t, to the CPI in 2018 (θ_{2018}). The formula is shown below

$$r_t = \frac{\theta_t}{\theta_{2018}}. \tag{1}$$

By definition, r_{2018} is 1. To adjust for inflation, r_t is multiplied by its corresponding cost in year t to get the inflation-adjusted cost. All values of r_t (other than r_{2018}) are less than 1, as CPI historically increases year over year due to inflation. Similarly, we compute the MCPI ratio, denoted as $r_t^{'}$, which is used to trend direct medical costs in an effort to better account for changes in the medical costs over time.

2.2.2. Estimation of the Direct Cost by State

To determine the direct medical cost of obesity, it is necessary to understand which diseases are linked to obesity. Therefore, the health consequences of obesity were examined by the Centers for Disease Control and Prevention (Consequences of Obesity 2021), which draws from many different scientific journals and studies to produce a single list of diseases where obesity is a significant risk factor. This list was referenced when looking at the available data from Murray et al. (2020) to ultimately create nine groups of major diseases where each disease in group j for $j = 1, \ldots, 9$ is mapped to the corresponding health risks associated with obesity as shown in Table 1.

Table 1. Summary of the obesity related health risks linked to the corresponding disease in group j. Source: Centers for Disease Control and Prevention, Consequences of Obesity (2021).

j—Disease by Group	Health Risk of Obesity by Condition
1—Cardiovascular Disease	Acute myocardial infarction; Coronary Atherosclerosis
2—Diabetes	Diabetes
3—Neoplasms	Breast Cancer; Colorectum Cancer; Esophagus Cancer Gallbladder Cancer; Kidney Cancer; Liver Cancer Meningioma Cancer; Myeloma Cancer; Ovarian Cancer Pancreatic Cancer; Stomach Cancer Thyroid Cancer; Uterine Cancer
4—Respiratory Diseases	Asthma; Chronic Obstructive Pulmonary Disease
5—Osteoarthritis	Osteoarthritis
6—Hypertension	Hypertension
7—Kidney Disease	Chronic Kidney Disease
8—Biliary Disease	Liver disease; Gallbladder diseases; Pancreatic disease
9—Cerebrovascular Disease	Stroke

Indeed, for each disease, obesity is only a risk factor. Therefore, obesity is not responsible for 100% of the medical costs incurred in each group of diseases. The national aggregate direct medical cost of each disease group is provided by the Medical Expenditure Panel Survey (MEPS 2021) on an annual basis. This large scale survey collects the data from individual households regarding spending on specific medical services, doctors' visits, supplemented with the data provided by medical providers. The MEPS data are not available at the state level.

Figure 3 shows an increasing trend for all medical costs associated with diseases defined in Table 1. These costs are provided in the value of 2018 dollars with an effort to adjust the historical cost data for inflation. A medical CPI provided by the Bureau of Labor Statistics is used as a cost deflator.

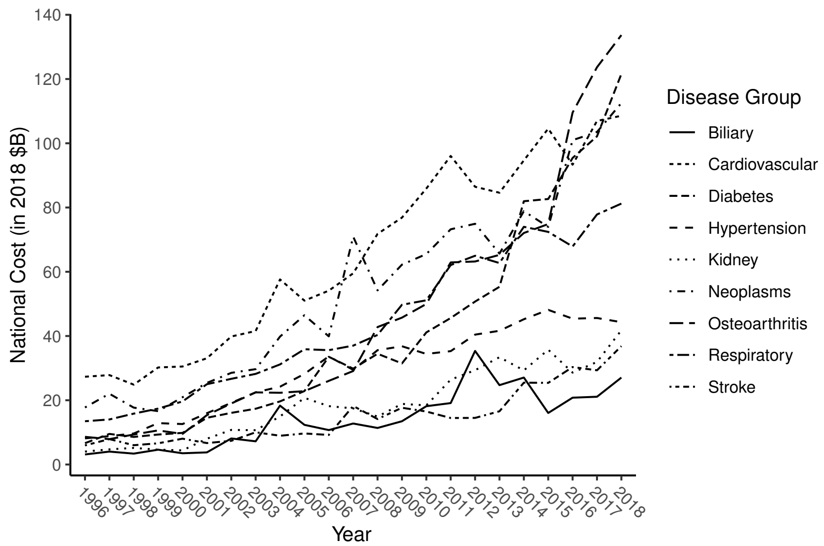

Figure 3. Direct medical cost in billions of 2018 dollars, allocated to each disease group, during the period from 1996 to 2018. Source: the Medical Expenditure Panel Survey (MEPS 2021).

We aim to develop a top-down approach in the estimation of the direct medical cost at state level. The first step in this estimation requires us to define a percentage of the costs of each disease group j attributable to obesity. This is done by using the relative risks (RRs) of each disease. The RR of a disease with a risk factor of obesity compares the prevalence of that disease in a normal population with the prevalence in a population with the risk factor (in this case, obesity). The value represents the ratio of these prevalences, which is meant to quantify how the risk factor increases or decreases the likelihood of having a disease. Using these RRs, the population-attributable risk percent (PAR%), denoted by ρ, as mentioned in Section 1 for each disease group j, is calculated in state i at year t as

$$\rho_{jit} = \frac{\pi_{it}(RR_j - 1)}{1 + \pi_{it}(RR_j - 1)} \quad j \in \{1\text{–}9\}, i \in \{1\text{–}50\}, t \in \{1996\text{–}2018\} \tag{2}$$

where π_{it} represents the obesity prevalence at state i in year t and RR_j denotes the relative risk of disease j with a risk of obesity. We consider longitudinal time series data for nine disease groups in all 50 US states for the time period 1996 to 2018. Table 2 shows the description of each disease group j with the corresponding RR.

Table 2. The relative risk of a disease with the risk factor of obesity in the disease group j based on Murray et al. (2020).

j—Disease Group	RR
1—Cardiovascular Disease	2.274
2—Diabetes	3.547
3—Neoplasms	1.195
4—Respiratory Diseases	1.406
5—Osteoarthritis	1.242
6—Hypertension	3.122
7—Kidney Disease	1.732
8—Biliary Disease	1.597
9—Cerebrovascular Disease	2.472

For the estimation of the state level direct cost, we used the top-down approach in which the national level cost is distributed to each state using the state's population as a proxy. In other words, the annual cost of each disease group is distributed at the state level on the basis of the fraction of the state's population to the national population. Then, the resulting estimate is multiplied by the PAR% using obesity as a risk factor, which scales the state costs for each year to only what is attributable to obesity in that state. Finally, the direct medical cost in 2018 dollars for the condition group j in state i at year t is estimated using the following formula

$$DC_{jit} = \psi_{jt} \times \frac{p_{it}}{\sum_{i=1}^{50} p_{it}} \times \rho_{jit} \times r_t^{'} \tag{3}$$

where ψ_{jt} is the annual cost of disease group j in year t, p_{it} is the population count in the state i in year t, and ρ_{jit} is defined by Equation (2). This cost estimate accounts for the inflationary adjustment $r_t^{'}$ in year t. The total direct cost for state i at time t is obtained by $DC_{it} = \sum_j DC_{jit}$, which combines all nine disease group costs. This top-down approach makes the direct cost calculation concise and gives an intuitive hierarchy to how the costs are calculated. This approach also minimizes error since the obesity-attributable costs are being scaled down by the national costs, instead of producing an estimate for the obesity-attributable cost per incidence of a disease group. It is for these reasons that we believe this is a strong method in estimating the state-level direct medical costs associated with obesity.

2.2.3. Indirect Cost by State

Estimation of indirect cost includes the major components associated with excess mortality, absenteeism, and disability. The indirect cost equations rely on the input variables as described in Section 2.1, as well as a few constants, which are discussed in details below. In general, we derive our cost calculations from the study by Behan and Cox (2010), but we propose some modifications to account for the calculations over multiple years. Rather than using a constant 19.4% for the average employee benefits over time, we keep a national estimate but define a new formula for the calculation of the average employee benefits by year

$$\tau_t = \frac{m_t}{1 - b_t} \tag{4}$$

where m_t represents the median income in year t and b_t denotes the average proportion of the employee benefit in year t. This allows us to account for changes in the employee benefits over time, which is an important aspect of the cost calculations, since the average ratio of employee benefits to tangible salary has dramatically increased according to the Employer Costs for Employee Compensation (2021). Additionally, it should be noted that τ_t accounts for total employee compensation (salary and employee benefits), so it is not necessary to multiply again by m_t, as it was done by Behan and Cox (2010) when using a constant to scale. The same calculation for τ_t applies to all three indirect cost equations. Any other proposed modifications to the methodology previously published by Behan and Cox (2010) will be explained in its respective category.

Cost of Excess Mortality

There has been great controversy over the correlation between excess mortality and increased BMI, as many scientific articles have come to differing conclusions (Tsai et al. 2011). However, it appears that when BMI is severely increased to the level that is considered obesity, there is increased risk of premature mortality (Flegal 2005). This is not necessarily true for those who are merely overweight, demonstrating that there is a notable difference between the two categories. Since there does seem to be a correlation between obesity and excess mortality, we include the cost calculations in our indirect costs. The computation of the cost from excess mortality takes the total employee compensation (Behan and Cox 2010), and multiplies by 5.8/12, the average "loss of worklife caused by excess mortality for overweight or obese individuals" (Behan and Cox 2010, p. 39) in months, adjusted to be represented annually. Although this does include those who are overweight, as mentioned above there is little correlation between overweight and excess mortality. Therefore, since the constant is an average of the groups, the estimate is likely mainly composed of the effect seen from those in the obese group. This estimate is over a 45 year span, so the constant 1/45 is used to scale the estimate down to a single year. Then, to factor in the proportion of the working population that is obese, the obesity prevalence, population, and employment average ratio are multiplied by the expression. The cost of excess mortality is denoted as M_{it} in state i at time t and it is defined as

$$M_{it} = c_1 \times c_2 \times \tau_t \times p_{it} \times \pi_{it} \times e_t \times r_t \tag{5}$$

where $c_1 = 5.8/12$ and $c_2 = 1/45$, p_{it} and π_{it} represent the population count and the obesity prevalence, respectively, at the state i in year t, and e_t denotes the national employment average ratio in year t. Further, τ_t is the average employee benefits in year t. This cost estimate accounts for the inflationary adjustment r_t in year t.

