COVID-19 Mortality Prediction

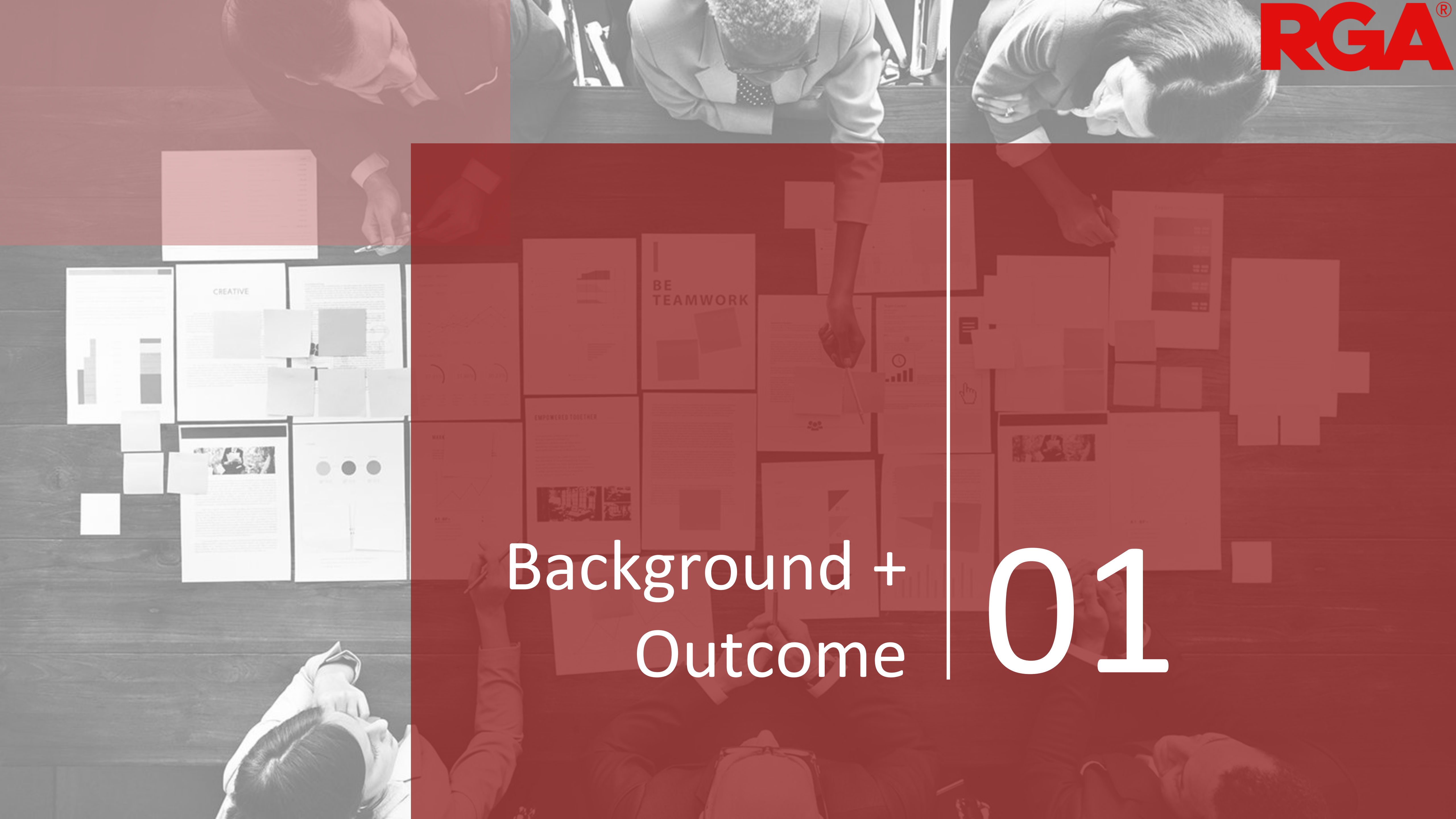
Group Wonder Penta (WashU)

- Ziwei Shen
- Shiyan Yang
- Stacey Shi
- Vivian Zhong

12/16/2022

Agenda

1	Background + Outcome
2	Data Description
3	Model Construction
4	Recommendation
5	Q&A
6	Appendix



Background + Outcome

01

Background + Outcome

Problem Background: COVID-19

- SARS-CoV-2
- Respiratory droplets, spread when breaths, talk, or sneeze
- Several variants

Original	Alpha & Beta	Delta	Omicron
Beginning of 2020	**Late 2020**	**Summer 2021**	**Nov 2021**
First discovery & Outbreak, WHO declared global pandemic	First appear in Great Britain and South Africa	First identified in Late 2020 in Great Britain	First identified in Botswana and South Africa.

Background + Outcome

Problem Background: Company

- Global life and health reinsurance company
- Business:
  - Reinsurance
  - Living benefits reinsurance
  - Group reinsurance
  - Health reinsurance
  - Financial solutions
  - Facultative underwriting
- Location
  - US and Latin America
  - Canada
  - Asia
  - Europe, Middle East and Africa

Background + Outcome

Problem Background: Problem Definition

- How to predict mortality rate due to COVID-19
  --Approach death by bass model and SIRD
  --Estimate the relationship between death and factors such as vaccine, gender, race, seasonal change, etc

- $11 million per 10,000 general population deaths

Background + Outcome

Outcome: Model Comparison

Bass Models

For U.S. & For States
Use Death Only
Daily/Weekly/Monthly

SIRD Model

For U.S. population
Include cases

GBM

For U.S. population
Include Vaccine
Daily/Weekly/Monthly

Outcome – Validation Result

Outcome: Model Comparison

Predictions	Next Day Forecast 11/30	7-Days Forecast 11/21-11/27	Next Month Forecast November 2022
U.S. Bass Model	356	2728 (11/23-11/29)	11057
State Bass Model	184	Daily Model: 1312 Weekly Model: 1798	Daily: 5755 Weekly: 7525 Monthly: 8926
SIRD	384	2572	12191
Actual	**577**	**2074**	**9985**

Outcome – Future Prediction

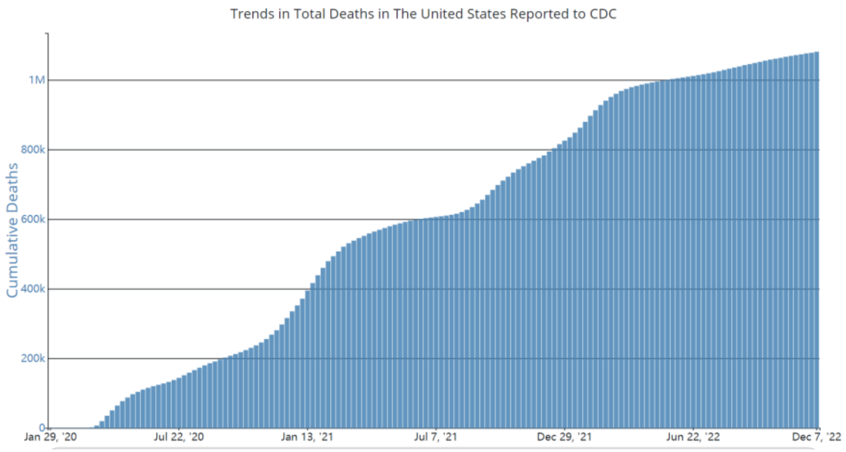
Outcome: Model Prediction

	Next Month Forecast December 2022	**Next Year Forecast 2023**
U.S. Bass Model	Daily: 10373 Weekly: 9955 Monthly: 9799	Daily: 59074 Weekly: 64740 Monthly: 56526
State Bass Model	Daily: 5484 Weekly: 6500 Monthly: 7877	Daily: 44377 Weekly: 40318 Monthly: 44527
SIRD	11189	63827
Range	**5484 ~ 11189**	**40318~64740**

