## Combining conventional and high dimensional tensor time series forecasting to assess COVID-19 pandemic excess deaths in the United States

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**Abstract**

The objective of this study was to estimate the COVID-19 excess deaths during the pandemic. Tensor time series mortality data from the 50 US states and the District of Columbia for the 15 major causes of death in 2020 (pandemic statistics) was used in this study. The data consisted of number of deaths between January 1999 to June 2024 reported monthly by state and cause of death. We proposed a combination of a non-linear trend and seasonality models that explained the structure of the data, followed by an autoregressive tensor model on the residuals of the initial model. We used several initial models for the trend and seasonality: (1) logarithm trend with monthly dummies and autoregressive terms, (2) exponential smoothing forecasting, (3) ARIMA models and (4) sinusoidal models first, to use the autoregressive tensor of the rest of the causes of death to improve the initial model. Exponential smoothing forecast and autoregressive tensor models showed the best performance in estimation of the COVID-19 excess death by state and cause of death during the pandemic.

This work provided a granular view at how individual US states and patients with existing health conditions were affected by the pandemic. The results of this analysis can be useful in shaping health policies in the future.

1. **Introduction**

In the US, different states instituted different policies in response to the COVID-19 outbreak. An accurate estimate of excess COVID-19 deaths by state is necessary to understand the effectiveness of the various health policies in reducing pandemic-related mortality since the reported COVID-19 deaths alone represent only a partial count of the total death toll from the COVID-19 pandemic. The number of excess COVID-19 pandemic deaths is defined as the difference between the number of deaths during the pandemic and the number of expected deaths as if the pandemic would not have happened. The expected deaths without COVID-19 are forecasted using historical data (before the pandemic). This study examined how the differences between the reported and the predicted numbers of deaths changed over time across different states and different causes of death.

To do this, mortality data before, during and after the pandemic for all states and several causes of death were obtained and analyzed. First, for each state and cause of death, the data before the pandemic was modeled using four different types of models. These models were employed to forecast the expected number of deaths without COVID-19: (1) logarithmic trend with monthly dummies and autoregressive terms, (2) exponential smoothing, (3) ARIMA, and (4) sinusoidal models. These models were fitted and validated using data up to February 2020; i.e., before the onset of COVID-19 in the US. The initial ARIMA and exponential models used data from 2010 to estimate the models (the ARIMA was not stable using less observations and the sinusoidal models provided beter results using more observations. The logarithmic trne and seasonlaity model and explonenetial smoothing used only data form 2015. These last models only estimate few parmeters or share parameters with all states with data froom 2015 only.The model with the best performance in the validation set was then used to forecast the expected mortality for the period from March 2020 to June 2024 - this is the period during which COVID-19 was rampant in the US, starting fading down till the end of the pandemic in May 2022 and being a disease to persist till this day. The differences between these expected number of deaths and the number of actual deaths provide estimates of the excess deaths for the COVID-19 pandemic.

In the next step, the residuals from all these models were utilized together to fit an autoregressive tensor model for causes of death other than COVID-19. This was done to account for the fact that information related to changes in one cause of death could influence and enhance the forecast for another cause of death. For instance, an increase in diabetes-related deaths in the last three months could affect heart disease deaths, potentially leading to either a decrease in deaths due to heart disease (competing risk between diseases) or an increase in deaths from heart disease due to the same reason diabetes deaths have increased. [Q: Could there be an interaction like this with COVID also? Should we say?. A: I think so, but given that our models are only till pre-COVID period, we can not used COVID as a tensor (there are only zeros in the data pre-COVID.]

1. **Methods** **and Results**
   1. **Data**

Mortality data by month, state and cause of death were downloaded from the CDC1-2 mortality database for the period from January 1999 to June 2024. For each month there were 51 observations for the states (i.e, for the 50 states and the District of Columbia) and 15 observations for the main causes of death of 2020. Of the 113 causes of death only the main 15 causes of death in 2020 (including COVID-19 deaths) were retained as individual causes of death; the rest were combined in a non-top 15 group. The data was used to build forecasting models for the number of deaths from 14 main causes of death (not including COVID-19) and the combination of the other causes of death of the non-top 15 group for the pre-Covid period from January 2010 or 2015 to February 2019.