Cost of Absenteeism

To obtain the cost of absenteeism, we consider the amount of sick days as a fraction of the average number of workdays (261) in a year, as specified by the United States Congress (1966). This results is then multiplied by the population, obesity prevalence, employment average, and the total employee compensation to obtain the cost of the days missed per year by obese people in the working population. Our methodology builds on the previous work by Andreyeva et al. (2014) and Alves et al. (2021). Andreyeva et al. (2014) estimated 1.17 days of greater-than-average absenteeism for those in Obesity Class I, 1.71 days greater-than-average for those in Obesity Class II, and 1.88 days greater-than-average for those in Obesity Class III. Using this information, we propose the computation of the weighted average of the number of days missed for all three classes. Weights are computed, for state i in year t, using the proportion of obese individuals in each class denoted as π^I, π^{II}, and π^{III}, respectively. The cost of absenteeism is denoted as A_{it} in state i at time t and it is defined as

$$A_{it} = (1.17\pi^I_{it} + 1.71\pi^{II}_{it} + 1.88\pi^{III}_{it}) \times c_3 \times p_{it} \times \pi_{it} \times e_t \times \tau_t \times r_t \tag{6}$$

where $c_3 = 1/261$, p_{it}, π_{it} represent the population count and the obesity prevalence, respectively, at the state i in year t. The proportions of obese individuals in state i and year t by obesity class are denoted as π^I_{it}, π^{II}_{it}, and π^{III}_{it}. Further, e_t denotes the national employment average ratio in year t, and τ_t denotes the average employee benefits in year t. This cost estimate accounts for the inflationary adjustment r_t in year t. Ramsay and Oguledo (2015) recognized the importance of the absenteeism cost to be considered by actuaries as they develop the techniques and insights needed to design disability insurance policies.

Cost of Disability

Along with absenteeism costs, disability costs can be substantial for employers. In fact, the indirect cost of individuals with Multiple Sclerosis, a disability that causes nerve damage and can impact motor functions, were found to be more than four times greater than employee controls (Ivanova et al. 2009). Moreover, obesity has been seen to be strongly linked with physical disabilities, increasing the chances of developing a disability, or exacerbating the symptoms if one already has a disability (Multiple Sclerosis Trust 2018). For the cost of disability attributed to obesity, the population count (p) and employment average ratio (e) are multiplied by the total employee compensation (τ) to represent the total earnings of employees in state i for the given year t. This allows us to produce estimates of the productivity of workers in each state for each year of observation, which improves on the work from Behan and Cox (2010), as they only calculated an estimate on the national level for 2009. Further, this estimate is multiplied by a factor of 0.06, representing the "6 percent loss of productivity caused by all physical disabilities" (Behan and Cox 2010, p. 41). We believe it is justifiable to keep this as a constant since the loss of productivity is not dependent on the prevalence of those with a physical disability, but rather represents the average loss for each individual with a physical disability. Therefore, even though the prevalence of those with a physical disability changes over time and varies between states, the average loss of productivity remains the same. This is then scaled by the PAR% of obesity on disability, using the RR_d of 1.24 (Behan and Cox 2010, p. 41), which reduces that value to an amount attributable to obesity. This relative risk is reasonable, as the corresponding study by Rillamas-Sun et al. (2014) offers a similar statistic for mobility disability. Alves et al. (2021) accounts for the cost of disability as well, but it is assumed to be included in a general "loss of productivity" category, including premature mortality, making it harder to compare their costs categories to our own. This factor employs the same formula as outlined in Equation (2), but for physical disability with a risk factor of obesity. The cost of disability is denoted as D_{it} in state i at time t and it is defined as

$$D_{it} = c_4 \times p_{it} \times e_t \times \tau_t \times \frac{\pi_{it}(RR_d - 1)}{1 + \pi_{it}(RR_d - 1)} \times r_t \tag{7}$$

where $c_4 = 0.06$, $RR_d = 1.24$, and p_{it}, π_{it}, e_t, τ_t have been previously defined. This cost estimate accounts for the inflationary adjustment r_t in year t.

2.2.4. Total Indirect Cost by State

Finally, the total indirect cost, IC_{it}, due to obesity in state i at time t is calculated as

$$IC_{it} = M_{it} + A_{it} + D_{it}. \tag{8}$$

which is the sum of the excess mortality, absenteeism, and disability costs. These three categories of costs impact productivity and are referred to as the productivity costs.

It should be noted, however, that there are other costs associated with obesity. For instance, presenteeism, which is the productivity lost while present at work, has gained traction in the cost analysis field. In fact, presenteeism "may be responsible for as much as three times the health-related lost productivity as compared to absenteeism" (Ramsay and Oguledo 2015, p. 143). These, along with other indirect social costs not directly related to employment (shirking, transportation, educational attainment, nursing home expenditures, and more) are not included in this paper, as they are not the focus of this study and are much more abstract in their cost calculations. Further work is necessary to understand the intricacies of these costs.

2.2.5. Total Cost

Finally, to account for the total impact of obesity in a given state at a given time, both the direct and indirect costs must be combined. The total cost in state i at year t is defined as the sum of both direct and indirect costs

$$TC_{it} = DC_{it} + IC_{it}. \tag{9}$$

We can look at this cost as it represents the total societal cost of obesity. The costs incurred by those with obesity to treat it and any associated diseases are combined with the costs incurred by impacted parties due to a reduction in productivity because of obesity.

Thus, the costs calculated in this paper are those that are deemed to be most pertinent to the discussion of the economic impact of obesity in the United States. These costs are the most focused on in the literature, and most reliable in terms of minimizing any judgement-based information within the calculations.

2.2.6. Obesity-Related Cost Ratio

We introduce the Obesity-related Cost Ratio ($OrCR$) as the ratio calculated by dividing total economic cost of obesity (TC) by the total health insurance premiums from Schedule T of the Annual Statement reported by state. The $OrCR$ for state i at year t is defined as follows

$$OrCR_{it} = TC_{it} / \varphi_{it}. \tag{10}$$

where φ_{it} is the total health insurance premium reported for state i and year t and the TC_{it} is the estimated total cost of obesity for the corresponding state i and year t. We expect this ratio to be fairly low as the total health premium covers a wide range of medical expenses including those that are not related to obesity. This ratio is also used in this study as a validation tool to validate our state-level estimates of the total economic cost of obesity.

This ratio provides the relative magnitude of the impact of obesity-related costs between states, as well as the patterns of the portion of obesity-related costs as they relate to healthcare premiums. The direct cost is what we have computed from the aforementioned formula, and the insurance premium cost is derived from Schedule T Premiums and Other Considerations of the Heath Industry, using the summation of the Accident & Health Premiums, Medicare Title XVIII, Medicaid Title XIX, and Federal Employees Health Benefits Plan Premiums columns (columns 2 through 5), on a state-level basis.

Note that the OrCR for California is excluded from the analysis due to data limitations related to California-domiciled health insurers. Significant amount of data for California health insurers is missing from the National Association of Insurance Commissioners (NAIC) annual statement database because only certain segments of the health insurance markets are required to file annual statements with the California Department of Insurance (refer to Cole et al. (2015)).

2.2.7. Forecasting the Total Cost by State

For modeling the obesity-related cost, we consider the exponential smoothing model with the trend proposed by Holt (1957). The forecast produced using this method is obtained by weighted averages of the past observations, with the weights decaying exponentially as the observations get older (see also Winters (1960)). Holt's method assumes the linear trend of obesity-related costs will continue in the future. The h-step-ahead forecast is defined by the following equation

$$\hat{TC}_{t+h|t} = l_t + b_t \tag{11}$$

where l_t denotes the obesity-related cost estimate of the level of the series at year t and b_t denotes an estimate of the trend (slope) of the series at year t.

$$\begin{aligned} l_t &= \alpha TC_t + (1-\alpha)(l_{t-1} + b_{t-1}) \\ b_t &= \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1} \end{aligned} \tag{12}$$

where α represents the smoothing parameter for the level, $0 \leq \alpha \leq 1$ and β^* represents the smoothing parameter for the trend. The level l_t is computed as the weighted average of the TC_t and the one-step-ahead training forecast at year t given by $l_{t-1} + b_{t-1}$. The trend is also computed as the weighted average of the estimated trend at year t based on $l_t - l_{t-1}$ and the previous estimate of the trend b_{t-1}. The forecasts generated by Equation (12) would show a constantly increasing trend of obesity-related costs in the future years. However, the long term forecast by Finkelstein et al. (2012) showed that there is some indication of the obesity prevalence leveling off in the future. This can be supported by the improved medical treatments, aggressive public health policies and local and regional levels promoting active life style and healthy eating. If we assume that the price of the health care continues to increase exponentially while the proportion of the obese population levels off, we may consider some tempering effect in the future. To consider a parameter that "dampens" the trend to a flat line some time in the future. Methods that include a damped trend have proven to be successful, and are arguably the most popular individual methods when forecasts are required automatically for many series. When a damping parameter ϕ, is introduced the forecasting Equation (12) is modified to

$$\hat{TC}_{t+h|t} = l_t + (1 + \phi + \phi^2 + \phi^3 + \ldots, + \phi^h)b_t \tag{13}$$

where the inclusion of ϕ for $0 \leq \phi \leq 1$ dampens the trend so that the forecast converges to a constant at some point in the future. In other words, the short-time forecasts are trended while the long-time forecasts are constant. The level and trend equations are modified to account for the dumping parameter as follows

$$\begin{aligned} l_t &= \alpha TC_t + (1-\alpha)(l_{t-1} + \phi b_{t-1}) \\ b_t &= \beta^*(l_t - l_{t-1}) + (1-\beta^*)\phi b_{t-1}. \end{aligned} \tag{14}$$