Data Description

02

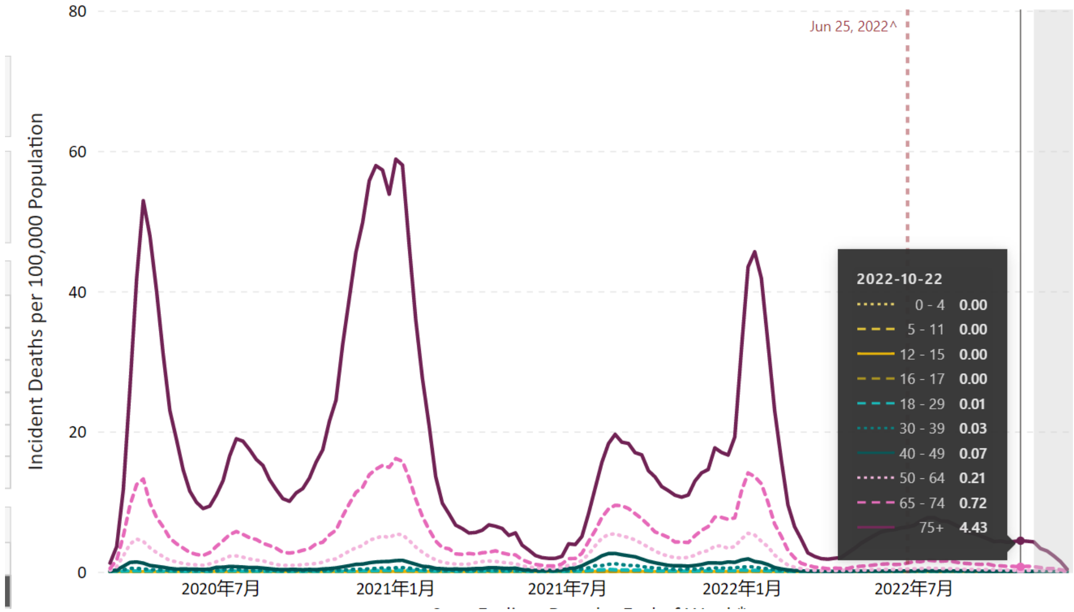
Data Description—Development timeline



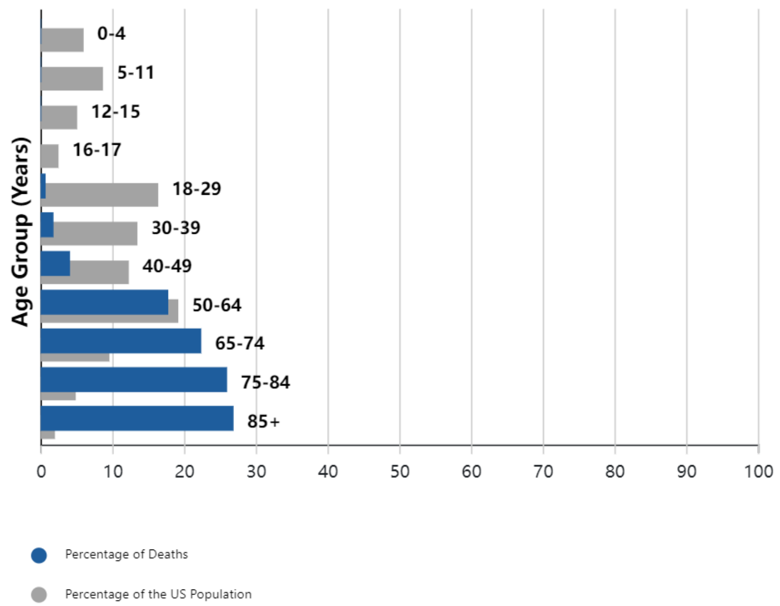
- Happened around Jan 2020
- Twice peak time—Jan 2021 and Jan 2022
- Number of daily deaths decreased to below 1k
- Reached the best situation ever

Data Description—Death by AGE

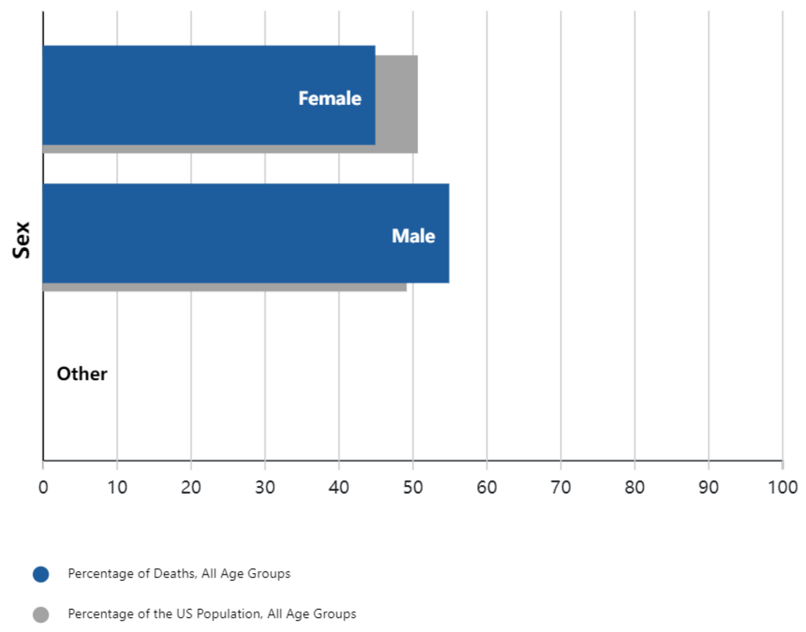
Same development pattern for all ages



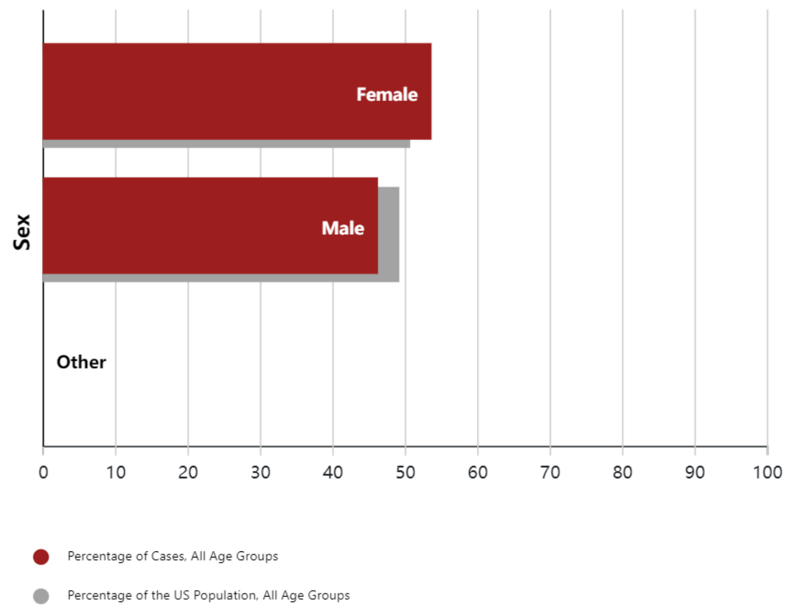
The older people are, the higher the death rate



