Article

Indexing Inefficacy of Efforts to Stop Escalation of COVID Mortality

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Abstract: *Background.* COVID-19 efforts were often ineffective in controlling the spread of the pandemic. Identifying ineffective controls during a pandemic is thus vital. *Method.* Utilizing publicly available data on COVID deaths in the counties of US states, we create an index to capture and interpret ineffectiveness in the efforts to reduce the spread of the pandemic in US counties. This index is based on the Intervened Poisson Distribution (IPD) introduced originally by Shanmugam. Motivation for the research idea occurred while we noticed the data dispersion of the COVID deaths is smaller than the average only in some counties. Under-dispersed data is common in statistical modeling. A novel approach we adapted in this article includes the estimation of an intervention parameter estimated through iterative non-linear optimization. *Results.* Twenty-five counties in California, Idaho, Minnesota, Mississippi, Montana, Nebraska, North Carolina, North Dakota, Texas, and Utah were found to be ineffective in controlling for fatalities based on the expected probability distribution. A review of the policies enacted in these areas would provide insight into ineffective prevention efforts, and some of these issues are documented in current literature. *Conclusion.* The IPD index an innovate way to document efficacy of interventions during pandemics.

Keywords: Positive Poisson distribution, Under dispersion, Bayesian analysis, prediction, index of infectivity.

MSC: 6204; 62E10; 62F30; 62P10

1. Introduction

As of September 2022, the pandemic SARS-COV2 (COVID-19) remains a public health concern for the United States of America as the world in general [1]. The number of COVID-19 cases worldwide as of September 2022 was over 611 million with an associated 6.5 million casualties [2]. About 16 percent of the worldwide cases and fatalities occurred in the United States [2]. Public health professionals all over the world implemented measures intended to reduce death and suffering from COVID-19 [3-5]. The efficacy of those measures is something that is not well understood, as the efforts varied from county to county, but ongoing work in this area is identifying best practice [6]. Thus, an index that evaluates intervention efficacy can be used post-hoc or even during the middle of an epidemic to help facilitate best-practice identification and control the spread of disease.

Developing appropriate models for evaluating efficacy of interventions by region is a necessary step to evaluate best practice. Previous studies have identified both state and county variations in response to the epidemic [7]; however, no local efficacy index exists in the literature, rather only country-level assessments which may have limited regional importance [8]. This work addresses that issue directly.

We propose a probability model as an abstraction of the reality for U.S. counties with respect to COVID deaths. Fatality rates themselves provide an indicator of the severity of the disease. These rates do not, however, consider interventional controls employed that may have affected the severity and outcomes. Our models address intervention as an unobserved (latent) variable. This research article constructs an appropriate probability model and applies statistical concepts to develop an index to portray the inefficacy level of public health policy to stop or at least reduce the COVID death in some US counties. A novelty in this article is the use of the intervention parameter, estimated using nonlinear optimization implemented in R Statistical Software [9]. We apply the index to categorize a qualifying subset of counties throughout the United States. Extensions of this research are also proffered.

2. Methods

2.1. Model Specification

In an outbreak of an epidemic (appearance of illness among a large number of people), endemic (regularly occurring illness), or pandemic (contagious deadly illness), public health professionals must collect and analyze data to disseminate information necessary to control disease spread and severity. COVID-19 is such a pandemic. Once a SARS-COV2-related death at a time epoch is reported, the data collection apparatus is activated and efforts to contain/reduce the pandemic are initiated. Let $\boldsymbol{x_{start}}$ be a random number of COVID deaths at a time the data collection apparatus is activated. The domain for $\boldsymbol{x_{start}}$ is the set $\boldsymbol{S_{start}} = \{\mathbf{1}, \mathbf{2}, \ldots\ldots, \infty\}$. With an inclusion of zero, the underlying model for the data would have been Poisson with an unknown, finite mortality rate, $\boldsymbol{\theta} > \mathbf{0}$. Because zero is not a possibility for $\boldsymbol{x_{start}}$, it is reasonable to assume that the model for $\boldsymbol{x_{start}}$ is a positive Poisson probability distribution (Equation 1).

$$\boldsymbol{Pr}(\boldsymbol{x_{start}} = \boldsymbol{i}) = (\boldsymbol{e^{\theta}} - \mathbf{1})^{-\mathbf{1}}\boldsymbol{\theta^{i}}/\boldsymbol{i}!; \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots, ; \boldsymbol{\theta} > \mathbf{0} \tag{1}$$

More often than otherwise, public health professionals do not stay idle but impose preventive efforts to stop any escalation of the mortality.