* 1. **Excess deaths definition and metric to forecast.**

Excess mortality during the Covid-19 pandemic covering the period from March 2020 to June 2024 was defined as the difference between the number of recorded deaths and the number of forecasted deaths calculated as if the pandemic had not occurred:

*Excess deaths = Actual deaths – Forecasted deaths without COVID* (1)

In order to compare across the states, the death rates were normalized to the state populations:

*Monthly crude death rate = 100,000\* (Monthly deaths)/Population* (2)

Additionally, the crude monthly crude death rate was adjusted for the number of days in each month to eliminate month length effect:

*Daily crude rate = Monthly crude rate / Number of days in the month* (3)

Figure 1 compared the monthly death counts in the US from January 1999 to June 2024 to the monthly crude rate. The seasonality from both metrics was the same, but the crude rate did not increase as much as the number of deaths due to the increasing population.

Figure 2 compared the daily crude rate in the US from January 1999 to June 2024 to the monthly crude rate. The trend was the same with both metrics, but the seasonality effect was smoother using the daily crude rate than the monthly crude rate because the daily crude rate takes into account the different number of days in each month.

The number of excess deaths was estimated using the dependency between excess deaths and daily crude rate as expressed in equation (4).

*Excess deaths = Observed deaths – Forecasted deaths without COVID*

*= Observed deaths - Forecasted daily crude rate \* Number of days in a month \**

*Population/100,000* (4)

Figure 1. Comparison of the Actual Monthly death and the monthly crude rate in the US from 1999 to June 2024. Update the plot with new data

A graph of death rate

Description automatically generated

Figure 2. Comparison of the Actual Monthly Crude Rate and the Daily Crude Rate in the US from 1999 to June 2024. Update the plot with the new data

A graph showing the amount of crude oil in the rate of the crude oil market

Description automatically generated with medium confidence

1. **Initial Models**

Existing forecasting models use techniques ranging from deep learning to exponential smoothing. Many models tend to be highly accurate when large number observations are provided for training the models. However, since the dataset for this study was relatively small, simpler initial models were chosen. The forecasting was improved in the second stage of modeling by adding the cause autoregressive tensor models.

* 1. **Non-linear trend with seasonality.**

Forecasting using a non-linear trend (the logarithm of the monthly count plus a constant) or autoregressive terms and seasonality (using monthly dummies to differentiate the month with the largest number of deaths) is a common way to forecast data into the future. The two components, seasonality and trend, are based on prior historical data. They come together to form a model that can be projected out for the near future. 15 models were estimated, one for each cause of death. There is a different intercept for each state (fixed effects for panel data), the trend is estimated by a non-linear trend or an autoregressive AR3, AR2 or AR1 (only one of these 4 options will be used depending on which one provides a better fit). The seasonality is added by significant monthly dummies. Using this model, 50 monthly periods times 51 states can be used at one time to estimate the daily crude rate of each cause of death.

where  is white noise.

* 1. **Triple Exponential Smoothing using Holt-Winters smoothing**

Forecasting using exponential smoothing is a time series forecasting method for forecasting time series when the data contains linear trends and seasonality. The forecast predicts future values by estimating three weights. The weights decrease as the observations get older, giving more importance to recent data points and progressively less weight to older data. The technique uses exponential smoothing applied three times:

* Level smoothing or intercept using weight *α*
* Trend smoothing using weight *β*
* Seasonal smoothing using weight γ

Exponential smoothing can be divided into two categories, depending on the seasonality. The Holt-Winter’s Additive Method (HWIM) is used for addictive seasonality. The Holts-Winters Multiplicative method (MWM) is used for multiplicative seasonality.

The formulas for the triple exponential smoothing are as follows:

=

= *α*( / ​)+(1−*α*)( ​+ ​)

*= β*( - ​)+(1−*β*)

= *γ* *α*( / ​) +(1−*γ*)

Where:

*t* = time period

being the smoothed statistic; it’s the simple weighted average of current observation Yt

*α* = level smoothing factor (0<*α*<1)

*β* = trend smoothing factor (0<*β*<1)

*γ* = seasonal smoothing parameter (0<*γ*<1)

= seasonal component at time t

= best estimate of a trend at time t

765 models were estimated (one for each state and cause of death) using 50 observations for each model with a 12-month seasonality to estimate 3 smoothing parameters.