In practice, the damping parameter is restricted to be at between 0.8 and 0.98, where values of ϕ closer to 1 indicate no difference in the results between the two models. Several values for the damping parameters ϕ are tested so that the optimal value is selected in order to achieve the minimum Root Mean Squared Error RMSE and the Mean Absolute Error (MAE) for the model used in prediction. The damping parameter of 0.9 is employed in this study. Computations of the forecasts for both exponential smoothing methods can be obtained using the R function *holt()* from the R (R Core Team 2021) package **forecast** (refer to Hyndman et al. (2021) and Hyndman and Khandakar (2008)).

3. Data Validation and Comparison with Existing Studies

In this section, we analyze and validate the obesity-related cost data developed using methodology presented in Section 2. These actual costs serve as an input in modeling the future obesity-related costs, thus it is important to cross check and validate our cost calculations with several other sources and explain any observations using tangible events in the United States. This also helps fortify the credibility of the input data itself for building a reliable statistical model for forecasting future cost.

Figure 4 shows the time series of the various obesity-related costs for the period 1996 to 2018. We observe a sharp increase in the total cost that almost triples during this time period reaching the level of $420 billion of dollars in 2018. Both direct and indirect costs follow a similar upward trend over time with a different intercept. In 1996, the indirect cost was $42.5 billion and the direct cost was $14.5 billion. Then, in 2018, the indirect and direct costs reached $257.3 billion and $165.1 billion, respectively. The gap between these two types of costs increased over time.

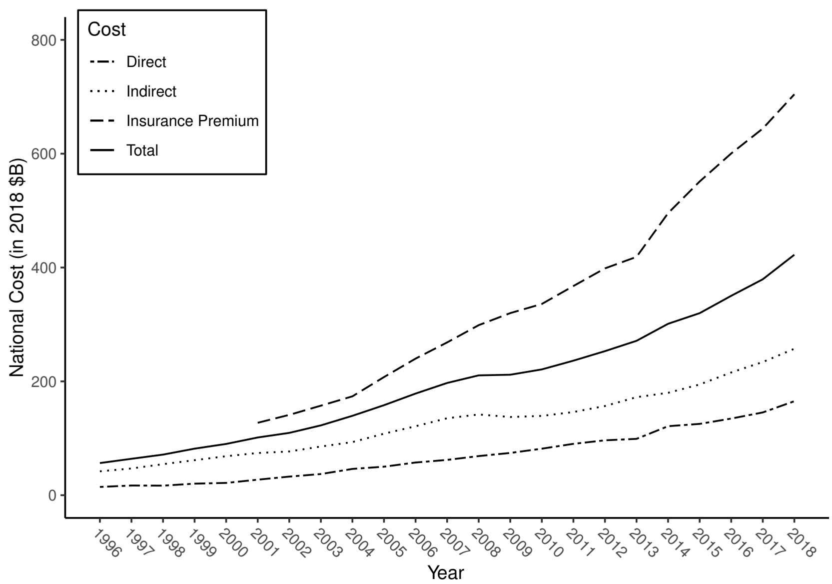

Figure 4. Total obesity-related cost with the breakdown between direct and indirect cost for the time period 1996 to 2018.

Since 1996, there were three years that showed a decrease in the medical cost of diseases related to obesity. The first and largest decrease of 9% happened in 1998 as a result of the Balanced Budget Act of 1997. In an effort to achieve a fully balanced budget by 2002, the goal of the act, costs and welfare needed to be cut so that the government could return to solvency (Schneider 1997). One of the consequences of this effort was that there was a severe decrease in Medicare spending, which takes up a large portion of overall medical spending. Therefore, a decrease would be expected because there is less financing available to the general population, and in turn, people who utilize the aid.

Another moderate dip of 5% in medical costs is observed in 2013. At this time there was slower growth overall in the health insurance industry, both with private and public care. Hartman et al. (2015) argued that this trend was caused by impacts from, "slower growth in enrollment, the impacts of the Affordable Care Act (ACA), and the federal budget sequestration of 2013" (Hartman et al. 2015, p. 150). Therefore, a combination of factors contributed to the overall medical insurance environment being less robust in 2013, which explains the moderate dip, but not a complete collapse.

Finally in 2015, there was an additional decrease of 2% as a result of the ACA. Schubel and Broaddus (2018) reported "from 2013 to 2015, the nationwide uninsured rate fell 35 percent" (Schubel and Broaddus 2018, p. 2). Because of this, a great increase of 15% was seen in 2014. However, since the observation of costs are year-to-year, the 2015 numbers were unlikely to keep up with the growth rate from 2014, since that is when the biggest reduction in uninsured individuals was seen. Therefore, the slight decrease is reasonable since it is in response to a readjusting landscape after experience a surge of new participants.

Table 3 provides cost estimates of the different cost categories as found in the reputable studies. The first column cites the published study from which the estimate came. The second column shows the year for which the reported estimate was computed. The third column presents the estimate, in billions of dollars, generated by the cited study. For example, the study by Ward et al. (2021) reported $172.7 billion in direct cost for 2019. This estimate is comparable to the estimate of $172.0 billion reported by Alves et al. (2021) for the same year.

Table 3. Summary of the nominal cost estimates previously reported in the literature.

Source	Year of Estimated Cost	Reported Estimate ($B)
	Direct Costs	
Thoenen (2002)	1995	$39.0
Finkelstein et al. (2003)	1998	$26.8
Finkelstein et al. (2009)	2008	$86.0
Behan and Cox (2010)	2009	$89.0
Alves et al. (2021)	2019	$172.0
Ward et al. (2021)	2019	$172.7
	Indirect Costs	
Wolf and Colditz (1998)	1995	$47.6
Alves et al. (2021)	2019	$211.8
	Excess Mortality Costs	
Behan and Cox (2010)	2009	$38.6
Alves et al. (2021)	2019	$80.9
	Absenteeism Costs	
Behan and Cox (2010)	2009	$43.0
	Disability Costs	
Behan and Cox (2010)	2009	$50.1

Table 4 shows the summary of our cost estimates for 2018. The total cost attributable to obesity is estimated in the range of $422 billion and is broken down by several categories. The last column of this table shows the 95% bootstrap prediction interval for the cost per person. Cost per person for each category is computed at the state level. Then, a sampling distribution based on 10,000 bootstrap samples is developed for each category of cost. To better qualify the accuracy of our generated per-person cost estimates, we believe it is necessary to report the cost within an interval rather than a point estimate. These 95% prediction intervals represent our bounds at the 95% prediction level for the per-person direct and indirect costs, given the constants used in the cost equations. They are not in attempt to assess the uncertainty within the constants used within the equations themselves. Figure 5 shows the bootstrap sampling distributions of the direct and indirect costs per person with their corresponding 95% prediction interval.

In order to put our estimate of $422.4 billion into perspective, we compare it to some other economic indicators. According to the report published by U.S. Bureau of Economic Analysis (see U.S. Bureau of Economic Analysis (2019)), the current dollar USA GDP in 2018 was estimated to be $20.50 trillion. National health care spending in 2018 was estimated at $3.6 trillion which is about 17.5% of the national GDP or $11,172 per person (see Health Affairs (2019)). Our total estimated cost of obesity represents about 2% of the 2018 USA GDP. It is important to note that there are other costs (i.e., pharmacy costs, out-of-pocket payments, cost of public Medicare programs, etc.) associated with obesity that are not included in our estimate. Therefore, our estimate is most likely closer to the lower bound of the true value of the total obesity-related cost. However, considering the complexity of the problem, the lack of publicly available data in this domain, and the amount of uncertainty involved, the true value of all obesity-related costs is almost impossible to know.

Table 4. Summary of the cost estimates by category, computed for 2018. Overall estimates in billions of dollars by category are listed in the second column. The third column shows the 95% prediction interval for the cost per person in dollars.

Category	Overall Estimate ($B)	Cost Per Person ($)
Mortality	$70.3	
Absenteeism	$100.3	
Disability	$86.7	
Indirect	$257.3	($2198, $2201)
Direct	$165.1	($1398, $1423)
Total	$422.4	($3596, $3624)

It is necessary to discuss the differences in estimation methods when comparing figures across different studies so that any imbalance between estimates in the table can be understood. For example, in Finkelstein et al. (2003), which is cited by Tsai et al. (2011) as being a "high-quality study", their estimate of the 2003 direct medical costs was $26.8 billion, whereas the study mentioned by Thoenen (2002) estimated these costs to be $39.0 billion in 1995 dollars. This seems counterintuitive, since it has been seen that direct medical costs tend to increase over time. However, there is a difference with what figures the studies produce. Finkelstein et al. (2003) has clearly broken down the portion of calculated costs that are attributable to obesity only, not overweight. This significantly reduced the estimate of the study from $51.5 billion to the reported $26.8 billion. Yet, some studies are less precise in their definition of costs. For instance, some studies report figures as they are attributable to obesity, but it is unclear whether these also include a portion of costs from the overweight group as well. Additionally, it appears that some studies employ different methodologies. Thus, we believe that the discrepancies between figures for similar years are due to the mentioned variations between the studies.