Data Description—Death by GENDER

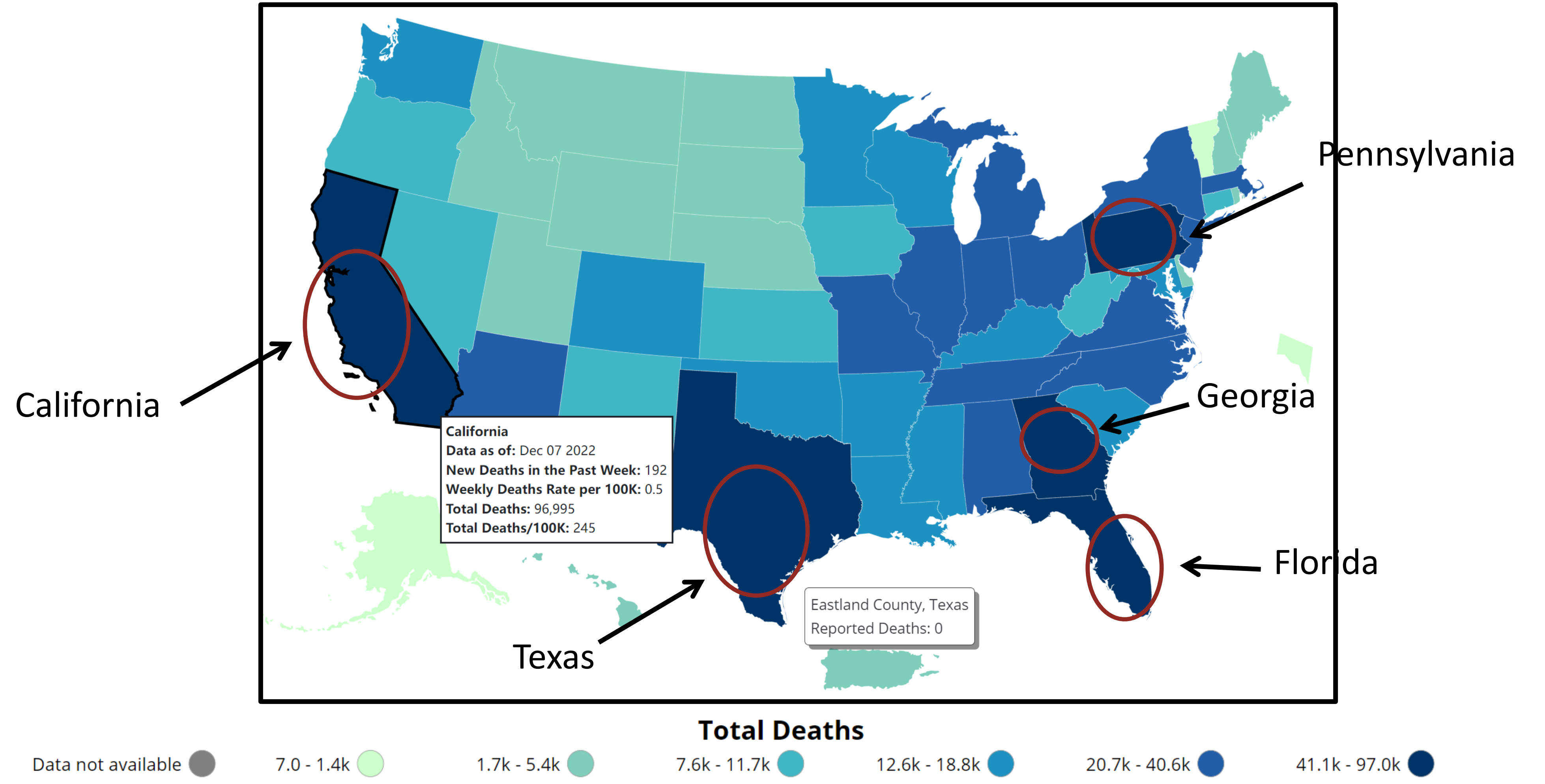


Deaths by Sex

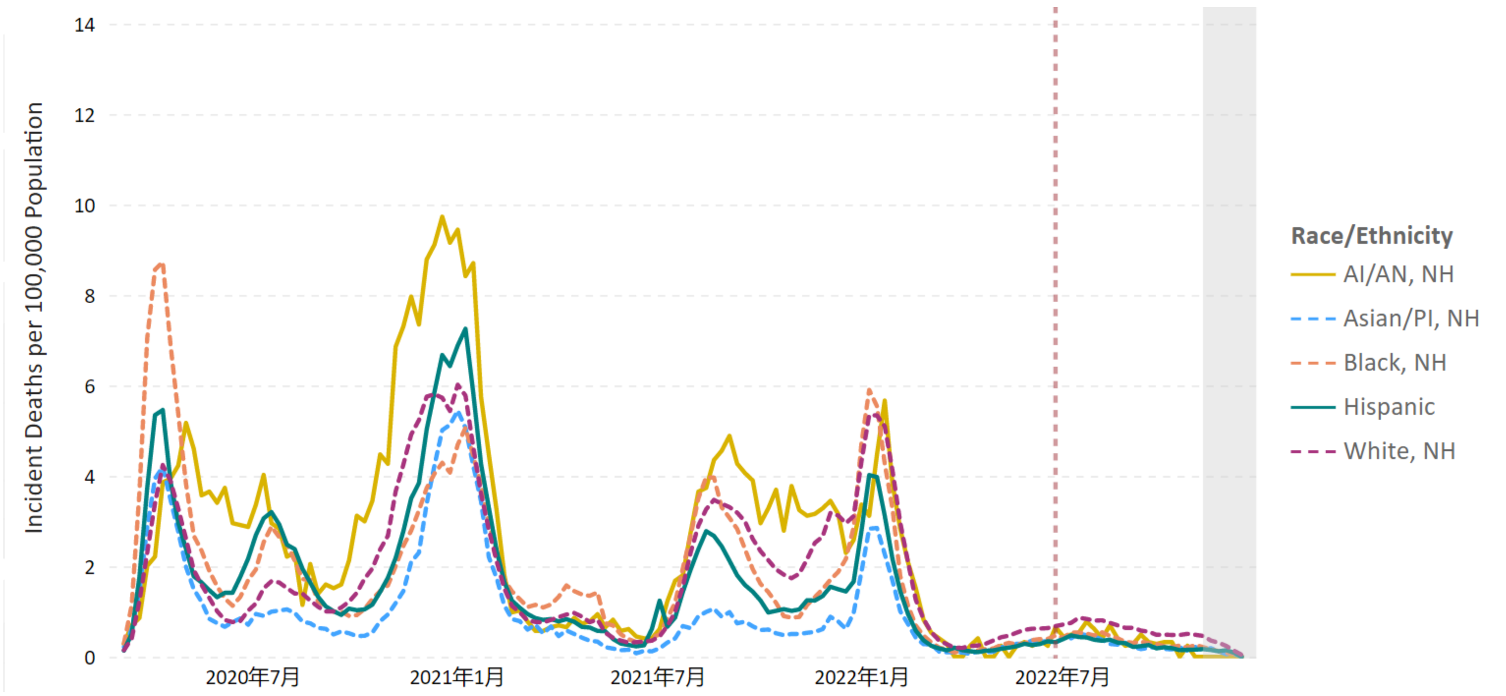


Cases by Sex

Data Description—Death by REGION



Data Description—Death by RACE

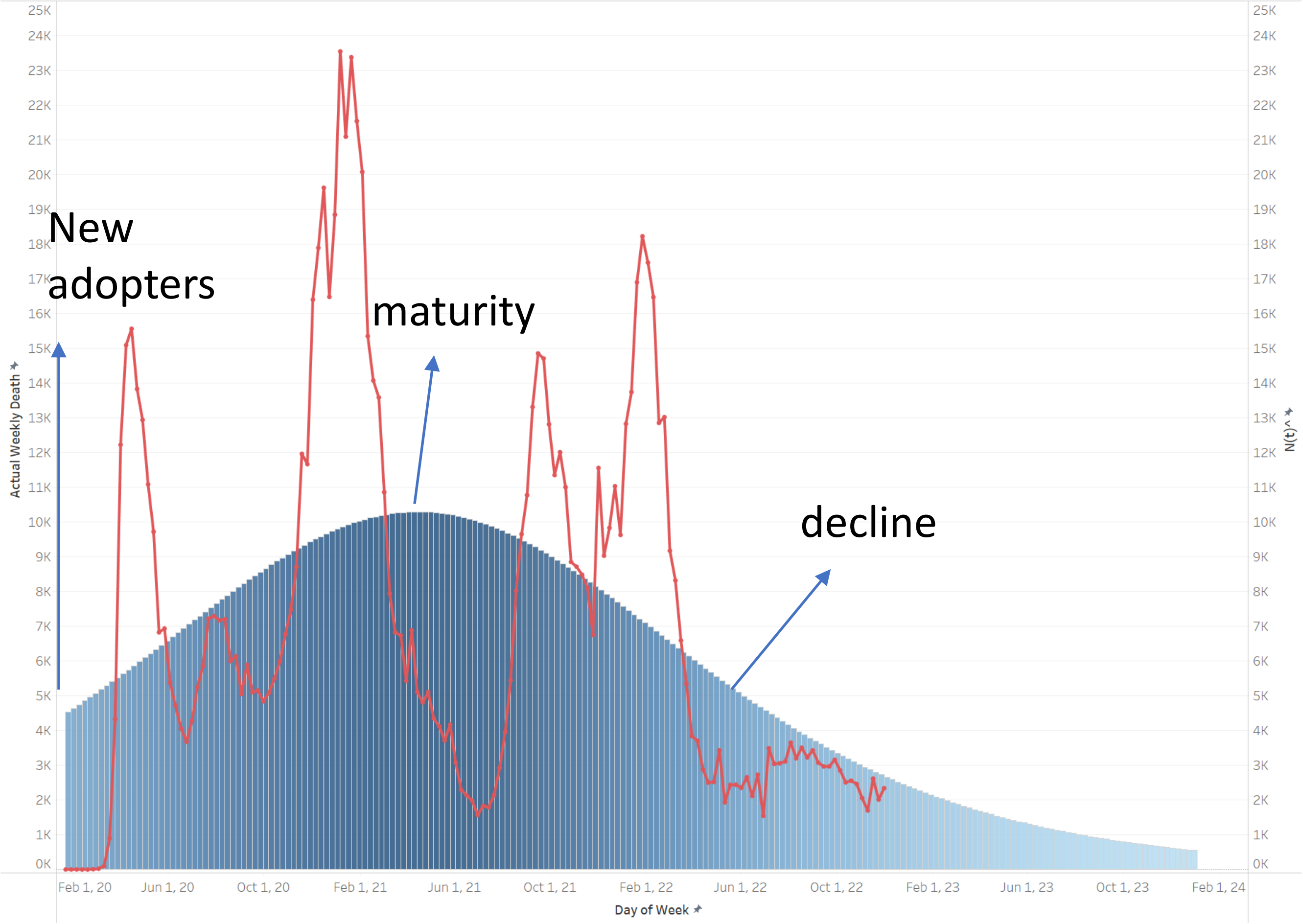


- No clear difference
- There was one time that American Indians and Alaska Natives had terrible number of death
- Asian race have relative better situation
- Death of black race from COVID-19 was most in the beginning.

03 Models Construction

Bass Model Overview

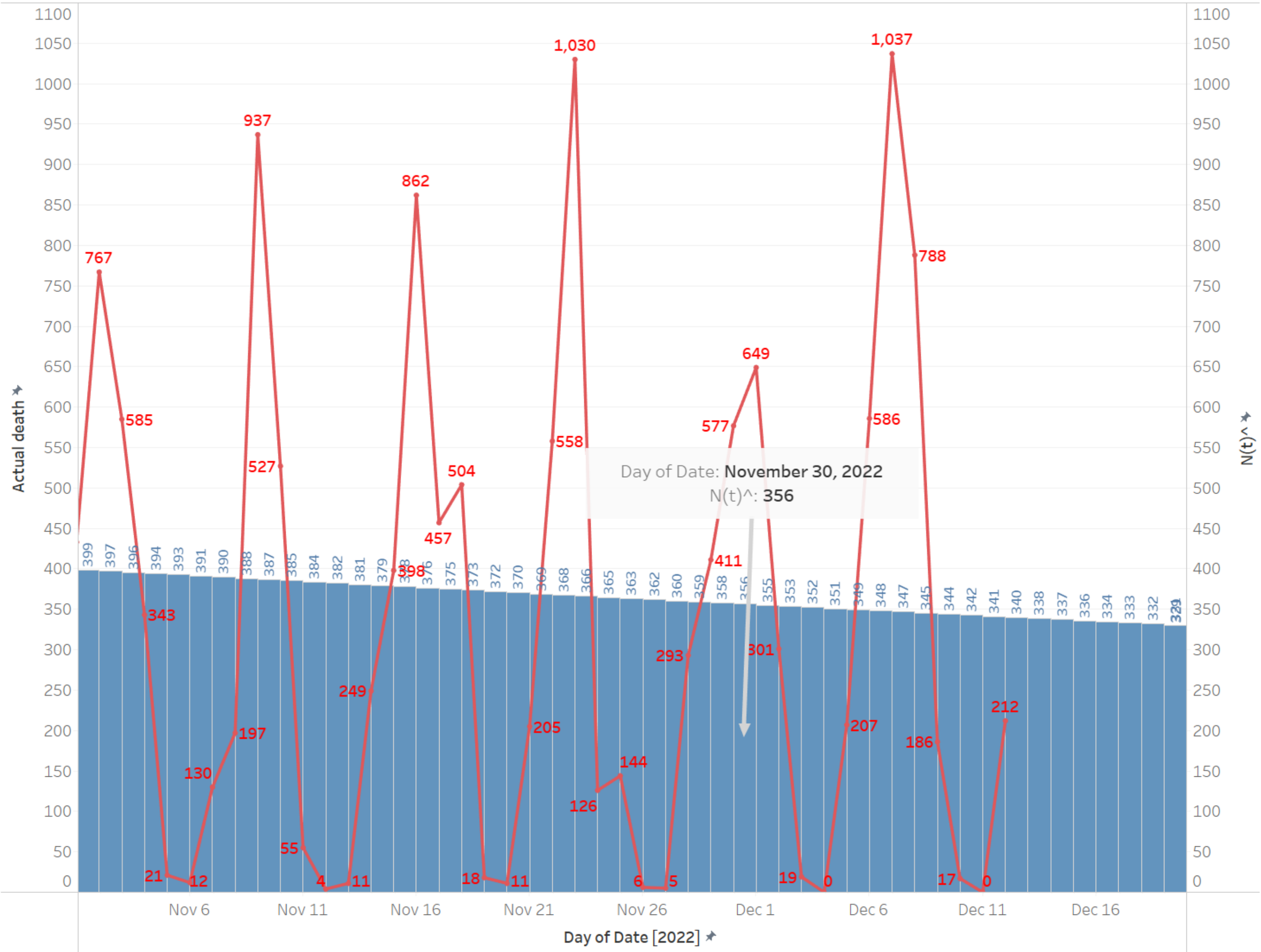
Like a new product adoption model in marketing



- The Bass Model approach and fit the model for COVID in a **bell shape**.