* 1. **Autoregressive Integrated Moving Average (ARIMA) model**

As its name indicates, the acronym ARIMA integrates Autoregression and Moving Average models into a single model depending on the parameters passed. These two ways of modeling change throughout the time series are related but have some key differences. In an autoregression model, we forecast the variable of interest using a linear combination of past values of the variable. This technique is similar to a linear regression model in how it uses past values as inputs to the regression. Autoregression is defined as:

where εt is white noise. We refer to this as an AR(p) model, an autoregressive model of order p.

A moving average model on the other hand uses the past forecast errors rather than using past values of the forecast variable in a regression. A moving average simply averages q values in a window, where q is the size of the moving average window, and then advances the window. The forecast values are evaluated using the actual values to determine the error at each step in the time series. A moving average is defined as:

εt is white noise. We refer to this as an MA(q) model, a moving average model of order q.

Typically, in an ARIMA model you'll use either the Auto-Regressive term (AR) term or the Moving Average term (MA). There are 3 key parameters for an ARIMA model which are typically referred to as p, d, and q.

In an ARIMA(p,d,q) model, the p is the order of the Autoregressive part, d is the degree of differencing involved. The "degree of differencing" refers to the number of times the original time series data needs to be differenced (subtracting the previous value from the current value) to achieve stationarity, q is the order of the Moving Average part.

Also 765 models were estimated (one for each state and cause of death) using 50 observations for each model with a 12-month seasonality to estimate the ARIMA models.

* 1. **Sinusoidal models DAVIT to describe**

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* 1. **Adding Autoregressive Tensor to previous Models**

Using tensors in time series (TS) forecasting can significantly improve model performance, especially when dealing with complex, multi-dimensional data. The improvement comes by capturing multi-dimensional relationships.

Tensors can naturally represent multi-dimensional data, like time series with multiple features or time series across multiple locations. This allows models to capture complex relationships between different variables and across different time steps. For example, an increase in diabetes-related deaths in the last three months could affect heart disease deaths, potentially leading to either a decrease in deaths due to heart disease (competing risk between diseases) or an increase in deaths from heart disease due to the same reason diabetes deaths have increased.

Once the three previous models are estimated, the errors for each one of the models is computed and used with the other causes of death to improve the model by running 15 more regressions.

We checked if death in other causes of death in one, two or three previous month most affected the other causes of death in the following time period.

1. **Results**

Crude death rate was defined as the number of deaths per 100,000 of the state’s population in that year. The states with the highest crude rate (without adjusting by age) before COVID-19 pandemic were West Virginia, Maine, Mississippi, Arkansas, and Alabama. The states with the lowest crude rates before COVID-19 were Utah, Alaska, DC, Colorado, Texas and California. The crude rate depends on the proportion of old population, the proportions of minorities and the access of health care on those states. Excess crude rate was calculated as the difference of the observed (actual) and the predicted (expected) crude rates (5).

Excess crude rate = Actual crude rate – Expected crude rate without COVID-19 (5)

The training set for all models included data from 2015 to February 2019, and the hold-out data set included observations from March 2019 to February 2020. Mean absolute error (MAE) was calculated on the hold-out data, and the model with the smallest MAE selected as the best fit model and used for the final forecast. Table 1 and Figure 3 provide the MAE by cause of death and type of model. TO BE INSERTED

for the hold out period (March 2019 to February 2020) where we are testing the model. The Exponential Smoothing Forecast is the one performing the best with this data as seen in Table 1. COMMENTS ON CAUSES

Table1. MAPE during the hold-out period (March 2019 to February 2020) for the three initial models.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Exponential Smoothing** | | **Non-Linear Trend and Seasonality** | | **ARIMA** | |
| **State** | **MAE initial Model** | **Average Daily crude rate** | **MAE initial Model** | **Average Daily crude rate** | **MAE initial Model** | **Average Daily crude rate** |
| **United States** | **13%** | **131** |  |  | **395** |  |
| Diabetes | 13% | 118 |  |  | 649 |  |
| Neoplasms | 12% | 100 |  |  | 535 |  |
| Influenza | 13% | 85 |  |  | 217 |  |

Plot 3. MAE by cause as Table 1

Table2 and Plot 4 provides the MAE of the final models besides the improvement of the cause tensor on the initial models. We can observe that the Cause Tensor improves the initial models by xxx% being the best model the exponential smoothing with cause tensor.