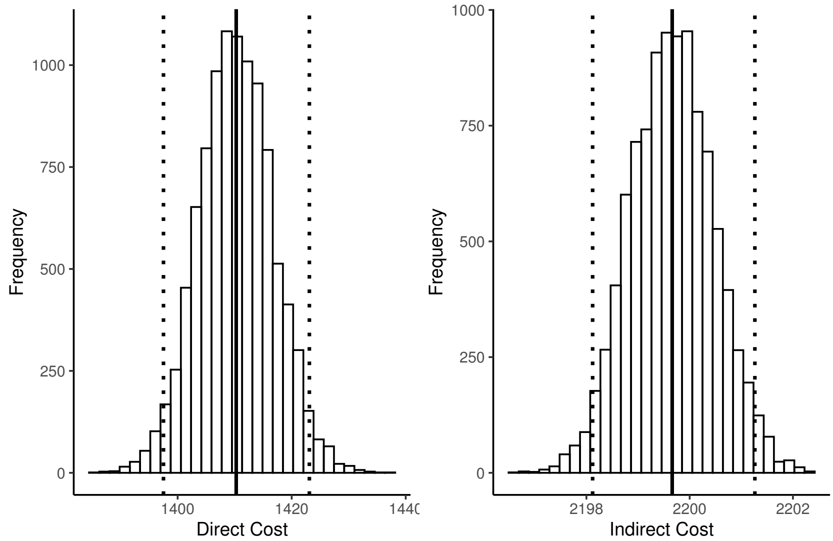

Figure 5. Sampling distribution of direct (**left**) and indirect (**right**) cost per person for 2018. Solid line indicates the mean of the distribution. Dotted lines show the lower and upper bound of the 95% prediction interval of the bootstrapping distribution.

Finkelstein et al. (2003) reported two different direct costs for obesity: $26.8 and $47.5 billion. The paper goes on to explain that the two estimates were produced using separate data sources for costs. The estimate of $26.8 billion was derived from the MEPS data and the other relied on data from the National Health Accounts (NHA). The two sources have a different emphasis. The NHA data include nursing home expenditures, which as mentioned before are out of the scope of our study. This further illustrates that while studies may be calculating the same costs, the scope of the data that are being utilized are very important as well and not always immediately apparent when reviewing others' research.

The 1996 Wolf and Colditz (1998) estimate for direct cost was not listed because the distribution of the study's costs were reviewed by a study from Columbia University, and found to be somewhat inaccurate (Thoenen 2002). They concluded that the "higher mortality rates of obese persons decrease[s] direct medical costs; because of this, however, the indirect costs of obesity may be larger than originally estimated due to lost productivity" (Thoenen 2002, See Executive Summary). Thus, after the revision of the costs, the direct costs are likely lower and indirect costs are likely higher. Therefore, only the total cost estimate for this study was used, since it does not rely on the distribution of costs between direct and indirect categories.

Still, the estimate for the direct medical cost from Thoenen (2002) is quite different than our estimate. Again, this has to do with the fact that there is some difference in the definition of direct medical cost. The study by Wolf and Colditz (1998) looked at the, "preventive, diagnosis, and treatment services related to the disease (e.g., hospital and nursing home care, physician visits, medications)" (Wolf and Colditz 1998, p. 98). Our study relies on the total reported medical costs by disease for each year, which "include payments for medical events reported during the calendar year" (MEPS 2021, See Notes), while this is more vague than what is outlined in the study by Wolf and Colditz (1998), it likely excludes the costs of nursing home care, certain preventative measures, and the cost of over-the-counter drugs. Therefore, the estimate that we have to go off of observes a different scope of costs. However, with this information, we can then find our estimate to be more reasonable, since we would expect an exclusion of cost categories to decrease cost estimates.

Moreover, the discrepancy between the Wolf and Colditz (1998) estimate of 1996 Indirect Costs is likely due to a difference in cost considerations. Our estimate includes costs from excess mortality, absenteeism, and disability, whereas the comparable cost is "lost output as a result of a reduction or cessation of productivity due to morbidity or mortality" (Wolf and Colditz 1998). Therefore, there is no consideration of disability costs. Furthermore, if our estimate for the costs of disability in 1996 ($14.5 B) are subtracted from the total indirect costs estimated ($42.0 B), the result is much more comparable ($27.5 B).

Alves et al. (2021) published per capita estimates as well as overall costs due to obesity for 2019. The study takes yet another approach toward defining the cost categories uniquely. For example, the category most analogous to direct costs is morbidity, which includes, "the cost for services such as doctor visits, hospitalization and prescription drug utilization" (Alves et al. 2021, p. 15). Therefore, although this is a more general definition, it seems to line up relatively well with what our study examines for direct costs. The definition of excess mortality is very comparable to how it is defined in our study. However, for the other indirect costs within the paper, the definitions of the disability and absenteeism categories are different from those in our study. In fact, Alves et al. (2021) defines disability costs to include presenteeism and absenteeism, whereas our study defines them distinctly. Therefore, for those individual cost subcategories, our estimates are not very comparable. Yet, when the overall costs are taken into consideration, we get results that are somewhat similar. The reported morbidity cost is $172.0 billion, whereas our direct costs are $168.4 billion, when using our 2018 estimate trended forward a year by the medical inflation rate from 2018 to 2019. For indirect costs, the reported cost is $211.8 billion, whereas our estimate is $263.2 billion, while this estimate is further from the reported cost estimate, as mentioned there is more of a significant difference in the definition of the cost categories for indirect costs. Thus, after recognizing these differences, the report validates our estimation methods.

Figure 6 shows how the cost changes across the United States for the different time periods: 1998 (top), 2008 (middle), and 2018 (bottom). The intensity of darker color is associated with the higher level of the estimated cost. Five regions are created on each map based on the following grouping of the state cost in billions of dollars: <1, 1–2, 2–5, 5–10 and >10. The intensity of darker color is associated with the higher level of the estimated cost. No states had a cost estimate over $10 billion in 1998. By 2008, the cost raised above $10 billion in four states-California, Florida, Texas, and New York. In 2018, this list of states is expanded to include also Illinois, Ohio, Pennsylvania, North Carolina, Virginia, Michigan, Georgia, and New Jersey. The increase in population combined with the increase in cost is slowly affecting a large portion of the Unites States.

Obesity is also recognized as a global health problem so it is important to discuss several studies conducted outside of the United States. Other countries around the world are also experiencing problems with obesity, mainly those that are economically developed. According to a review study done by Helble and Francisco (2020), many countries in Asia are rapidly growing in their prevalence of adults with obesity, and the estimate of obesity-related costs is about 0.78% of the region's GDP, while the prevalence of obese adults in these countries is still significantly lower than that of the United States, a growing overweight population will likely lead to an increased obese population as well. In Europe a study by Müller-Riemenschneider et al. (2008) finds that "relative economic burdens ranged from 0.09% to 0.61% of each country's GDP". In a study done by Boachie et al. (2022), it was found that about 0.67% of South Africa's GDP is attributable to the combined impact of overweight and obesity. Another review study by Duran et al. (2019) found that in Latin America, there could be a wider range of obesity-related costs as a percent of each country's GDP, from 0.54% in Chile, up to 2.5% in Mexico. Therefore, even on a national scale, obesity is a pressing issue, and pervades virtually all economically developed countries. More research into the costs included within each of these figures is necessary so that an equal comparison can be made across the various regions.

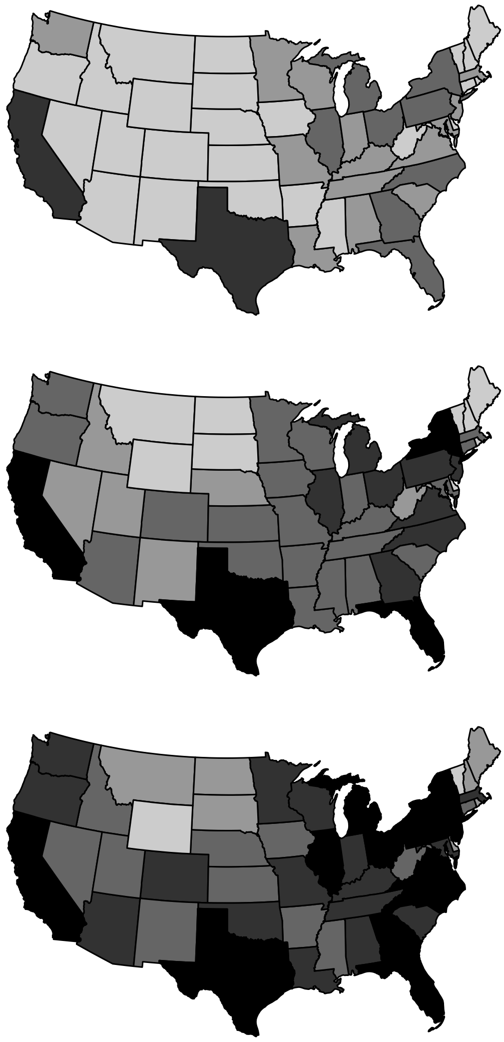

Figure 6. Maps of the total cost (in 2018 dollars) for three years: 1998 (**top**), 2008 (**middle**), 2018 (**bottom**). The intensity of darker color is associated with the higher level of the estimated cost. Five regions are created on each map based on the following grouping of the state cost in billions of dollars: <1, 1–2, 2–5, 5–10 and >10.