- Approximate the ***p, q, m*** with the smallest SSE between prediction and actual death in Solver:
  - p: coefficient of intrinsic susceptibility
  - q: coefficient of infectable susceptibility
  - m: susceptible population, the total number of people who will die from COVID
- Like a new product adoption with **new adopters, maturity and decline stage**
- Bass model believes we are in **a decline stage of death**

Bass Model - Daily

Predict death daily from Bass Model is not very accurate.



Red Line: Actual Death

The reporting of daily death is fluctuating. Daily prediction is not very accurate. Hospitals may not update records every day.

Blue Bar: Predicted Death on Nov. 30, 2022

356

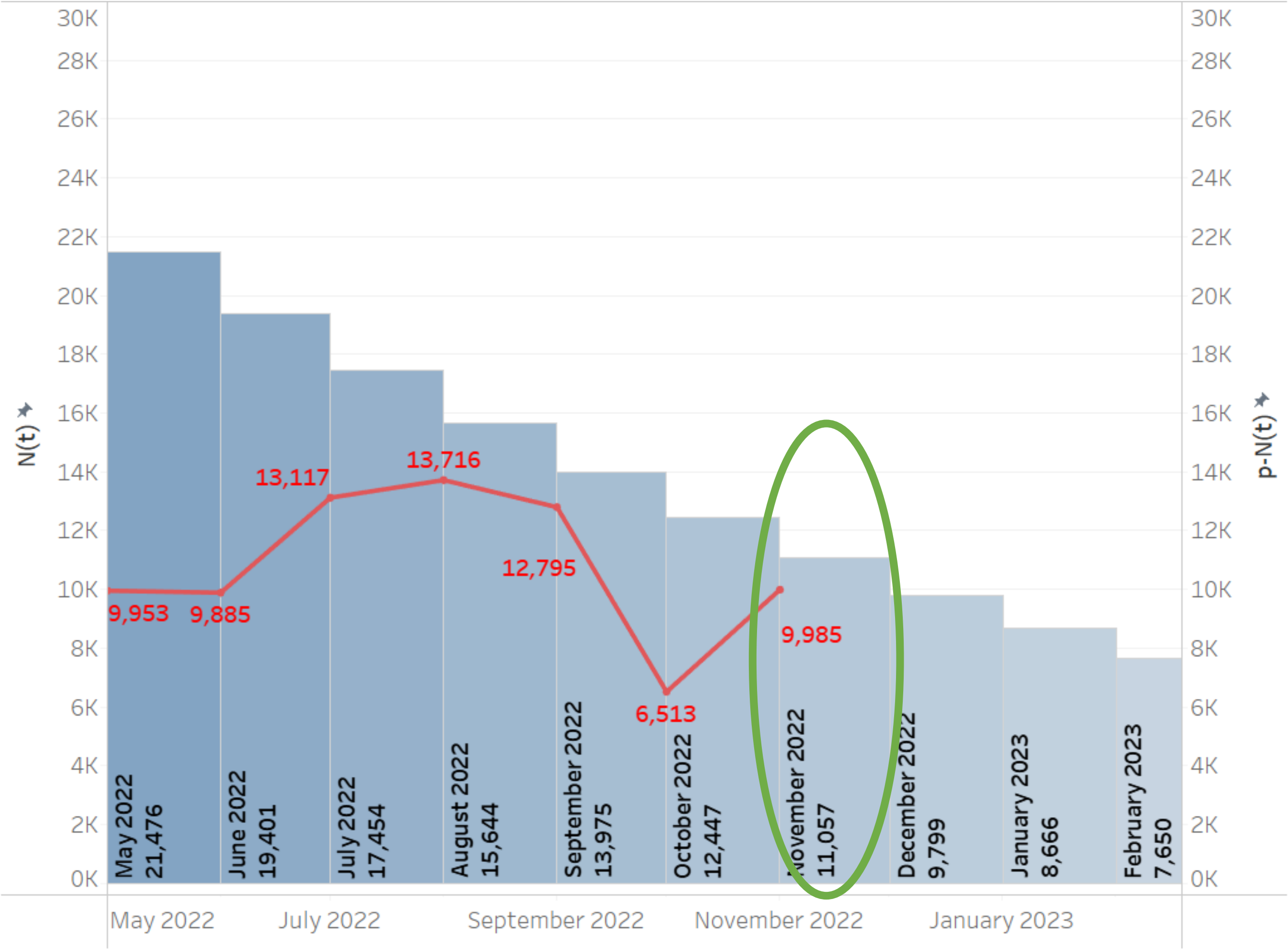
Average Difference between test and validation