Table2. MAE during the hold-out period (March 2019 to February 2020) using the cause tensor on the residual of the previous models.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Exponential Smoothing & Cause Tensor** | | **Non-Linear Trend and Seasonality & Causse Tensor** | | **ARIMA & Cause Tensor** | |
| **State** | **MAE** | **Pct improvement from Initial Model** | **MAE** | **Pct improvement from Initial Model** | **MAE** | **Pct improvement from Initial Model** |
| **United States** | **13%** | **131** |  |  | **395** |  |
| Diabetes | 13% | 118 |  |  | 649 |  |
| Neoplasms | 12% | 100 |  |  | 535 |  |
| Influenza | 13% | 85 |  |  | 217 |  |

Plot 4. Overall MAE comparing the 6 models by disease

Some results on the cause tensor models showing which cause of death influenced other causes of deaths.

Once the best model is identified, the models can be rerun on the entire data set before COVID-19 to add 12 months of data to the training set. The forecast will be done till May of 2022 (end of the Pandemic). These kinds of models cannot be forecasted too long because other excess death can pick up instead as: change in policies, climate disasters and others.

Table 3 US Excess death differences among different models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Excess Deaths** | **Reported** | **Exponential Smoothing & Cause Tensor** | **Non-Linear forecast and Cause Tensor** | **ARIMA & Cause Tensor** |
| **COVID-19 Deaths** | **1,134,722** | **866,175** | **832,909** | **vvv** |
| **Percent Reported** | **100%** | **76%** | **73%** | **0%** |

We can provide the Forecasted Daily Crude Rate, the reported Crude Rate and the excess crude rate by disease in Plot 3. Observations of the plot. The same plot at the state level will provide the states most affected by COVID-19 in Plot 4. Observations of the plot. And the plot can be provided at the month level to see our recovery from COVID-19 in Plot 5. Observations of the plot.

Plot 3. Forecasted Daily Crude Rate, the reported Crude Rate and the excess crude rate by disease

COMMENTS ON CAUSES INSTEAD OF STATES. states that better fit by the exponential smoothing models are Maine, Wisconsin, and Oregon with the smallest MAE. The states with worst MAE are Delaware and Oregon. Add possible causes for bad models like poor data , etc once you know the states performing the worst.

The exponential smoothing estimates an excess crude rate of 312 while the ARIMA model estimates 72. There are 7 states with an excess crude rata larger than 500 using the exponential smoothing model: Oregon, West Virginia, Arizona, Arkansas, District of Columbia, Alaska and South Carolina. The Farrington model does not estimate and excess crude rate larger than 500 in state. The largest excess crude rate estimated by the Farrington model is 215 for West Virginia. The Farrington model estimates estates with an excess death less than 100 in 4 states, meaning that those states had less deaths due to the pandemic, those states are: Rhode Island, south Dakota, Massachusetts, and District of Columbia.

Plot 4. Forecasted Daily Crude Rate, the reported Crude Rate and the excess crude rate by state

Plot 5 Forecasted Daily Crude Rate, the reported Crude Rate and the excess crude rate by month

Breaking down the pandemic on variants and compare the effect of those variant son the population.

**Conclusion** on the importance of finding the best model to most accurate find our forecast and the ultimate results. How the causse tensor has helped on improving the model

I do not think we need 3 case studies

**Case study with 3 different states: New York (first state hit by COVID-19), West Virginia (worst crude rate before the pandemic) and Alaska (best crude rate before the Pandemic)**

**New York**

Let’s use the state of New York as the case study and example of the previous computations. This will help on understanding he differences between the Exponential smoothing and the Farrington results. Plot 3 shows the daily crude rate for New York from 2015 to May 2023. The

peak on the plot shows the increase in deaths in April 2020 due to the COVID-19 pandemic in New York city. The exponential smoothing model uses the prior data, and its forecast is much lower because it does not take COVID-19 in the forecast. Instead, the Farrington model seems to increase the expected death in April 2020 while it is not supposed to do so because the forecast should not consider the COVID deaths. The Farrington model forecast is too high, and it does not discount the COVID-19 deaths, that provides a bias excess crude rate estimation. Focus on the April peak to verify the prior statement by plotting the April daily deaths in Plot 4 an comparing the actual daily crude rate and the forecasted using Farrington and Exponential smoothing algorithms. The actual April daily deaths are 2 in 2015 and 2016, it increases to 2.5 in 2017 and 2019, the forecast using exponential smoothing is 2.5 from 2019 to 2022 (following the trend from 2015 to 2018. Instead, the Farrington algorithm forecast 5 daily crude rates in 2020 without following the previous data without pandemic deaths. The 95% prediction interval

ranges from 1.9 to 3.1 while the actual daily crude rate is 6.1 in 2020, outside the prediction interval as shown in Plot 5. We can report the excess death considering the difference between the actual and the forecast and we can report the significant excess death only considering any quantity that lies outside the prediction interval. Table 3 shows the excess daily crude rate and the significant excess crude rate in New York. In 2020 the significant daily crude rate is larger

Plot3. Comparing the Actual daily crude rate in New York estate and its daily crude rate forecast using Farrington and exponential models’ algorithms.