Let the inefficacy of their efforts to stop an escalation of COVID mortality is a non-observable *inefficacy parameter* $\rho \geq 0$ such that the COVID's mortality rate becomes $\rho\theta$. Suppose the random number x_{after} refers the number of new COVID deaths since the imposition of efforts. Note that the frequency pattern of x_{after} could be a regular Poisson probability distribution (Equation 2).

$$\boldsymbol{Pr}(\boldsymbol{x_{after}} = \boldsymbol{j}) = \boldsymbol{e^{-\rho\theta}}(\boldsymbol{\rho\theta})^{\boldsymbol{j}}/\boldsymbol{j}!; \boldsymbol{j} = \mathbf{0}, \mathbf{1}, \mathbf{2}, \ldots, ; \boldsymbol{\theta} > \mathbf{0}; \boldsymbol{\rho} \geq \mathbf{0} \tag{2}$$

When the inefficacy parameter is $\rho = 0$ in this scenario, the preventive efforts ought to have been a greatest success. When the inefficacy parameter was $\rho \leq 1$, the scenario would be thought to have reduced the COVID mortality. Beware that when $\rho \geq 1$ (which is an undesirable, adversarial), the COVID mortality rate might have worsened as the pandemic outpowered the efforts. However, the registry of COVID incidences records only the sum $Y = x_{start} + x_{after}$. An analyst ought to consider a convoluted probability distribution of the random number Y. Such a convoluted probability distribution is the *intervened Poisson distribution* (IPD, Equation 3).

$$\boldsymbol{Pr(Y = y) = [e^{\rho\theta}(e^{\theta} - 1)]^{-1}[(1+\rho)^{y} - \rho^{y}]\theta^{y}/y!; y = 1, 2, \ldots, \infty; \theta > 0; \rho \geq 0} \quad (3)$$

Equation 3 was introduced by Shanmugam [10] and studied in Shanmugam [11]. Joyce et al. [12] designed a mixed sampling plan to judge an IPD chance mechanism. Utilizing dispersion and mean, Shanmugam [13] revelated a shrunken quantity to portray the public perception of situations which might spread AIDS or HIV. Earlier, Shanmugam [14] modeled the web changes data to recatch during a spread of internet virus using IPD. Also, Shanmugam [15] predicted a "successful" inefficacy of an epidemic, using IPD.

The *expected number* of the IPD in (3) is Equation 4, and it is intrinsically related to its *dispersion*, Equation 5.

$$\mu = E(Y) = \theta[1 + \rho + (e^{\theta} - 1)^{-1}] \quad (4)$$
$$\upsilon = Var(Y) = E(Y) - e^{\theta}(\frac{\theta}{e^{\theta} - 1})^{2} \quad (5)$$

The dispersion reflects the volatility in the COVID deaths. If the dispersion is lesser than the expected number, the efforts ought to have been effective, no matter what is the level of the expected number of the COVID deaths in a county? Before examining it in the data, realize that the second term $e^{\theta}(\frac{\theta}{e^{\theta}-1})^{2}$is nonnegative, and hence $Var(Y) \leq E(Y)$ in the IPD model. This characteristic property is a litmus test to decide whether the IPD model (4) is indeed the underlying model for the chance mechanism which generated the data on COVID mortality and the existence of successful efforts. In other words, in those counties in which the mortality data-based estimate of the *inefficacy parameter* is less than one is indicative of successful efforts.

2.2. Index of Inefficacy

Consider two mutually exclusive dichotomous scenarios in an effort to stop escalation of COVID mortality. One scenario encompasses an effective, $0 < \rho < 1$efforts. The other scenario is an adversarial ineffective, $\rho > 1$ efforts. Only one of these two scenarios could have ever happened in a county with respect to efforts by the health professionals dealing with COVID mortality. Combining the data dispersion, $\upsilon > 0$, expected number, $\mu > \upsilon$ of the COVID mortality, we introduce an index $\Psi = \frac{\upsilon\rho}{\mu(1+\rho)}$to portray the inefficacy of the efforts by the health professionals. Note that $0 < \upsilon \leq \mu$ and the *balancing factor*, $\frac{\rho}{(1+\rho)} < 1$.

When the efforts were ideal and the best (that is,$\rho = 0$), the target index is $\Psi_{target} = 0$ whose level is data dependent as the estimates of υ and μ vary from a county to another.

When the efforts were adversarial and worst (that is, $\rho > 1$), the index $\Psi = \frac{\upsilon\rho}{\mu(1+\rho)}$ is negative and is indicative of how much trailing behind the target level, $\Psi_{target} = \frac{\upsilon}{\mu}$.