4. Cost Estimation and Forecasts

In this section, we present the results of the long-term cost estimation and forecasts by state. Since the time series by state exhibit a strong increasing trend we consider three exponential smoothing methods: Holt's linear trend only, the damped Holt's method, and the simple exponential smoothing.

The model building is performed in two steps which include training and testing. The training step is referred to as the learning step. In this step, the three models are built on 21 years of data. Cross validation and forecast accuracy is evaluated using the test set created on the last two years of data allowing for a true assessment of the forecasting ability by comparing the out of sample errors. The damping parameter $\phi = 0.90$ is selected, the value that generates the results with the most accuracy or least Root Mean Squared Error RMSE the Mean Absolute Error (MAE).

Figure 7 provides the side by side box-plots of the RMSE and the MAE across the three methods. We observe that the simple exponential smoothing has the worst performance among the three methods as it does not capture the trend well. Holt and the damped Holt method have similar performance based on RMSE and MAE with Holt's being a bit superior. The distribution of RMSE and MAE for the Holt and damping Holt methods generate several outliers. These outliers indicate larger RMSE and MAE for their respective states (NY, TX, OH for Holt's and damped Holt's method; as well as FL for the damped Holt's method). A detailed summary of the RMSE results by state across three methods for 2018 is provided with Table A1 in the Appendix A.

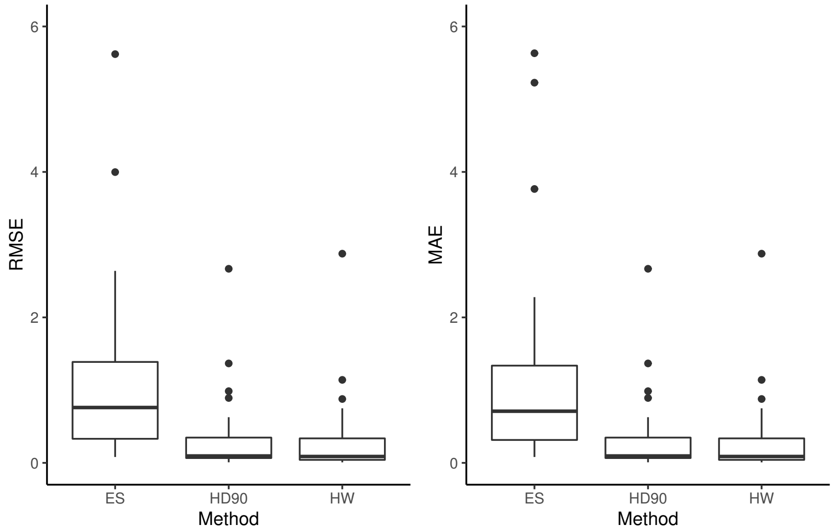

Figure 7. Side-by-side boxplots of RMSE (**left**) left and MAE (**right**) across three different methods-exponential smoothing (ES), Holt Winter Trend only (HW), and the damped Holt with the damping factor 0.90 (HD90).

Table 5 provides the summary of the Holt's trend and the damped Holt's forecasts with their corresponding 95% and 99% prediction intervals for 2018. The actual values shown in the second column of this table are the 2018-cost by state computed using the method described in Section 2. Both forecasting methods tend to underestimate the true value for most of the states. Additionally, both methods produce nearly the same estimate for 2018 total costs (about $393 billion). However, the damped model offers more consistency into the future, as the current trend is expected to be damped in later durations. Obesity-related public policies have already been implemented at the federal and state levels, and we expect they would slow down the growth of the obesity pandemic. This aligns with the future trends of obesity, as we are approaching 50% prevalence of obesity in the adult population and the sharp increase in obesity from year to year is less likely to continue. Therefore, we adopt the damped Holt's method for out of sample forecasts. Table 5 also includes the $OrCR$ results by state for year 2018. We see that most values are between 0.15 and 0.25, with an average of 0.24. This means that our calculated total costs of obesity are about 1/4 of overall health premium costs, on average.

The future 3 year forecasts are summarised in Table 6 with their 95% prediction intervals. Based on this forecast, we observe that the national level obesity-related cost will reach level of $451 billion of dollars. An increase of over 7% would be expected over the 3-year period. The top five states with the highest costs are: California, Texas, New York, Florida, and Illinois (for all 3 years). Illinois is 6th in population, but 5th for overall cost. The other four states are the most populous.

It should be noted that the prediction intervals included in Tables 5 and 6 are a reflection of the uncertainty in the forecasting of future costs. A visual representation of these intervals is shown in Figure 8, which depicts the 99% prediction intervals for the 2018 damped Holt's forecast by state ordered from highest to lowest magnitude of point estimate. The estimated actual cost values, as denoted with the symbol (x) are shown in relation to the prediction intervals. These estimated actual values are computed based on the methodology presented in Section 2. We observe that all estimated actual values are contained within the forecasted 99% prediction interval.

Table 5. Summary of the Holt's (HW) and the damped Holt's (HD) forecast by state for 2018. The 95% and 99% prediction intervals are provided with each forecasting method. Column labeled "Actual" values shows the 2018-cost calculated based on the method developed in Section 2. All costs are expressed in the values of 2018 billions of dollars.

State	Actual	HW	HW 95% CI	HW 99% CI	HD90	HD90 95% CI	HD90 99% CI	OrCR
Alabama	6.94	6.44	(5.90, 6.99)	(6.03, 6.86)	6.64	(5.79, 7.49)	(6.00, 7.29)	0.26
Alaska	0.93	0.97	(0.84, 1.09)	(0.87, 1.06)	0.95	(0.82, 1.08)	(0.85, 1.05)	0.40
Arizona	8.90	7.58	(6.88, 8.28)	(7.05, 8.11)	7.82	(6.93, 8.71)	(7.14, 8.50)	0.43
Arkansas	4.16	3.93	(3.55, 4.31)	(3.64, 4.22)	3.90	(3.42, 4.38)	(3.54, 4.27)	0.29
California	45.34	40.27	(36.83, 43.70)	(37.65, 42.88)	40.68	(36.47, 44.88)	(37.48, 43.88)	N/A
Colorado	5.97	5.76	(5.24, 6.29)	(5.36, 6.16)	5.68	(5.08, 6.27)	(5.22, 6.13)	0.24
Connecticut	4.20	3.81	(3.47, 4.15)	(3.55, 4.07)	3.71	(3.29, 4.13)	(3.39, 4.03)	0.27
Delaware	1.35	1.17	(1.03, 1.30)	(1.06, 1.27)	1.18	(1.01, 1.35)	(1.05, 1.31)	0.48
Florida	27.36	25.91	(22.69, 29.14)	(23.46, 28.37)	25.42	(21.83, 29.00)	(22.69, 28.14)	0.17
Georgia	13.65	12.43	(11.44, 13.42)	(11.68, 13.19)	12.64	(11.25, 14.02)	(11.58, 13.69)	0.29
Hawaii	1.52	1.38	(1.20, 1.55)	(1.24, 1.51)	1.41	(1.18, 1.65)	(1.23, 1.59)	0.09
Idaho	2.18	1.92	(1.74, 2.11)	(1.78, 2.06)	1.98	(1.72, 2.23)	(1.78, 2.17)	0.27
Illinois	16.29	16.46	(15.14, 17.78)	(15.46, 17.47)	16.17	(14.71, 17.63)	(15.06, 17.28)	0.20
Indiana	9.16	8.30	(7.64, 8.96)	(7.80, 8.81)	8.52	(7.59, 9.44)	(7.81, 9.22)	0.28
Iowa	4.49	4.13	(3.77, 4.48)	(3.86, 4.40)	4.07	(3.65, 4.49)	(3.75, 4.39)	0.18
Kansas	4.03	3.61	(3.22, 4.01)	(3.32, 3.91)	3.52	(3.04, 4.00)	(3.15, 3.88)	0.28
Kentucky	6.57	5.94	(5.42, 6.46)	(5.55, 6.34)	5.80	(5.07, 6.54)	(5.25, 6.36)	0.17
Louisiana	6.81	6.72	(6.10, 7.33)	(6.25, 7.19)	6.58	(5.86, 7.30)	(6.03, 7.13)	0.17
Maine	1.69	1.56	(1.44, 1.68)	(1.47, 1.65)	1.60	(1.45, 1.76)	(1.48, 1.72)	0.22
Maryland	7.90	7.77	(7.00, 8.53)	(7.19, 8.35)	7.70	(6.83, 8.57)	(7.04, 8.36)	0.25
Massachusetts	7.71	7.10	(6.50, 7.69)	(6.65, 7.55)	7.09	(6.25, 7.92)	(6.45, 7.72)	0.15
Michigan	13.56	12.40	(11.53, 13.28)	(11.74, 13.07)	12.83	(11.59, 14.06)	(11.89, 13.77)	0.18
Minnesota	7.18	6.39	(5.67, 7.12)	(5.84, 6.95)	6.51	(5.55, 7.46)	(5.78, 7.23)	0.16
Mississippi	4.60	4.05	(3.67, 4.42)	(3.76, 4.33)	4.22	(3.73, 4.71)	(3.85, 4.60)	0.30
Missouri	8.31	7.59	(6.96, 8.21)	(7.11, 8.06)	7.75	(6.94, 8.57)	(7.13, 8.37)	0.27
Montana	1.35	1.12	(1.02, 1.22)	(1.04, 1.20)	1.20	(1.06, 1.34)	(1.09, 1.30)	0.34
Nebraska	2.77	2.44	(2.21, 2.67)	(2.27, 2.61)	2.54	(2.24, 2.83)	(2.31, 2.76)	0.24
Nevada	3.61	3.15	(2.85, 3.46)	(2.92, 3.39)	3.27	(2.84, 3.70)	(2.94, 3.59)	0.21
New Hampshire	1.69	1.51	(1.38, 1.64)	(1.41, 1.61)	1.55	(1.36, 1.73)	(1.41, 1.69)	0.21
New Jersey	10.86	9.87	(8.97, 10.76)	(9.19, 10.54)	10.04	(8.81, 11.27)	(9.11, 10.97)	0.17
New Mexico	2.65	2.48	(2.20, 2.76)	(2.26, 2.69)	2.42	(2.16, 2.68)	(2.22, 2.62)	0.16
New York	25.14	26.61	(23.41, 29.81)	(24.17, 29.04)	25.93	(22.50, 29.36)	(23.32, 28.54)	0.20
North Carolina	13.63	13.55	(11.98, 15.12)	(12.35, 14.75)	13.68	(11.79, 15.58)	(12.24, 15.12)	0.33
North Dakota	1.08	1.01	(0.90, 1.12)	(0.92, 1.09)	0.99	(0.87, 1.11)	(0.89, 1.08)	0.19
Ohio	16.57	14.59	(13.08, 16.11)	(13.44, 15.74)	14.77	(12.74, 16.79)	(13.23, 16.31)	0.18
Oklahoma	5.47	5.02	(4.55, 5.49)	(4.66, 5.38)	4.97	(4.41, 5.54)	(4.54, 5.40)	0.36
Oregon	5.35	4.67	(4.16, 5.17)	(4.28, 5.05)	4.77	(4.07, 5.48)	(4.24, 5.31)	0.20
Pennsylvania	16.91	15.41	(14.02, 16.79)	(14.35, 16.46)	15.59	(13.61, 17.58)	(14.08, 17.11)	0.15
Rhode Island	1.28	1.22	(1.11, 1.33)	(1.13, 1.30)	1.21	(1.08, 1.34)	(1.11, 1.30)	0.12
South Carolina	7.06	6.78	(6.14, 7.42)	(6.30, 7.27)	6.61	(5.90, 7.32)	(6.07, 7.15)	0.30
South Dakota	1.21	1.07	(0.98, 1.17)	(1.00, 1.15)	1.07	(0.95, 1.19)	(0.98, 1.16)	0.29
Tennessee	9.53	8.35	(7.76, 8.94)	(7.90, 8.80)	8.69	(7.95, 9.43)	(8.13, 9.25)	0.21
Texas	39.03	37.01	(34.01, 40.01)	(34.73, 39.29)	36.14	(32.80, 39.48)	(33.60, 38.69)	0.24
Utah	3.91	3.58	(3.25, 3.91)	(3.33, 3.83)	3.50	(3.13, 3.86)	(3.22, 3.78)	0.26
Vermont	0.74	0.69	(0.63, 0.75)	(0.64, 0.73)	0.71	(0.62, 0.79)	(0.65, 0.77)	0.35
Virginia	11.14	10.18	(9.28, 11.09)	(9.49, 10.88)	10.06	(8.90, 11.23)	(9.18, 10.95)	0.23
Washington	9.36	9.11	(8.31, 9.91)	(8.50, 9.72)	8.92	(8.02, 9.82)	(8.24, 9.60)	0.21
West Virginia	2.71	2.57	(2.32, 2.82)	(2.38, 2.76)	2.59	(2.30, 2.89)	(2.37, 2.82)	0.22
Wisconsin	7.91	7.25	(6.64, 7.87)	(6.79, 7.72)	7.37	(6.53, 8.20)	(6.73, 8.00)	0.21
Wyoming	0.70	0.64	(0.58, 0.70)	(0.60, 0.69)	0.64	(0.56, 0.73)	(0.58, 0.71)	0.42
Total	422.46	393.47			393.60			0.24