577-356=221

The prediction is more of average of recent days instead of approaching the actual number of that day.

Bass Model - Monthly

The difference between actual and prediction is smaller than daily model



Actual Death in November 2022

9985

Predicted Death in November 2022

11,057

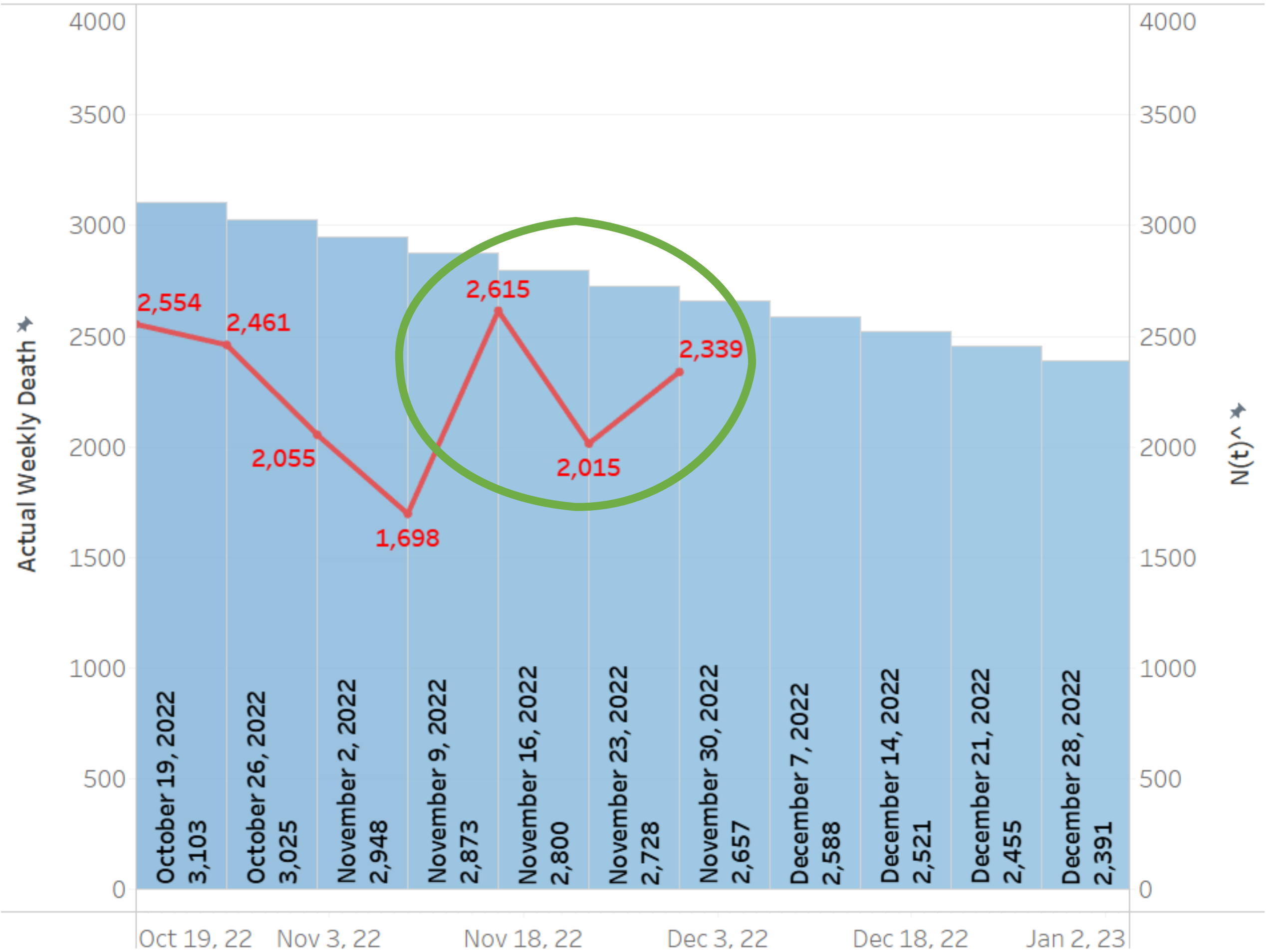
Difference between test and validation

1072

Prediction for next month is the most accurate

Bass Model - Weekly

The most accurate among US bass models



Red Line: Actual Death

2055; 2615; 2015; 2339

Blue Bar: Predicted Death in those three weeks

2948; 2800; 2728; 2657

Difference between test and validation

645

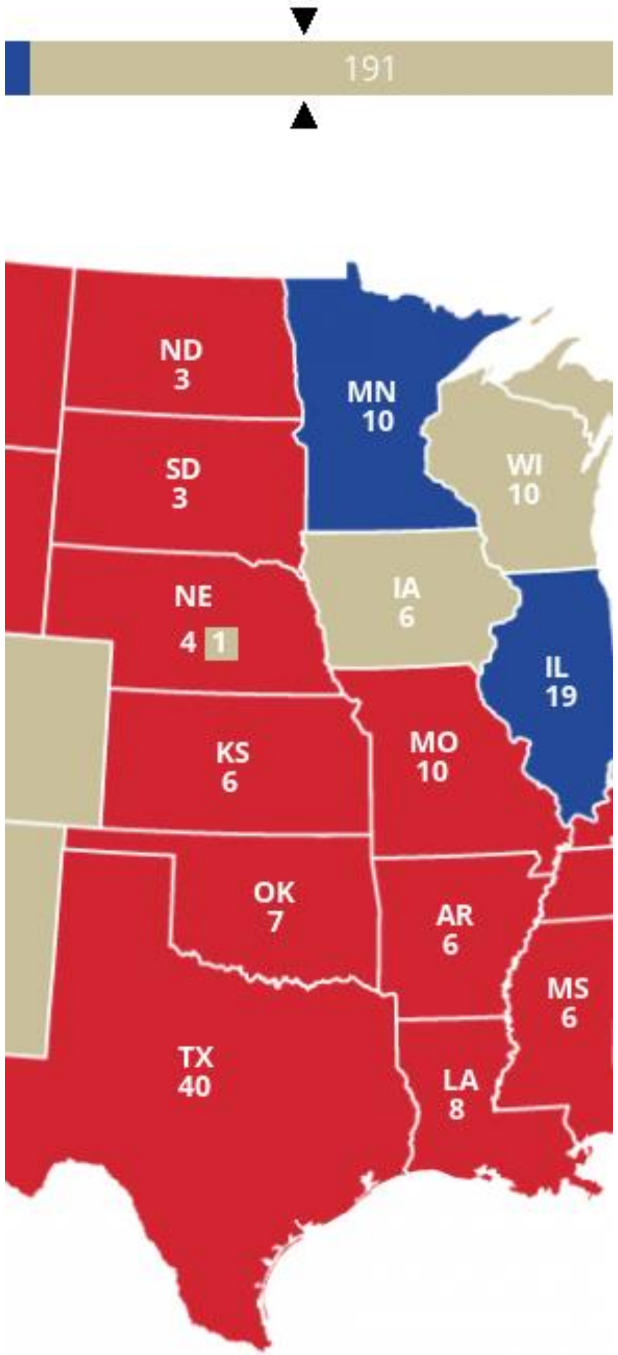
Having Weekly level in bass model approaching total death in the U.S. is the most accurate