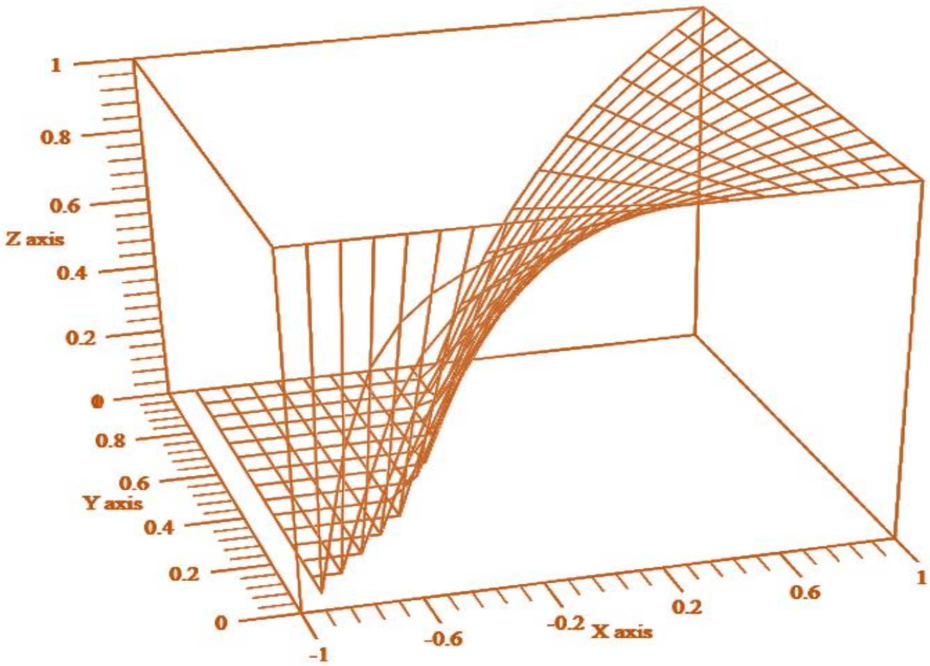

Figure 1. The dynamics of the inefficacy confronting COVID pandemic in which $(\frac{1}{1+\rho})$ in the $x - axis$, $\frac{\upsilon}{\mu}$ in the $y - axis$, and $(\frac{1}{1+\rho})(1 - \frac{\upsilon}{\mu}) + (\frac{\rho}{1+\rho})(1 + \frac{\upsilon}{\mu})$ in the $z - axis$

Also, the factor $\tau = (1 - \frac{\upsilon}{\mu})$ is indicative of how much the chance mechanism of COVID mortality has tilted away from the regular Poisson chance mechanism at zero level because the mean μ and variance, υ are equal in regular Poisson mechanism. The dynamics of the tilt is visualized in the Figure 1 after denoting $(\frac{1}{1+\rho})$ in the $x - axis$, $\frac{\upsilon}{\mu}$ in the $y - axis$, and $(\frac{1}{1+\rho})(1 - \frac{\upsilon}{\mu}) + (\frac{\rho}{1+\rho})(1 + \frac{\upsilon}{\mu})$ in the $z - axis$.

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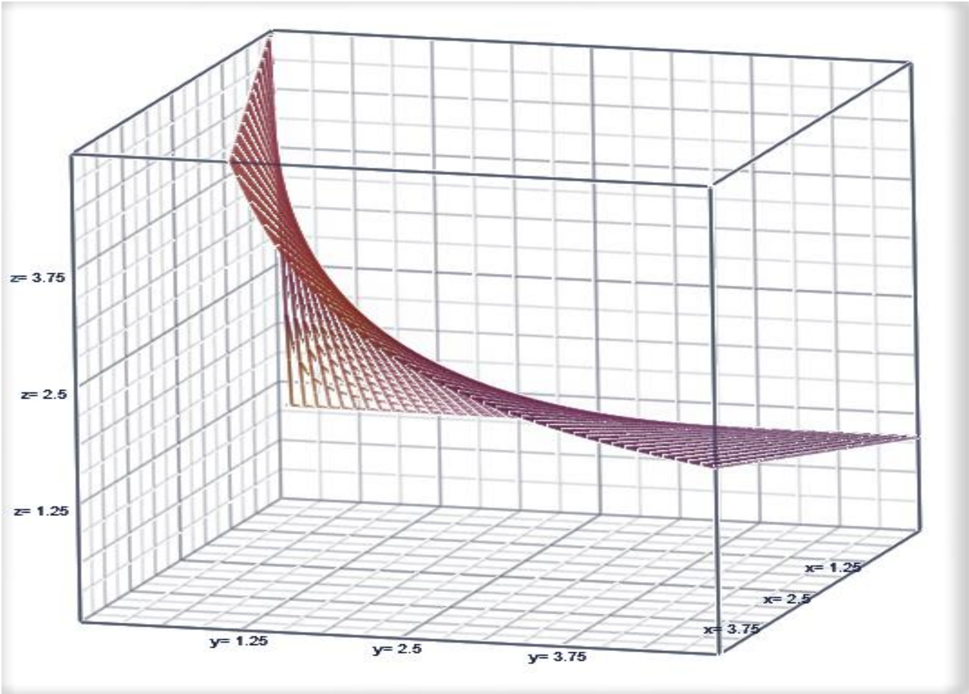

Figure 2. The nonlinear configuration of the pandemic index $\Im_{pandemic-index}$. The pandemic-index $\Im_{pandemic-index} = (1 + \frac{v}{\mu})$ is in vertical z-axis, μ and v are in the breath and x-axes respectively.

We name the factor $\Re = (\frac{\rho}{1+\rho})(1 + \frac{v}{\mu})$ as a unique *deflated risk level* to die in COVID pandemic because of the efforts by the health professionals. In the deflated risk to die of COVID at a county during the pandemic, the co-proportion $\Im_{efforts-index} = (\frac{\rho}{1+\rho})$ in interval [0, 1] gets the name *efforts index* and the other co-factor could be named *pandemic index* $\Im_{pandemic-index} = (1 + \frac{v}{\mu})$. The nonlinear configuration of the pandemic index is seen in Figure 2.