Table 6. Summary of the forecast by state for 2019, 2020, and 2021 with their corresponding 95% prediction intervals. All costs are expressed in the value of 2018 billions of dollars.

State	Forecast 2019	2019 95% CI	Forecast 2020	2020 95% CI	Forecast 2021	2021 95% CI
Alabama	7.22	(6.303, 8.144)	7.65	(6.322, 8.974)	8.07	(6.294, 9.850)
Alaska	0.97	(0.882, 1.054)	1.01	(0.908, 1.106)	1.05	(0.935, 1.157)
Arizona	8.47	(7.630, 9.319)	8.97	(7.818, 10.123)	9.47	(7.975, 10.957)
Arkansas	4.19	(3.788, 4.601)	4.42	(3.889, 4.941)	4.64	(3.980, 5.292)
California	42.64	(39.254, 46.019)	44.59	(40.358, 48.826)	46.55	(41.442, 51.654)
Colorado	6.17	(5.611, 6.733)	6.59	(5.815, 7.359)	7.00	(5.997, 8.008)
Connecticut	4.00	(3.666, 4.343)	4.18	(3.747, 4.608)	4.35	(3.824, 4.877)
Delaware	1.23	(1.102, 1.368)	1.29	(1.127, 1.455)	1.35	(1.152, 1.542)
Florida	28.62	(25.194, 32.043)	31.16	(26.370, 35.950)	33.70	(27.339, 40.064)
Georgia	13.45	(12.377, 14.518)	14.12	(12.758, 15.476)	14.79	(13.129, 16.446)
Hawaii	1.47	(1.298, 1.651)	1.54	(1.325, 1.760)	1.61	(1.352, 1.869)
Idaho	2.08	(1.874, 2.288)	2.18	(1.922, 2.446)	2.29	(1.967, 2.607)
Illinois	17.59	(16.093, 19.092)	18.72	(16.573, 20.861)	19.84	(16.972, 22.710)
Indiana	8.75	(8.124, 9.369)	9.10	(8.373, 9.826)	9.45	(8.631, 10.273)
Iowa	4.36	(3.993, 4.731)	4.60	(4.108, 5.097)	4.84	(4.212, 5.473)
Kansas	3.79	(3.393, 4.182)	3.95	(3.456, 4.450)	4.12	(3.516, 4.722)
Kentucky	6.22	(5.727, 6.720)	6.52	(5.885, 7.155)	6.82	(6.036, 7.596)
Louisiana	7.17	(6.539, 7.805)	7.64	(6.770, 8.508)	8.11	(6.968, 9.244)
Maine	1.70	(1.563, 1.836)	1.79	(1.606, 1.966)	1.87	(1.646, 2.100)
Maryland	8.26	(7.473, 9.050)	8.75	(7.695, 9.797)	9.23	(7.898, 10.565)
Massachusetts	7.61	(6.734, 8.478)	7.96	(6.751, 9.159)	8.30	(6.737, 9.873)
Michigan	13.45	(12.372, 14.519)	14.09	(12.697, 15.484)	14.74	(13.004, 16.466)
Minnesota	6.72	(5.995, 7.440)	7.00	(6.124, 7.874)	7.28	(6.257, 8.305)
Mississippi	4.15	(3.812, 4.489)	4.29	(3.896, 4.679)	4.42	(3.987, 4.862)
Missouri	8.33	(7.473, 9.191)	8.76	(7.563, 9.948)	9.18	(7.620, 10.738)
Montana	1.29	(1.173, 1.413)	1.37	(1.214, 1.529)	1.45	(1.250, 1.650)
Nebraska	2.76	(2.455, 3.057)	2.92	(2.508, 3.341)	3.09	(2.550, 3.636)
Nevada	3.53	(3.152, 3.899)	3.74	(3.239, 4.232)	3.95	(3.316, 4.575)
New Hampshire	1.65	(1.497, 1.807)	1.74	(1.535, 1.940)	1.82	(1.568, 2.077)
New Jersey	10.61	(9.637, 11.581)	11.11	(9.880, 12.338)	11.61	(10.113, 13.104)
New Mexico	2.62	(2.279, 2.970)	2.77	(2.264, 3.276)	2.92	(2.231, 3.600)
New York	29.40	(25.677, 33.126)	32.18	(26.794, 37.574)	34.97	(27.703, 42.231)
North Carolina	14.60	(12.912, 16.285)	15.62	(13.315, 17.918)	16.63	(13.664, 19.606)
North Dakota	1.07	(0.946, 1.196)	1.13	(0.958, 1.310)	1.20	(0.965, 1.429)
Ohio	15.72	(14.072, 17.361)	16.46	(14.383, 18.541)	17.21	(14.670, 19.745)
Oklahoma	5.30	(4.809, 5.795)	5.56	(4.920, 6.201)	5.82	(5.022, 6.615)
Oregon	5.03	(4.497, 5.560)	5.27	(4.609, 5.932)	5.51	(4.718, 6.306)
Pennsylvania	16.55	(14.845, 18.255)	17.32	(15.106, 19.543)	18.10	(15.337, 20.862)
Rhode Island	1.29	(1.174, 1.400)	1.36	(1.206, 1.505)	1.42	(1.234, 1.613)
South Carolina	7.30	(6.594, 8.001)	7.81	(6.814, 8.812)	8.33	(6.992, 9.663)
South Dakota	1.12	(1.032, 1.212)	1.17	(1.062, 1.284)	1.22	(1.090, 1.357)
Tennessee	9.46	(8.671, 10.255)	10.06	(8.914, 11.206)	10.66	(9.116, 12.198)
Texas	39.65	(36.152, 43.150)	42.29	(37.248, 47.339)	44.94	(38.146, 51.726)
Utah	3.84	(3.471, 4.206)	4.10	(3.577, 4.616)	4.35	(3.665, 5.045)
Vermont	0.75	(0.680, 0.811)	0.78	(0.698, 0.866)	0.82	(0.716, 0.922)
Virginia	10.76	(9.846, 11.664)	11.30	(10.123, 12.476)	11.84	(10.386, 13.302)
Washington	9.81	(8.899, 10.721)	10.51	(9.206, 11.813)	11.21	(9.464, 12.954)
West Virginia	2.72	(2.471, 2.969)	2.86	(2.537, 3.174)	2.99	(2.600, 3.382)
Wisconsin	7.91	(7.117, 8.707)	8.32	(7.238, 9.399)	8.73	(7.335, 10.116)
Wyoming	0.68	(0.620, 0.747)	0.71	(0.635, 0.792)	0.74	(0.649, 0.837)
Total	424.04		449.31		474.59	