Bass Model Prediction

All bass models predict that in 2025 COVID-19 death would fade out

~60,000 deaths -> $60m-70m extra claims

	12/17/2022	12/17/2022-12/23/2022	December 2022	2023	2024	2025
Daily Bass Model Prediction	333	2305	10373	59074	12129	2374
Weekly Bass Model Prediction		2455	9955	64740	14137	2962
Monthly Bass Model Prediction			9799	56526	11402	2202



Predict Death in State Degree

- Run Bass model in every state
- Make predictions through daily, weekly, monthly levels
- Utilize python to find the optimal solution of parameters(p, q, m) for each state
- Sum up all predicted data from all states
- Compare the predicted outcomes and the real value

Bass Model on State degree-Daily

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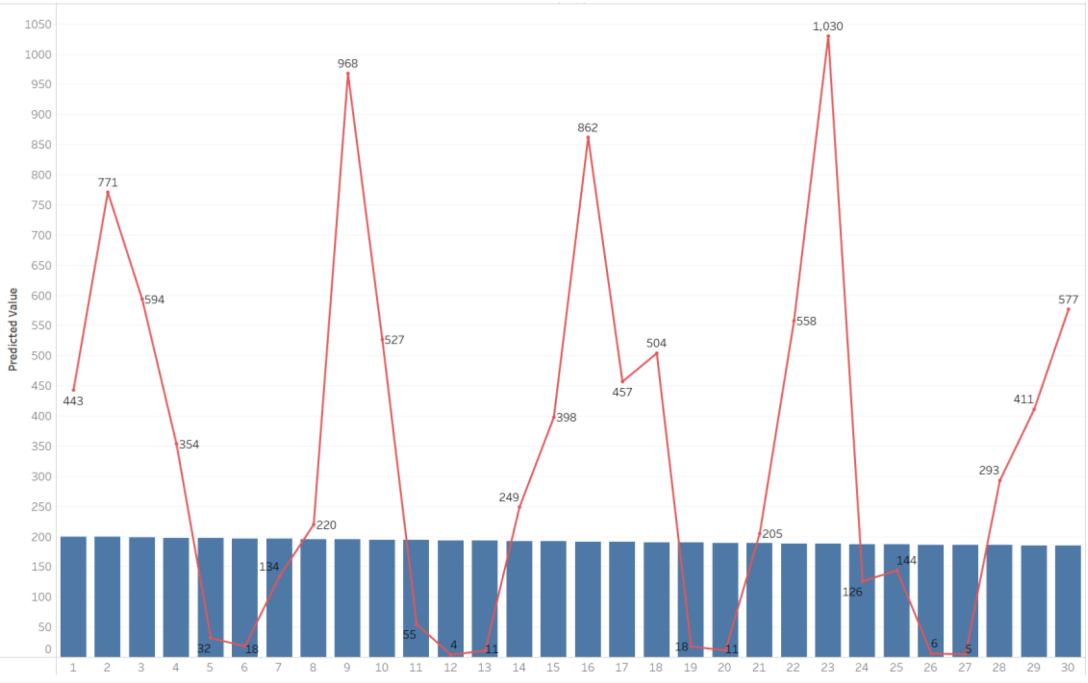


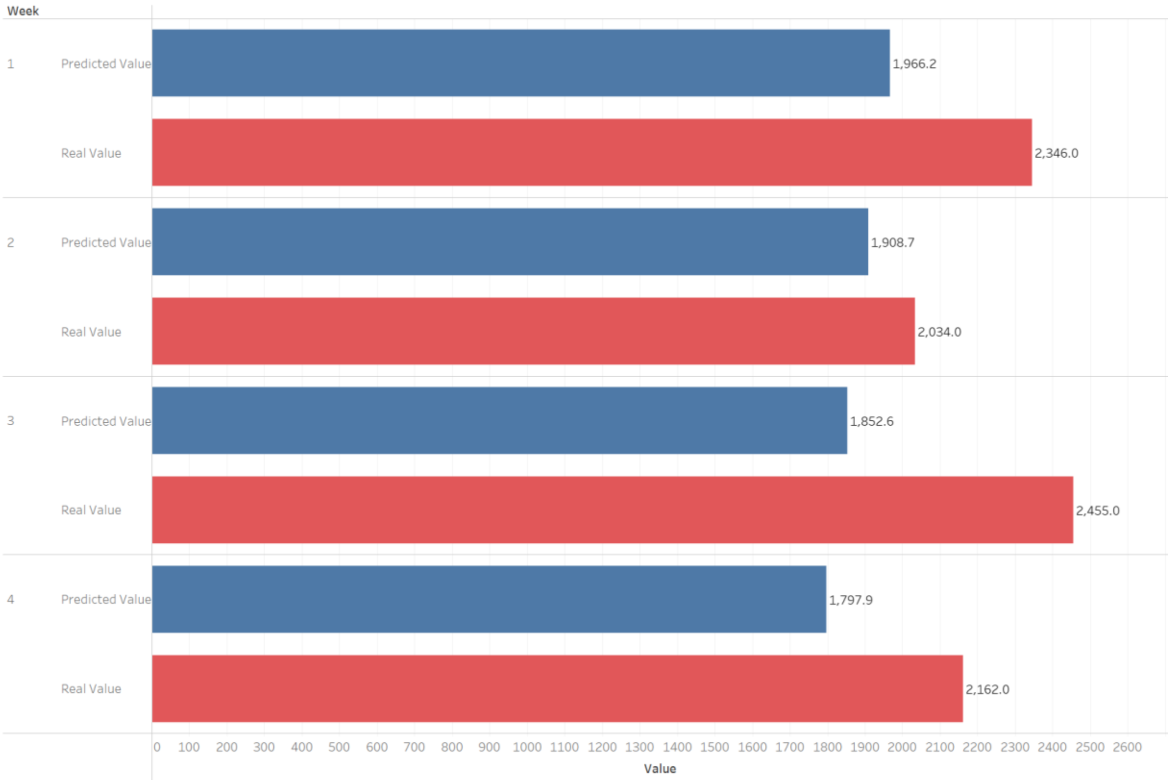
- In the validation month of November, differences between predicted and actual deaths are big (>50)

Week o..	Sunday	Monday	Tuesday	Date Wednesday	Thursday	Friday	Saturday
Week 45			✗ -243	✗ -572	✗ -396	✗ -156	✗ 165
Week 46	✗ 179	✗ 62	✓ -24	✗ -773	✗ -332	✗ 139	✗ 190
Week 47	✗ 182	✗ -56	✗ -206	✗ -670	✗ -266	✗ -314	✗ 172
Week 48	✗ 178	✓ -16	✗ -370	✗ -842	✗ 61	✓ 43	✗ 180
Week 49	✗ 181	✗ -108	✗ -226	✗ -393			