The genesis of IPD (intervened Poisson distribution) follows. With no intervention efforts, the expected number of deaths would have been just the incident rate (θ). The intervention efforts impact the expected deaths to change to ρθ. When the intervention parameter ρ is less than one, the efforts have been effective, as the expected number of deaths (after the intervention) reduced. When the intervention parameter ρ is greater than one, the variance is still lesser than the mean but the scenario is indicative of inefficient efforts. Hence, we the analysis proceeds in two steps. When variance is lesser than one, the IPD is the underlying model for the pattern of COVID-19 deaths. When the intervention parameter is lesser than one, the efforts were effective. Otherwise (that is, when the intervention parameter is greater than one and the variance is lesser than the mean), the efforts were inefficient.

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2.3. Estimating the Efficacy Parameter

In this section, we provide an innovative approach to estimate the IPD's parameters using R Statistical Software [16] and the *nloptr* non-linear optimization package [17]. First, we cite below the major expressions to be exercised to obtain the estimates of the mortality parameter θ and the efficacy parameter ρ from the data mean $\bar{y}$ and data variance $s_{\bar{y}}^2$ of the COVID deaths in a county. The mean and the variance are $\mu = E(Y) = \theta[1 + \rho + (e^{\theta} - 1)^{-1}]$ and $v = Var(Y) = E(Y) - e^{\theta}(\frac{\theta}{e^{\theta}-1})^2$. The p-value of the data based estimate, $\hat{\rho}$ is computed using the expression $Z_{\hat{\rho}} = \{\frac{1}{\hat{\rho}}\sum_{i=1}^{n}\frac{y_i\hat{\rho}^{y_i}}{(1+\hat{\rho}^{y_i})-\hat{\rho}^{y_i}} - n)\}\sqrt{\{\frac{1+\hat{\rho}\bar{y}}{n\hat{\rho}(\bar{y}-1)}\}}$, which was derived by Shanmugam [11] using the so called Neyman's $C(\alpha)$ procedure. The p-value is the left tail probability area, $Pr(Z < z_{\hat{\rho}})$ under the standard Gaussian frequency curve.

2.4. Data.

Daily COVID-19 fatality data were obtained from USA Facts [18] where were compiled from the Centers for Disease Control and Prevention (CDC) [19] at the county level for all United States counties from March 28, 2020 through January 26, 2022. County-level data were selected to prevent smoothing due to aggregation, which would be associated with filtering out the ineffectiveness of the prevention efforts. This study specifically focuses on the United States, as disparate control efforts were implemented from state to state and county to county. In many more homogenous countries, controls were constant. One-hundred and thirty-seven counties with the variance less than the mean were retained to develop the inefficiency index, as this is a characteristic of the IPD. A variance greater than the mean implies efficiency in interventions. Further, when the variance is less than the mean, there is evidence that a pure Poisson process is not appropriate. In the pure Poisson process, the mean and variance should be equal, and this equality is the characteristic property. In the COVID-19 data for some counties in US, this characteristic property is not met and is thus indicative of the reality that the data deviated from the Poisson process.

3. Results

3.1. Map of Counties with Potentially Ineffective Interventions

The 137 counties retained in the study where the mean exceeds the variance are depicted in Figure 3 with shading associated with logarithm of the sum of their deaths. Many of the observations are located in the center of the country. The large majority of the counties are in the central United States. The interactive plots designed with *leaflet [20]* are available online [21].

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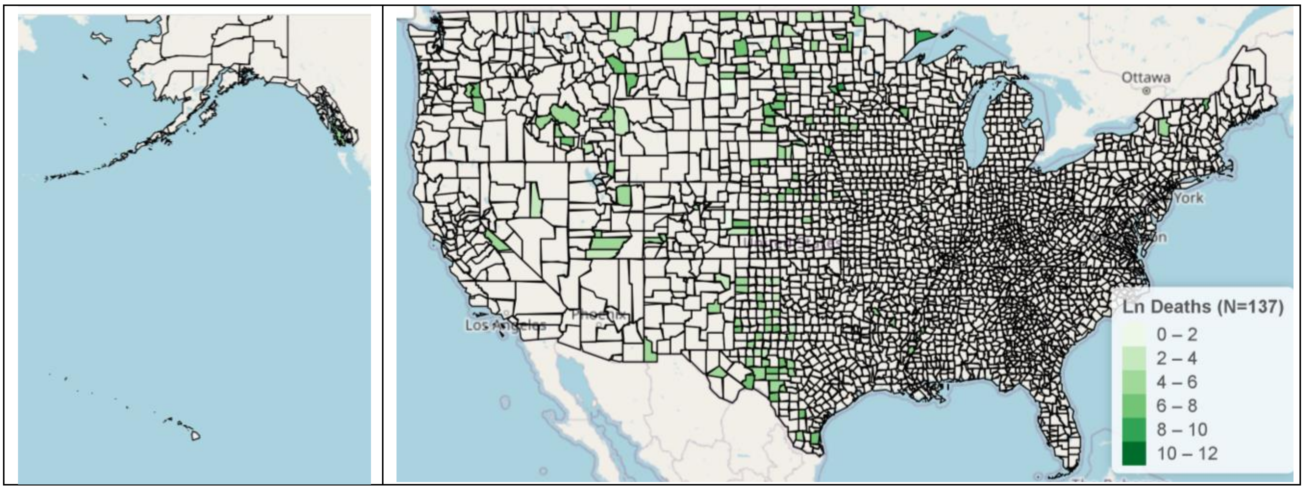