A picture containing text, font, screenshot, line

Description automatically generated

hold-out period

Plot4. Comparing the Actual APRIL daily crude rate in New York estate and its daily crude rate forecast using Farrington and exponential models’ algorithms.

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than the excess daily crude rate because it does not consider the insignificant negative excess

daily crude rate from June to October. The excess daily crude rate and the significant excess daily crude decrease over time and it is not positive in 2023 (the end of the pandemic). The cumulative significant Excess crude rate is smoother than the not significant one as seen in Plot 6 and it is flat from 2022 till now, meaning that the pandemic is not adding new deaths in America.

Plot5. Actual daily crude rate in New York estate and its daily crude rate forecast using exponential models’ algorithms and its prediction interval.

A picture containing text, line, font, screenshot

Description automatically generated

Plot6. Actual daily crude rate in New York estate and its daily crude rate forecast using Farrington algorithms and its prediction interval.

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Table 3. Actual daily crude rate in New York estate and its daily crude rate forecast using exponential models’ algorithms and its prediction interval.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Exponential Smoothing** | | **Farrington** | |
| **New York** | **Excess daily crude rate** | **Significant Excess daily crude rate** | **Excess daily crude rate** | **Significant Excess daily crude rate** |
| 2020 | 6.45 | 7.09 | 7.42 | 7.17 |
| 2021 | 1.80 | 0.60 | 3.59 | 3.49 |
| 2022 | 1.18 | 1.32 | 2.28 | 2.05 |
| 2023 | (0.08) | - | 0.04 | 0.16 |

1. Sinusoidal models are used to build a model on the training set, the model is evaluated in the hold-out period and the MAPE is computed.
2. The model with the smallest MAPE will be chosen to provide the initial excess crude rate rate and excess death.
3. The best model will be rerun till February 2020 and the final

The Farrington algorithm forecast is very close to the actual deaths before and after COVID. Even though we took the estimated excluding COVID, it does not seem to ignore the COVID

Plot explanations

Table3. Final Excess crude rate using data till February 2020 for the first year the second year and third year of the pandemic.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Excess crude rate** | **Model Type** | **Excess crude rate 1st year** | **Excess crude rate 2nd Year** | **Excess crude rate 3rd Year** |
|  |  |  |  |  |
| Alaska |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |

Point out difference between years and the previous forecast.

MAP with data on pervious table

We want to know if COVID-19 was overreported or under-reported by state. We will compare the excess death to the reported COVID cases and provide the percent of overreported or underreported COVID deaths by state. If COVID-19 was over reported or underreported means that other causes of death were affected by the pandemic also. We will use the same methodology described above with data at the state and cause of death level. We will know the excess death by state and disease and that will let us know which causes of death were more affected by the COVID-19 pandemic.

Table4 percent over or under-reported covid by state. And map

Table 4.with percent change excess death by disease and bar plot

Map with the percent change of excess death by state for major diseases or diseases with the most change.

Task:

1. Switch to muilti-dimensional data with few observations
2. Send programs to Jin
3. QC results
4. Write…

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Exponential Smoothing** | | | **Non-Linear Trend and Seasonality** | | | **ARIMA** | |  |
| **State** | **MAE initial Model** | **MAE with cause Tensor** | **Percent Reported COVID-19 cases** | **MAE initial Model** | **MAE with cause Tensor** | **Percent Reported COVID-19 cases** | **MAE initial Model** | **MAE with cause Tensor** | **Percent Reported COVID-19 cases** |
| **United States** | **13%** | **258** | **131%** |  |  |  | **395** | **86%** |  |
| Mississippi | 13% | 424 | 118% |  |  |  | 649 | 77% |  |
| Arizona | 12% | 414 | 100% |  |  |  | 535 | 77% |  |
| District of Columbia | 13% | 392 | 85% |  |  |  | 217 | 153% |  |
| West Virginia | 13% | 391 | 118% |  |  |  | 518 | 89% |  |
| South Carolina | 13% | 373 | 107% |  |  |  | 507 | 78% |  |
| New Mexico | 14% | 369 | 114% |  |  |  | 488 | 86% |  |
| Alabama | 14% | 351 | 120% |  |  |  | 552 | 76% |  |
| Alaska | 14% | 347 | 57% |  |  |  | 237 | 84% |  |
| Oklahoma | 15% | 346 | 133% |  |  |  | 489 | 94% |  |
| Oregon | 12% | 344 | 62% |  |  |  | 340 | 63% |  |
| Louisiana | 13% | 343 | 110% |  |  |  | 489 | 78% |  |
| Tennessee | 13% | 332 | 130% |  |  |  | 468 | 92% |  |
| Montana | 15% | 328 | 109% |  |  |  | 384 | 93% |  |
| Arkansas | 13% | 314 | 132% |  |  |  | 485 | 85% |  |
| Georgia | 12% | 305 | 110% |  |  |  | 474 | 71% |  |
| Kentucky | 14% | 299 | 149% |  |  |  | 451 | 99% |  |
| Ohio | 15% | 297 | 141% |  |  |  | 389 | 108% |  |
| New York | 14% | 297 | 134% |  |  |  | 391 | 102% |  |
| Texas | 13% | 295 | 119% |  |  |  | 439 | 80% |  |
| Nevada | 12% | 292 | 133% |  |  |  | 380 | 102% |  |
| South Dakota | 13% | 292 | 133% |  |  |  | 262 | 148% |  |
| Florida | 12% | 292 | 126% |  |  |  | 424 | 87% |  |
| Michigan | 13% | 283 | 129% |  |  |  | 392 | 93% |  |
| New Jersey | 15% | 277 | 138% |  |  |  | 340 | 112% |  |
| Kansas | 13% | 270 | 127% |  |  |  | 314 | 109% |  |
| Wyoming | 15% | 268 | 118% |  |  |  | 308 | 103% |  |
| North Carolina | 13% | 266 | 121% |  |  |  | 376 | 85% |  |
| Indiana | 13% | 239 | 164% |  |  |  | 383 | 102% |  |
| Connecticut | 14% | 236 | 146% |  |  |  | 261 | 133% |  |
| Pennsylvania | 13% | 233 | 174% |  |  |  | 357 | 113% |  |
| Colorado | 12% | 233 | 113% |  |  |  | 316 | 83% |  |
| Missouri | 13% | 231 | 163% |  |  |  | 382 | 99% |  |
| Idaho | 15% | 230 | 128% |  |  |  | 333 | 88% |  |
| Illinois | 13% | 227 | 133% |  |  |  | 363 | 83% |  |
| California | 13% | 225 | 122% |  |  |  | 355 | 78% |  |
| Virginia | 13% | 219 | 121% |  |  |  | 320 | 83% |  |
| North Dakota | 13% | 216 | 183% |  |  |  | 256 | 155% |  |
| Iowa | 13% | 213 | 161% |  |  |  | 274 | 125% |  |
| Massachusetts | 14% | 204 | 147% |  |  |  | 223 | 135% |  |
| Wisconsin | 12% | 198 | 145% |  |  |  | 274 | 105% |  |
| Nebraska | 13% | 180 | 163% |  |  |  | 232 | 127% |  |
| Maine | 12% | 178 | 130% |  |  |  | 223 | 103% |  |
| Rhode Island | 15% | 170 | 217% |  |  |  | 195 | 189% |  |
| Delaware | 17% | 164 | 206% |  |  |  | 275 | 123% |  |
| Washington | 12% | 157 | 121% |  |  |  | 239 | 80% |  |
| Maryland | 14% | 156 | 186% |  |  |  | 222 | 131% |  |
| Utah | 13% | 138 | 127% |  |  |  | 188 | 93% |  |
| Vermont | 15% | 134 | 109% |  |  |  | 226 | 64% |  |
| Minnesota | 13% | 123 | 215% |  |  |  | 200 | 132% |  |
| Puerto Rico | 13% | 113 | 164% |  |  |  | 272 | 68% |  |
| New Hampshire | 16% | 107 | 206% |  |  |  | 127 | 173% |  |
| Hawaii | 13% | 89 | 144% |  |  |  | 73 | 176% |  |