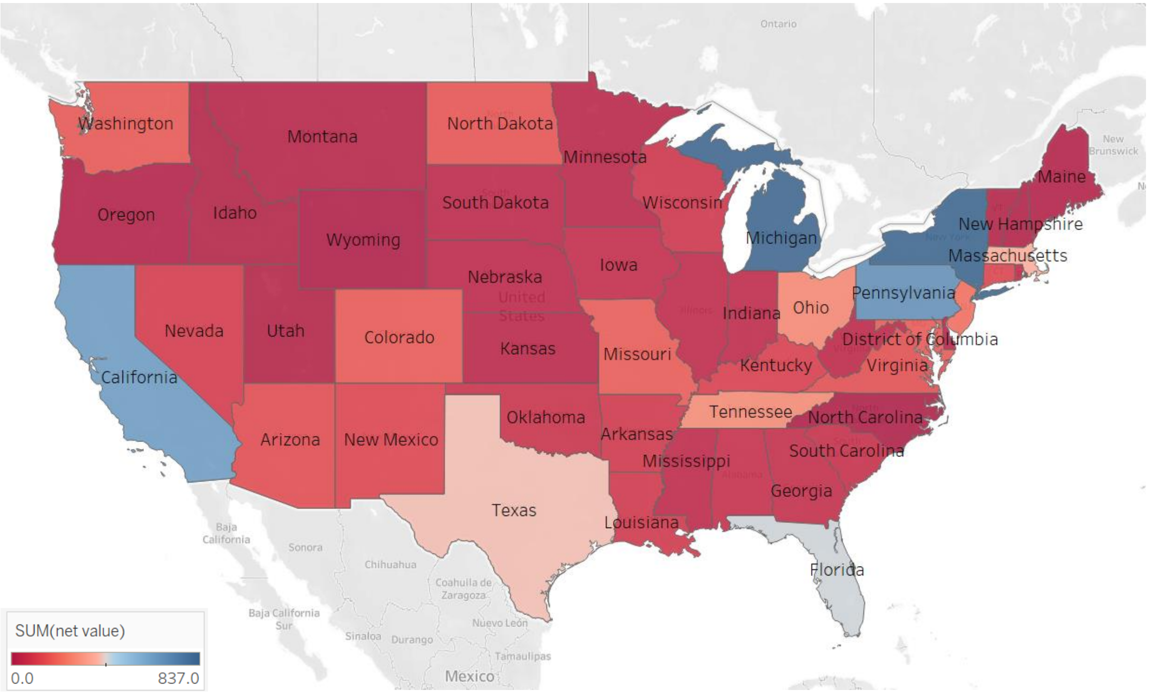
- Difference between predicted value and real value is big
- The predicted values have a smooth line without big fluctuations
- Perform poorly compared to the U.S. degree

Bass Model on State degree-Weekly

- Predicted death in November 2022--1966, 1908, 1852, 1797
- Quite similar between predicted values and real values
- Performs better than the daily model
- A decreasing tendency for predicted model while real value is fluctuating



Bass Model on State degree-Monthly



Red areas have better performance in approaching bass model

Predicted Death in November 2022

8916

Difference between predicted death and real death:

1068

No fit area: not suitable for Bass Model

California, Michigan, New York

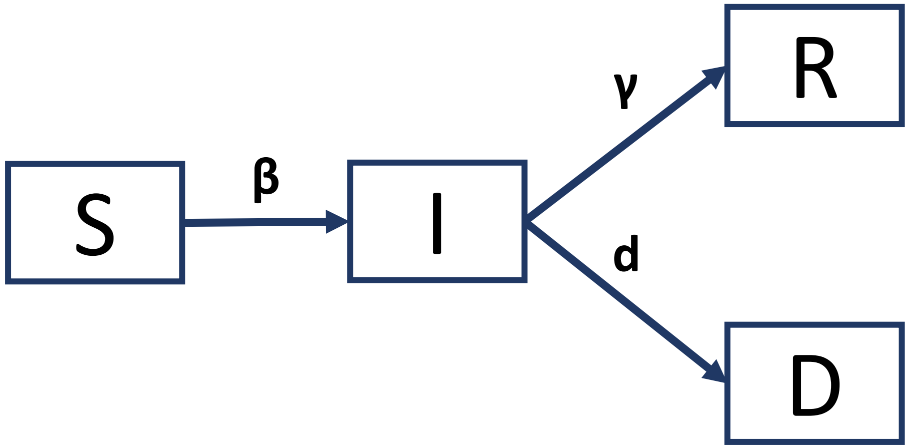
- These states have a huge difference between predicted and actual death when running a bass model

Compare All State Degree Bass Models

	2022/11/30	Real Death	2022/11/21-2022/11/27	Real death	2022/11	Real death
Daily Bass model	184	577	1312	2074	5755	9985
Weekly Bass model			1798		7525	
Monthly Bass model					8926	

SIRD Model Intro

The Susceptible-Infectious-Recovered-Deceased model



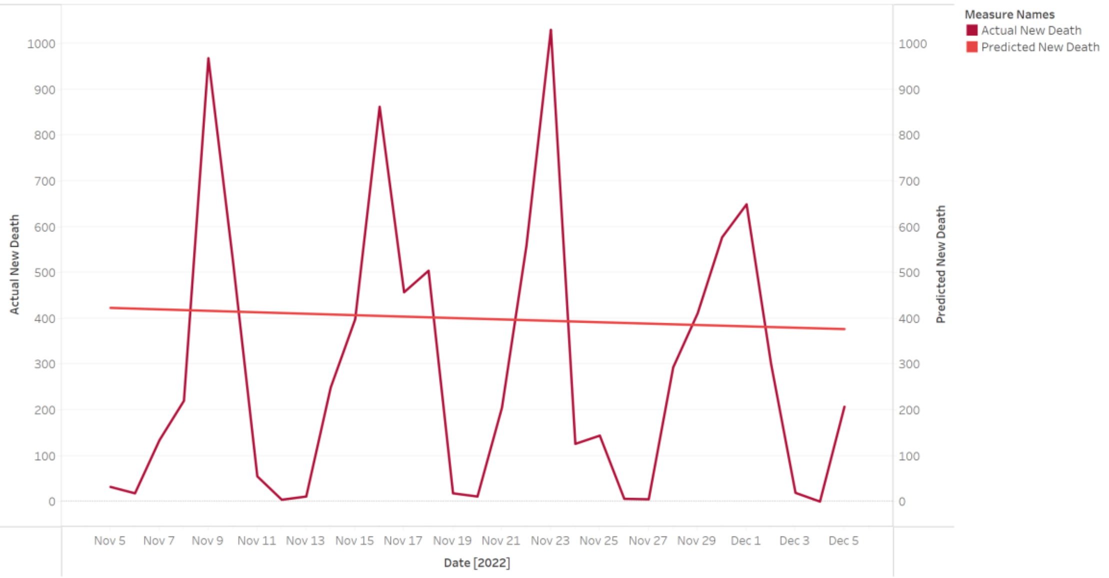
S = The number of susceptible individuals (S0: number of initial susceptible individuals)	
I = The number of infectious individuals (I0: the number of individuals who get infected)	
Beta = Contact Rate	
Gamma = Recovery Rate	
d = Death Rate	

SIRD Model

Comparisons and Predictions

	2022/11/30	Real Death	2022/11/21-2022/11/27	Real death	2022/11	Real death
SIRD	384	577	2572	2074	12191	9985

Recent Comparison



The trends of Actual New Death and Predicted New Death for Date. Color shows details about Actual New Death and Predicted New Death. The data is filtered on F1, which ranges from 1018 to 1048.