Figure 3. Counties where the mean is greater than the variance

3.1. Map of Counties with Potentially Ineffective Interventions

To estimate both θ and ϱ for each county, a positive semi-definite non-linear objective was formed that minimized the squared difference (sum of squares) between $\mu = E(Y) = \theta[1 + \rho + (e^{\theta} - 1)^{-1}]$ as specified previously and the observed mean mortality ($\bar{X}$) for each of the counties: $Min_{\theta,\rho}\,(\theta[1 + \rho + (e^{\theta} - 1)^{-1}] - \bar{X})^2$. For each county, the objective function was solved using Constrained Optimization by Local Approximation (COBYLA), a derivative-free optimization algorithm developed by Powell [22] and implemented in *nloptr* [17]. While we might have chosen one of a number of optimization algorithms, we chose COBYLA, as it does not require gradient specification. The code is available for review online [21].

3.2. Analysis of COVID Fatalities

In the illustration, we considered COVID deaths in all counties of USA from 01/22/2020 till 11/09/2022. There were approximately 3,142 counties in USA with COVID deaths in the above specified duration; however, there were another 50 observations, one per state, reflecting fatalities unallocated to a specific county. Descriptive statistics are shown in Table 1

Table 1. Descriptive statistics

Variable (n=3,192 Counties)	**Mean**	**SD**	**Median**	**Sum / Rate**
County Population	102,905.20	331,222.69	25,177.50	328,473,403
Sum of Fatalities	330.200	1301.39	102.00	1,054,320
Fatalities per 100,000 residents	339.32	337.10	258.71	320.98 per 100K

The population in this study was 328.5 million representing the United States population. The 'average' county was about 103 thousand (median ~25 thousand) in population and experienced 330 deaths (median of 102). The rate of fatalities per 100,000 population was about 339 on average (median of 259), and the overall fatality rate per 100,000 was 321.

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The fatality rates per 100,000 and logarithm of the sum of the total fatalities (+1) are depicted in Figures 4 and 5.

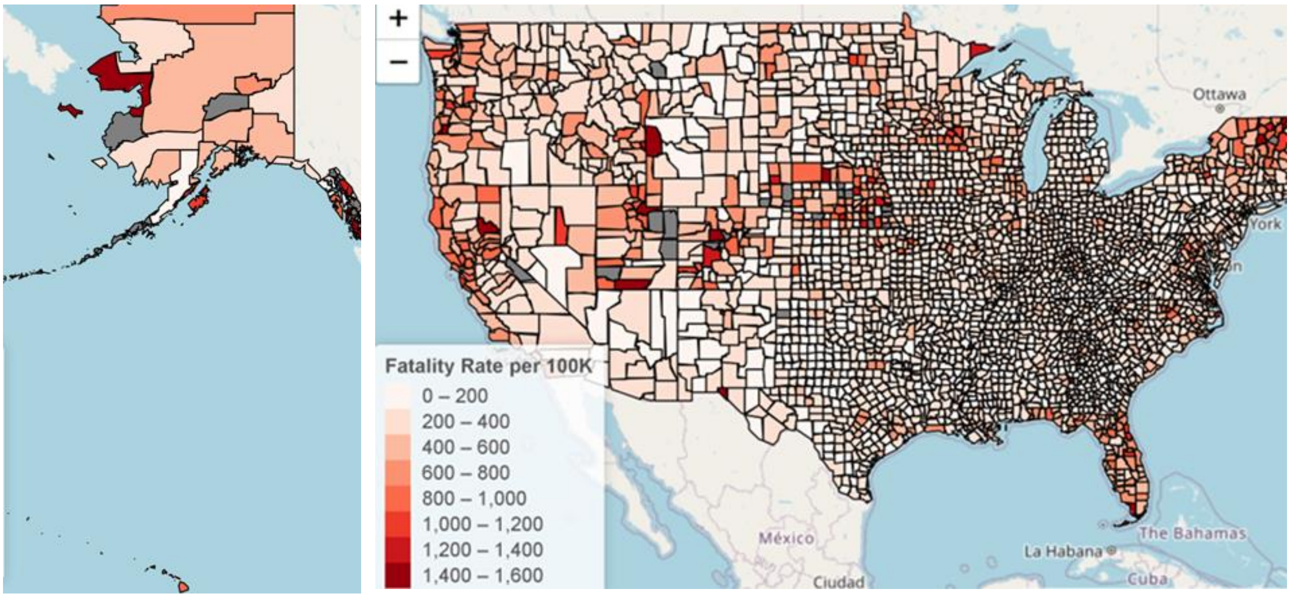

Figure 4. COVID-19 Fatality Rate per 100,000 population (county level). NOTE: counties in gray have in excess of 1,600 fatalities per 100,000.