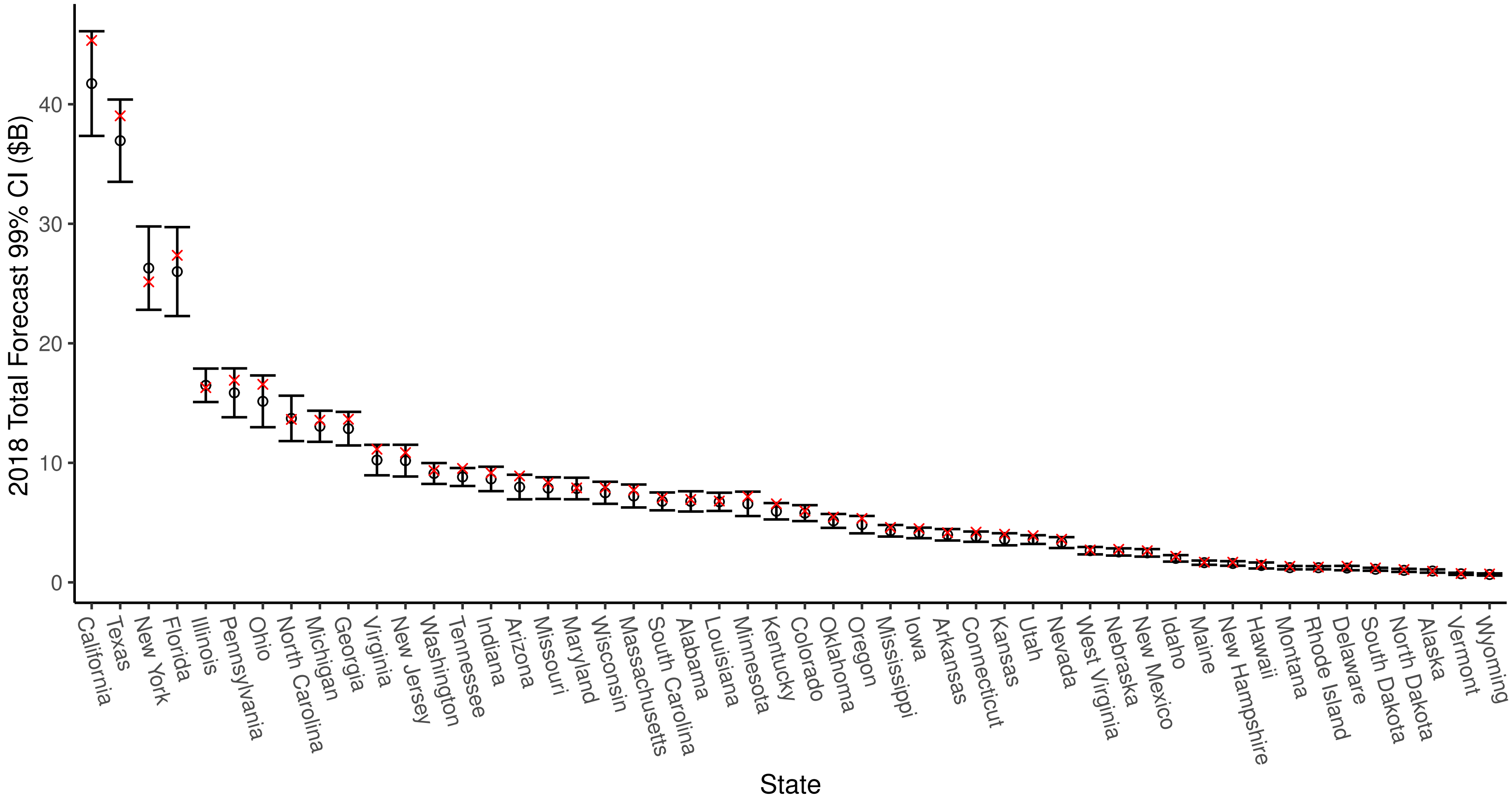

Figure 8. Side by side 99% prediction intervals by state for the forecast produced using damped Holt method as of 2018. The symbol (o) denotes the point estimate of the forecasted cost while the symbol (x) denotes the actual cost as computed using methodology of Section 2. Prediction intervals are arranged in descending order based on the magnitude of the point estimate.

5. Study Limitations

As is with any large-scale analysis using aggregated data, there are several limitations to this study. We are going to discuss several of them but we acknowledge that this list may be exhaustive. The primary limitation is the uncertainty related to the input variables, while the data sources themselves are reputable, the metrics being used from these sources are not entirely objective. For example, the data related to BMI and obesity prevalence by state rely on participants to self-report their heights and weights, which can lead to the self-reported bias. Moreover, the constants acquired for the cost calculations are based off of estimates as well, and there can be some disconnect when deriving constants calculated in one context and applying them to another, while there was concentrated effort to minimize the effects of these uncertainties, they still exist and must be acknowledged.

Another limitation of the study was the utilization of a proxy to distribute national costs between states. As outlined, this study uses each state's population count as a ratio to the national population count to scale the direct costs. This approach distributes national costs among the states using the most accurate metric we can find on a state level. However, we recognize that state population count is not completely analogous to the difference in medical costs between states. One could possibly consider building medical inflation indexes and using those in the cost distribution from a national level to the state level (see Dhaene and Hanbali (2019)). However, further efforts toward obtaining state-level demographics, payer information, and product-specific costs would be required, as the cited work observes inflation in Belgium. Thus, the same methodology could be applied to augment this study, but a more comprehensive effort would be needed.

Moreover, as mentioned in Section 2, this study only observes 3 types of indirect costs. Other studies have examined more of these costs, which would contribute to a greater overall indirect cost, but the costs examined in this paper were deemed to be the most important and impactful to the usefulness of our findings.

People at risk of obesity may have higher out-of-pocket costs. Pharmacy costs related to prescription drugs are also higher for overweight and obese people and these costs are not included in our estimate. Most state insurance plans are required to cover certain services with no cost-sharing, including obesity screening and counseling for all adults and children (see Jannah et al. (2018)). The Affordable Care Act was passed in 2010 and offered a reduction in health care costs while simultaneously providing the means of obtaining health insurance. For people at risk of obesity, Medicaid extension includes coverage for bariatric surgery on a state-by-state opt-in basis, increasing insurance coverage of the highly-effective bariatric surgery. However, there is still a need to increase insurance coverage as well as to develop health-related policies that will overcome the societal and cultural barriers to bariatric surgery use (see Brooks et al. (2021)). Thus, additional costs associated with the bariatric surgeries are not considered in this estimation.

Among many factors that influence the increase in the level of obesity are the quality of food, children's nutrition in kindergartens and schools, agricultural production and policies, food processing, etc. However, our study does not evaluate the economic impact of these factors.

We recognize that it is now 2022 and the most future projections from our study are only through 2021. However, it is important to note that there is a lag of approximately three years in the availability of the obesity prevalence data used to produce estimates and projections. This is a necessary lag, as there are many factors that contribute to the prevalence of obesity by state. The majority of these factors can be seen in the diseases associated with obesity. When initially processed, for example, a case of cardiovascular disease may not at first be linked to obesity, but then after further treatment or tests, etc. it is discovered that the initial episode was linked to obesity. Therefore, in order to have a comprehensive view of the impact of obesity in more recent years, it is necessary that only years with completed data be used. Still, these results are relevant with regard to two principal factors: data validation and trend monitoring. As is with all uncertain outcomes in the future, we have no way to definitively determine what the prevalence nor cost of obesity will be in the coming years. We can use sound statistical methods to produce our best estimates for these outcomes, but they primarily rely on historical data, and therefore are not necessarily reflective of future events. Therefore, by having three years of predictions, as newer data becomes available, the resulting cost estimates can be compared to the previous cost predictions to assess whether the cost of obesity is rising more rapidly year over year than expected. In this way our predictions can be used as a sort of baseline for how we expect costs to grow.

Finally, it is important to impose a qualifying statement on the forward trends of this data, due to the COVID-19 Pandemic. There are likely many changes to see in the cost structure of obesity in the United States. This could be seen through a change in the type of treatment sought out, the de-prioritization of treating non-emergent conditions, or a myriad of other impacts that are obscured from the data we currently have available. These possibilities are not examined in this study, and therefore offer a promising area of follow-up on this research.

6. Discussion and Conclusions

In this paper, we developed the state-level direct and indirect costs attributable to obesity in the United States for the time period 1996 to 2018. The direct cost consists of direct medical costs and indirect costs. The indirect cost includes the costs associated with absenteeism, disability, and excess mortality.