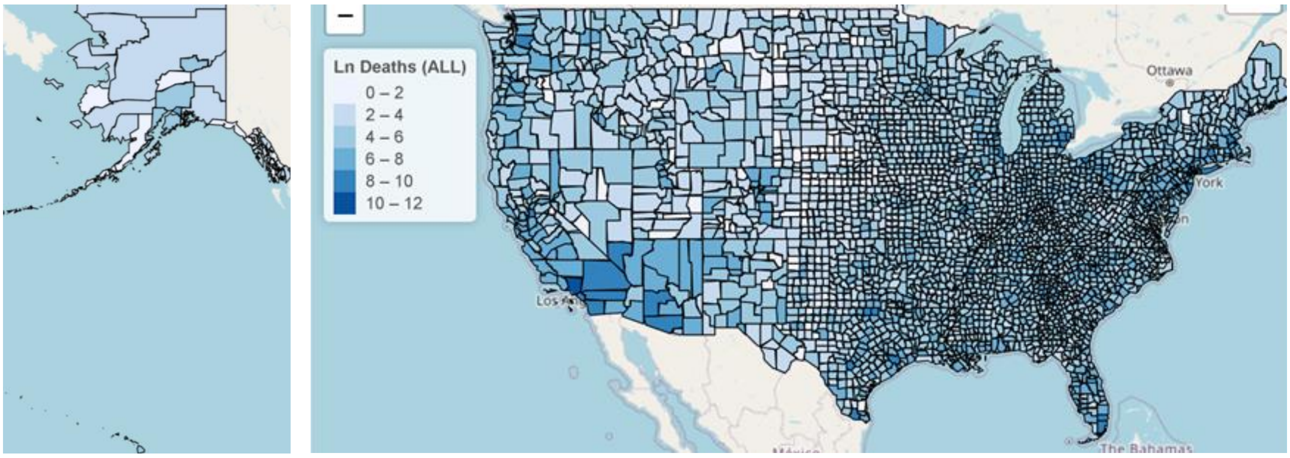

Figure 5. COVID-19 Logarithm of the Sum of Deaths (+1)

Aggregated at the state level, fatality rates per 100,000 individuals (not adjusted for age) were highest in Mississippi (436.54), West Virginia (420.61), Alabama (419.28), and Arizona (414.97), while they were lowest in Hawaii (121.2), Vermont (122.28), Utah (157.99), and Alaska (184.68). Table 2 provides a complete enumeration of deaths, populations, and fatality rates per 100,000, while Figure 6 provides a map of the logarithm of the sum of COVID-19 Deaths (+1) for counties where the mean is greater than the variance (N=137).

Table 2. Deaths, population, and fatality rate per 100,000 persons (sorted by fatality rate)

State	ΣDeaths	Population	Rate / 100 K	State	ΣDeaths	Population	Rate / 100 K
MS	12,992	2,976,149	436.54	MO	19,993	6,137,428	325.76
WV	7,538	1,792,147	420.61	IA	10,229	3,155,070	324.21
AL	20,558	4,903,185	419.28	DE	3,148	973,764	323.28
AR	12,523	3,017,804	414.97	IL	39,381	12,671,821	310.78
NM	8,675	2,096,829	413.72	CT	11,034	3,565,287	309.48
TN	28,113	6,829,174	411.66	TX	89,662	28,995,881	309.22
AZ	29,852	7,278,717	410.13	MA	21,035	6,892,503	305.19
MI	39,574	9,986,857	396.26	ID	5,237	1,787,065	293.05
NJ	34,940	8,882,190	393.37	ND	2,232	762,062	292.89
LA	18,136	4,648,794	390.12	WI	15,516	5,822,434	266.49
KY	17,363	4,467,673	388.64	VA	22,231	8,535,519	260.45
FL	82,541	21,477,737	384.31	NC	27,264	10,488,084	259.95
GA	40,449	10,617,423	380.97	MD	15,578	6,279,560	248.07
OK	14,992	3,956,971	378.88	CA	95,990	39,512,223	242.94
NV	11,580	3,080,156	375.96	NE	4,562	1,934,408	235.83
NY	73,097	19,453,561	375.75	CO	13,409	5,758,736	232.85
PA	47,994	12,801,989	374.89	MN	12,806	5,639,632	227.07
IN	24,950	6,732,219	370.61	OR	8,726	4,217,737	206.89
RI	3,698	1,059,361	349.08	NH	2,761	1,359,711	203.06
SD	3,078	884,659	347.93	ME	2,711	1,344,212	201.68
SC	17,869	5,148,714	347.06	DC	1,392	705,749	197.24
OH	40,249	11,689,100	344.33	WA	14,653	7,614,893	192.43
MT	3,577	1,068,778	334.68	AK	1,351	731,545	184.68
WY	1,917	578,759	331.23	UT	5,065	3,205,958	157.99
KS	9,620	2,913,314	330.21	VT	763	623,989	122.28
				HI	1,716	1,415,872	121.2

After finding the mean, $\bar{y}$ and dispersion, s_y^2, we eliminated all those counties in which the dispersion is more than the mean. In other words, we screened and selected the counties with under dispersion, which is a requirement for the IPD model. Exactly 137 counties had under dispersion. These counties are depicted in Figure 6 and online.

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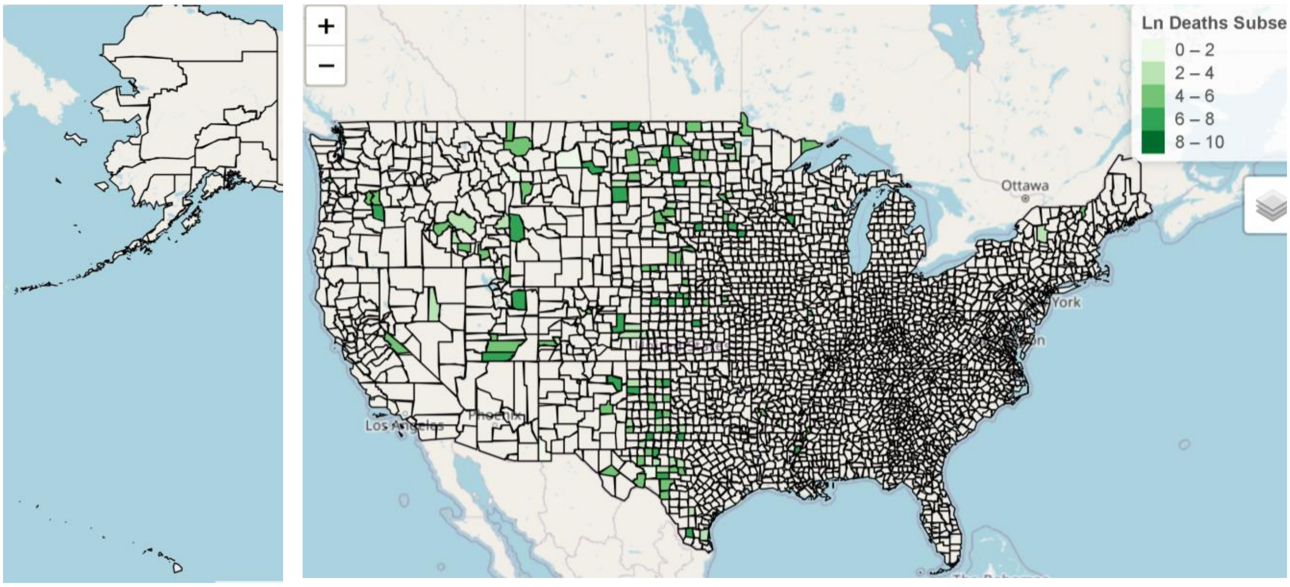

Figure 6. Logarithm of the Sum of COVID-19 Deaths (+1) for counties where the mean is greater than the variance (N=137)

The efficacy and the mortality parameters of these counties were estimated using non-linear optimization as described previously. Of the 137 counties which were observed to have under dispersion, only 25 were statistically significant at the α=.05 level. The estimates for the statistically significant counties are summarized in Table 3 and depicted in Figure 7.

Table 3. Summary of county, state, n, dispersion, mean, estimate of efficacy of efforts, p-value for COVID mortality.

County	State	s_y^2	$\bar{y}$	$\hat{\theta}$	$\hat{\rho}$	p-value
Mono	CA	0.00681	0.00685	0.00183	0.03846	0.023
Fremont	ID	0.02852	0.02935	0.00776	0.08412	0.032
Mahnomen	MN	0.01732	0.01761	0.00468	0.06017	0.027
Humphreys	MS	0.04588	0.04599	0.01244	0.01312	<0.001
Meagher	MT	0.00970	0.00978	0.00261	0.03624	<0.001
Brown	NE	0.00196	0.00196	0.00052	0.02345	0.037
Hooker	NE	0.00196	0.00196	0.00052	0.02345	0.037
Phelps	NE	0.00970	0.00978	0.00261	0.03624	<0.001
Rock	NE	0.00196	0.00196	0.00052	0.02345	<0.001
Sherman	NE	0.00390	0.00391	0.00104	0.04787	0.043
Camden	NC	0.00970	0.00978	0.00261	0.03624	0.001
Benson	ND	0.02202	0.02250	0.00606	0.01428	<0.001
Cavalier	ND	0.00681	0.00685	0.00183	0.03846	0.004
Griggs	ND	0.00196	0.00196	0.00052	0.02345	<0.001
Steele	ND	0.00196	0.00196	0.00052	0.02345	<0.001
Armstrong	TX	0.00970	0.00978	0.00261	0.03624	<0.001
Cochran	TX	0.02202	0.02250	0.00606	0.01428	<0.001
Kenedy	TX	0.00196	0.00196	0.00052	0.02345	<0.001
Martin	TX	0.02482	0.02544	0.00688	0.00024	<0.001
Roberts	TX	0.00196	0.00196	0.00052	0.02345	0.037