Our study suggests that the total cost attributed to obesity is estimated to a level of $422 billion as of 2018 (95% CI for the cost per person: [$3596, $3624]), representing about 2% of the national GDP for the same year. By 2021, we forecast that this cost will reach the level of $475 billion. The 2018 costs of obesity for indirect costs are estimated at $257.3 billion (95% CI for the cost per person: [$2198, $2201]) and direct costs are estimated at $165.1 billion (95% CI for the cost per person: [$1398, $1423]). In order to eliminate the impact of inflation, all cost estimates are expressed in the value of 2018 dollars.

Having the 23 years of cost data by state, we then employed the exponential smoothing methods to generate the 3-year-ahead forecasts by state. To provide further analysis, as well as to serve as a check, we compared the 2018 estimates to the health premiums from Schedule T of the Annual Statement in the insurance industry by introducing the Obesity-related Cost Ratio (OrCR). This allowed us to roughly gauge how much insurance premium can be attributable to overall obesity costs, which help to demonstrate the impact of obesity costs on the insurance industry. The calculation of the OrCR is excluded for California due to the lack of health premium data for that state.

All data sources used in this report are publicly available. For the purpose of forecasting the future cost, we have selected the damped Holt method as it performs the best among a few other methods used in the model development. We have utilized the bootstrapping method to develop the 95% prediction intervals for the cost per person. The 95% prediction interval for the total obesity-related cost per person is [$3596, $3624] as of 2018. Our results present the most comprehensive evaluation of the cost due to obesity at the state level and we hope that our study will provide the motivation for additional discussion and research related to the obesity pandemic.

At the state level, our estimate of the obesity-related costs is still significantly lower than the health insurance premium. A possible avenue for future research would be to investigate if the relationship between the premium and cost is sustainable in the long run.

Actuaries may be interested in studying the smartwatch data related to the health and physical activities of their policyholders, assuming their consent. This would be especially important for people at risk of obesity. Health-related data are already used in several research areas. A study conducted by Seifert and Vandelanotte (2021) investigated the extent to which adults aged 65 and older in Switzerland utilize mobile health tracking tools in everyday life. The survey of 1149 adults showed that mobile device users were significantly more open to sharing their data with medical or research institutions than non-users of mobile devices. The authors found that the older adults reported substantial levels of smartphone and tablet use but fairly low levels of fitness tracker, smartwatch, and health-related app use. A large number of participants were willing to share health-related data, encouraging findings that can be used to promote a similar study targeting younger age groups. By monitoring physical activity via smartwatch data, an insurance company may be able to study the lifestyle of insured people at risk of obesity and monitor their physical activity, and explore pricing options according to the "Pay-as-you-live (PAYL)" insurance. However, for a successful implementation of PAYL insurance, Wiegard et al. (2019) emphasized the importance of multi-party agreements (insurance companies, service providers, and manufacturers of wearables) in order to arrive at solutions for more data security and data protection before implementing further features of the devices. The same study reported that the influence of perceived privacy risk on perceived value among German insureds is almost twice as high as that of perceived benefit. A similar study can be conducted in the United States to obtain clarity about critical success factors from a people-at-risk perspective and therefore insights for insurance companies.

Besides PAYL insurance, actuaries may investigate what other benefits enhance the perceived value such as adding monetary compensation (discounts, coupons, bates, or health promotions)as an additional benefit factor to motivate the policyholders at risk of obesity to undertake regular physical activities. Chapman (2012) reported that health promotion represents one of the most effective strategies for reducing medical costs and absenteeism as well as reducing the average sick leave, health plan costs, and workers' compensation and disability insurance costs.

Finally, our cost predictions for years 2020 and 2021 can be used as another baseline for how we would expect the costs of obesity to progress in the absence of the COVID-19 pandemic. Again, when the actual numbers for those years are available, they can be compared to the predictions from this study to determine how large of an impact the COVID-19 pandemic had from what we would expect to see. Further investigation into the links between COVID-19 and obesity from a cost standpoint would be needed to offer an informed perspective on this topic.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Summary of the RMSE results by state across three different methods: Holt (HW) Trend, the Damping Holt (HD90) with $\phi = 0.90$, and the exponential smoothing (ES).

State	HW	HD90	ES
Alabama	0.0072	0.0681	0.7609
Alaska	0.0409	0.0279	0.0810
Arizona	0.3923	0.4547	1.4867
Arkansas	0.0756	0.0419	0.4375
California	0.7499	0.6280	6.3491
Colorado	0.0200	0.0082	0.7748
Connecticut	0.1775	0.2241	0.5678
Delaware	0.0881	0.0868	0.2239
Florida	1.1408	1.3674	3.9978
Georgia	0.5240	0.5702	1.7787
Hawaii	0.0569	0.0501	0.1993
Idaho	0.1189	0.1089	0.3309
Illinois	0.2364	0.1245	1.4922
Indiana	0.4679	0.4049	1.1897
Iowa	0.3624	0.3800	0.7392
Kansas	0.1686	0.2144	0.5742
Kentucky	0.2512	0.3001	0.9565
Louisiana	0.1229	0.0773	0.7438
Maine	0.0084	0.0081	0.1884
Maryland	0.0119	0.0262	0.8445
Massachusetts	0.2595	0.3224	0.9233
Michigan	0.0229	0.0238	1.5259
Minnesota	0.3920	0.3557	1.0375
Mississippi	0.0186	0.0698	0.6172
Missouri	0.0595	0.1112	0.9487
Montana	0.0637	0.0708	0.2024
Nebraska	0.0610	0.0799	0.3987
Nevada	0.0681	0.0830	0.5416
New Hampshire	0.0637	0.0723	0.2235
New Jersey	0.3966	0.4204	1.3875
New Mexico	0.0240	0.0462	0.3456
New York	2.8762	2.6683	2.6395
North Carolina	0.1089	0.2169	1.6117
North Dakota	0.0202	0.0290	0.1481
Ohio	0.8782	0.9857	2.3933
Oklahoma	0.2259	0.2400	0.7471
Oregon	0.0872	0.0812	0.7754
Pennsylvania	0.5544	0.6239	2.1191
Rhode Island	0.0600	0.0666	0.1656
South Carolina	0.0352	0.1079	0.9573
South Dakota	0.1015	0.1017	0.1999
Tennessee	0.2298	0.2906	1.4378
Texas	0.5355	0.8923	5.6198
Utah	0.0486	0.0822	0.6267
Vermont	0.0194	0.0168	0.0858
Virginia	0.4032	0.4517	1.5757
Washington	0.0234	0.0450	1.1971
West Virginia	0.0712	0.0663	0.3179
Wisconsin	0.0332	0.0884	0.9190
Wyoming	0.0428	0.0460	0.0921
Total	12.8064	13.9277	55.4973

Table A2. Summary of the MAE results by state across three different methods: Holt (HW) Trend, the Damping Holt (HD90) with $\phi = 0.90$, and the exponential smoothing (ES).

State	HW	HD90	ES
Alabama	0.0072	0.0681	0.7087
Alaska	0.0409	0.0279	0.0809
Arizona	0.3923	0.4547	1.3950
Arkansas	0.0756	0.0419	0.3648
California	0.7499	0.6280	5.6318
Colorado	0.0200	0.0082	0.7026
Connecticut	0.1775	0.2241	0.5373
Delaware	0.0881	0.0868	0.2130
Florida	1.1408	1.3674	3.7655
Georgia	0.5240	0.5702	1.7040
Hawaii	0.0569	0.0501	0.1889
Idaho	0.1189	0.1089	0.3175
Illinois	0.2364	0.1245	1.3701
Indiana	0.4679	0.4049	1.1447
Iowa	0.3624	0.3800	0.7284
Kansas	0.1686	0.2144	0.5372
Kentucky	0.2512	0.3001	0.8922
Louisiana	0.1229	0.0773	0.6587
Maine	0.0084	0.0081	0.1722
Maryland	0.0119	0.0262	0.7848
Massachusetts	0.2595	0.3224	0.8820
Michigan	0.0229	0.0238	1.3599
Minnesota	0.3920	0.3557	0.9886
Mississippi	0.0186	0.0698	0.5072
Missouri	0.0595	0.1112	0.8679
Montana	0.0637	0.0708	0.1885
Nebraska	0.0610	0.0799	0.3723
Nevada	0.0681	0.0830	0.4958
New Hampshire	0.0637	0.0723	0.2120
New Jersey	0.3966	0.4204	1.3209
New Mexico	0.0240	0.0462	0.3139
New York	2.8762	2.6683	2.0895
North Carolina	0.1089	0.2169	1.4997
North Dakota	0.0202	0.0290	0.1376
Ohio	0.8782	0.9857	2.2786
Oklahoma	0.2259	0.2400	0.7115
Oregon	0.0872	0.0812	0.6875
Pennsylvania	0.5544	0.6239	2.0076
Rhode Island	0.0600	0.0666	0.1620
South Carolina	0.0352	0.1079	0.8788
South Dakota	0.1015	0.1017	0.1953
Tennessee	0.2298	0.2906	1.3423
Texas	0.5355	0.8923	5.2271
Utah	0.0486	0.0822	0.5659
Vermont	0.0194	0.0168	0.0819
Virginia	0.4032	0.4517	1.4822
Washington	0.0234	0.0450	1.0950
West Virginia	0.0712	0.0663	0.3028
Wisconsin	0.0332	0.0884	0.8315
Wyoming	0.0428	0.0460	0.0904
Total	12.8064	13.9277	51.0748

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