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Stonewall	TX	0.00681	0.00685	0.00183	0.03846	0.023
Throckmorton	TX	0.00970	0.00978	0.00261	0.03624	0.012
Upton	TX	0.01732	0.01761	0.00468	0.06017	0.027
Yoakum	TX	0.03945	0.04110	0.01092	0.07399	<0.001
Garfield	UT	0.00970	0.00978	0.00261	0.03624	<0.001

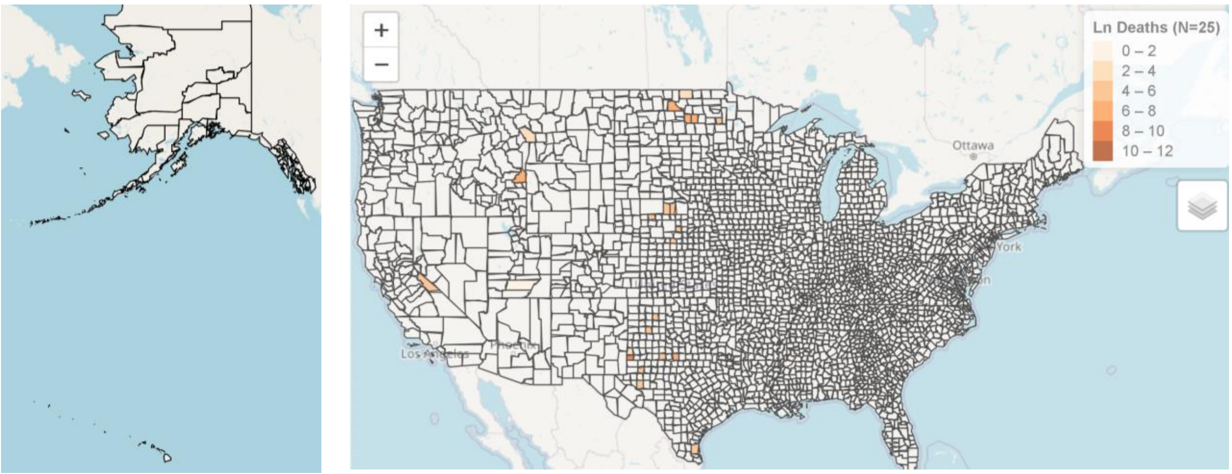

Figure 7. Logarithm of the Sum of COVID-19 Deaths (+1) for N=25 counties where the mean is greater than the variance and with p<.0.05.

4. Discussion

The IPD provides a probabilistic method for indexing inefficacious response efforts during pandemics. In our analysis we discovered that 25 of the 137 counties were likely inefficient. By identifying these counties during a pandemic, efforts to identify and address the inefficiencies might be pursued. Since COVID-19 is likely not to be the last pandemic, the index generated by our analysis will be useful for future pandemics.

Some of these counties may have reasonable explanations for under dispersion. For example, Mono County, California experienced extreme particulate matter due to the wildfires in 2020, and COVID-19 deaths on these 'wildfire days' were higher [23]. Thus, a sustained high level of COVID-19 fatalities might be associated with environmental conditions. Kenedy, Texas was considered 'high-risk' for transmission of COVID-19 for various reasons, and thus might have experienced under dispersion [24]. Garfield County, Utah experienced a decline in population due to death during the pandemic [25], which might be due to pandemic prevention efforts themselves. Hooker County, Nebraska was previously identified as a high-incident outlier [26]. Neighboring Brown County may be associated with the same problematic interventions. Many of the counties in Texas had populations with high-risk comorbidities [27]. Failure to implement effective prevention measures might have exacerbated death rates. Other counties would need additional investigation to determine explanations.

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5. Conclusions

COVID-19 is only a single pandemic; however, it resulted in the death of millions. The ability to identify efficacy of prevention measures using distributions such as the IPD is critical to policymakers, as a finite number of assets are available for intervention. The human suffering and mortality rate had shaken the trust and peace of mind in everyone. Government agencies did formulate and implement preventive and treatment policies; however, the assessment of these policies might have been assisted through the use of mathematical models such as the IPD. Policies that were assumed to be effective might have been rapidly assessed using reasonable probability distribution assumptions.

The study is based on secondary analysis, which is common when experimental designs are infeasible. Still, the classification of inefficacious versus efficacious is based on a reasonable probability model that might be affected by other factors not included in the study. Additional models would probe this limitation further. Finally, the study is limited by the validity of the data collected by the Centers for Disease Control & Prevention, although the results are likely not influenced largely by accidental input errors.

The findings in research article identified those United States counties in which the efforts to stop the escalation of COVID-19 mortality were inefficient. In this research process, we have created an approach of indexing the inefficiency of the healthcare operations *during* a pandemic prior to formal modeling. This index might be used in future pandemics to identify those entities which are implementing inefficacious policies. The index can provide decision makers areas that require interventional assistance. The techniques proffered herein should prove useful for indexing efforts in future pandemics.

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All four authors equally contributed to all five sections.

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Data Availability Statement: The data are open source as referenced in the paper.

Conflicts of Interest: There is no conflict of interest to publish the findings in this research.

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