Daily Predictions for Dec 16, 2022

360

Monthly Prediction for Dec 2022

11189

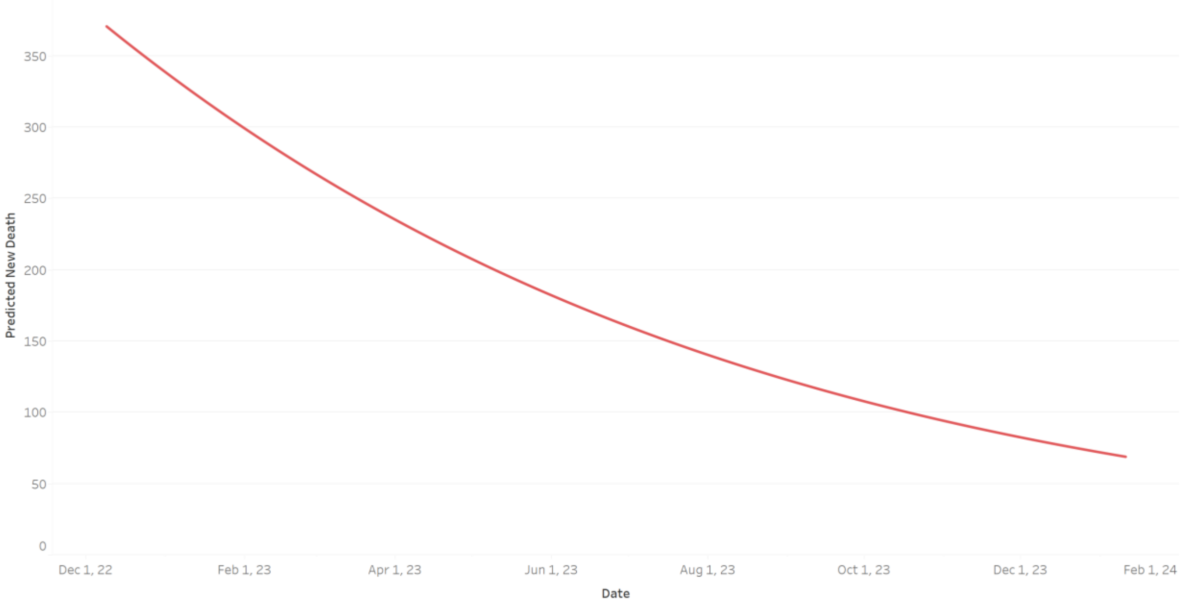
Yearly Prediction for 2023

63827

SIRD Model

Predicted Future Trends

Predicted New Death



The trend of sum of Predicted New Death for Date. The view is filtered on Date, which ranges from 12/9/2022 to 1/11/2024.

Model Trends for Future Deaths

Decreasing Trend

Parameters for S0 + I0

18.3 M:
Total number of people who will be influenced by COVID-19

Generalized Bass Model (GBM)

Allow seeing the influence of Vaccines

$$A(t) = M \frac{1-\exp(-(p+q)t^*)}{1+\frac{q}{p}\exp(-(p+q)t^*)}$$

p	0.000652209
q	0.007680922
M	669025.1021
b	-34.63850985

$$t^* = t + b * \ln\left[\, Vaccine\,(t) \,/\, Vaccine\,(1) \,\right]$$

$- \; - \; * \; +$

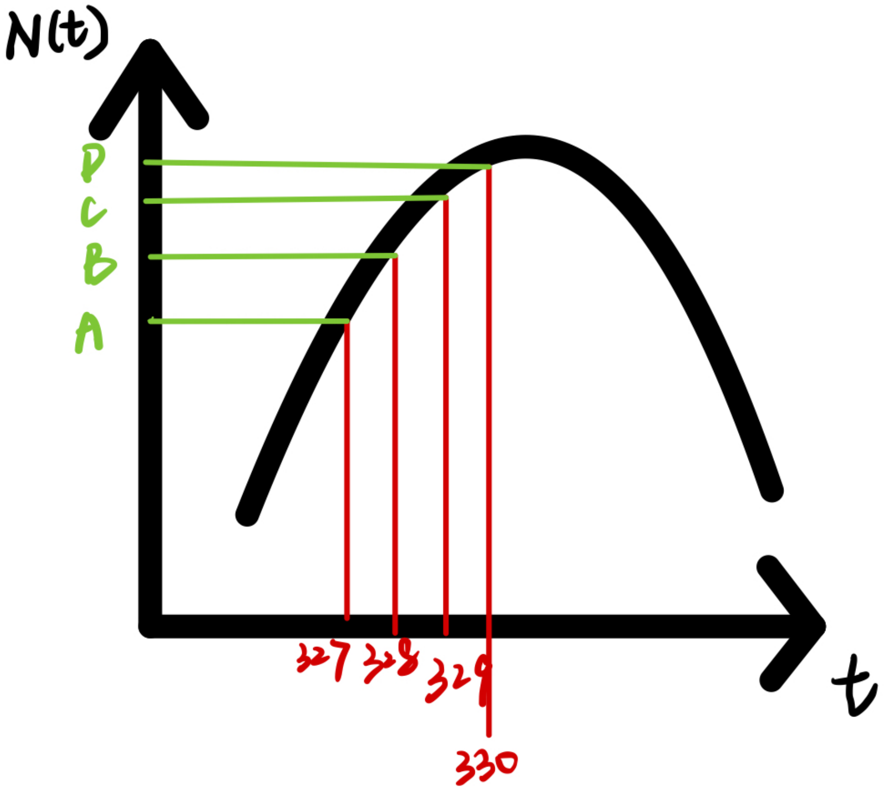
b is negative!

$t^* < t$

Generalized Bass Model (GBM)

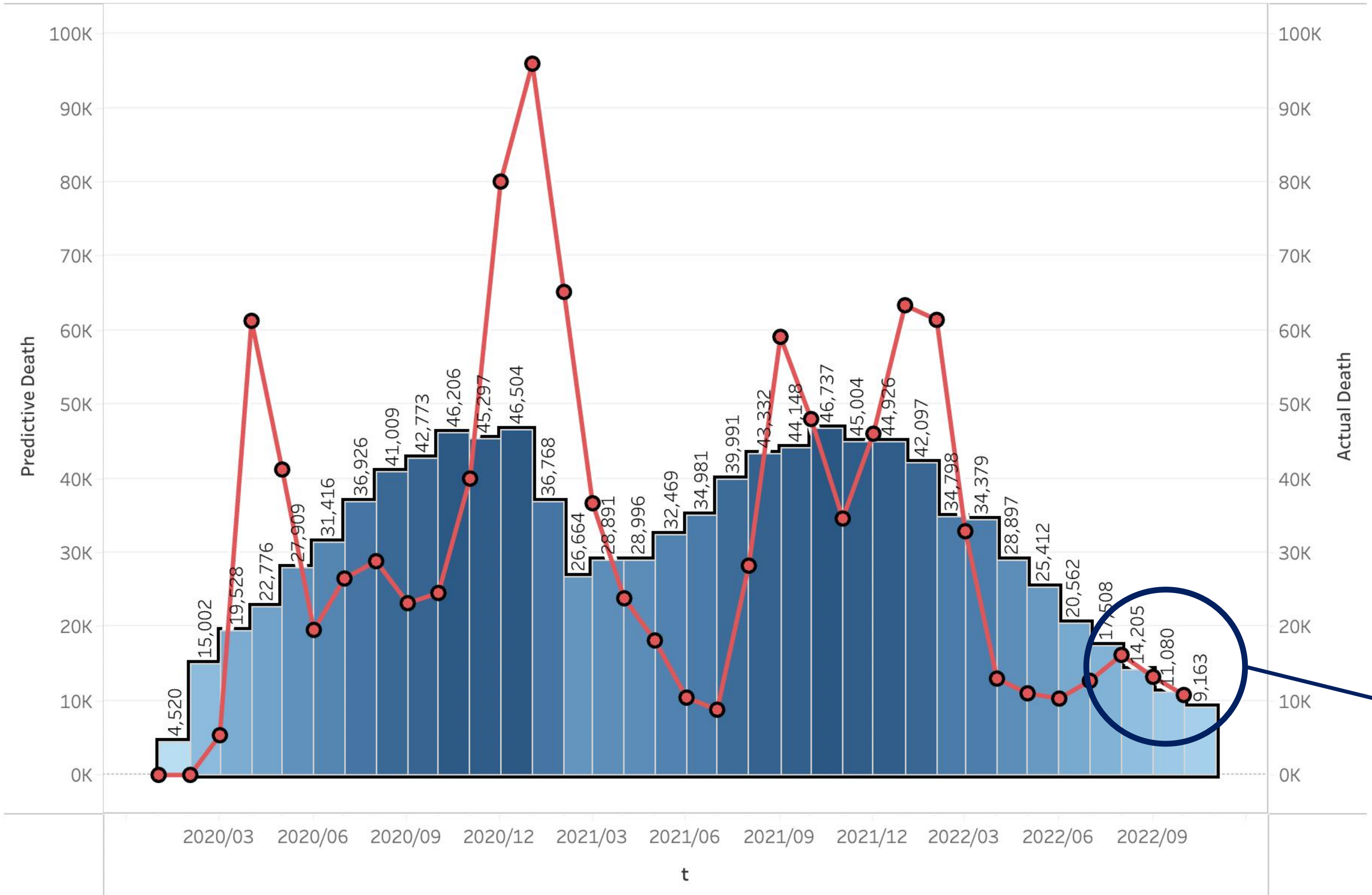
Vaccines effectively <u>slower</u> the speed of new death.

	t		t^*	
B	328		327.40	A
C	329	>	327.21	A
D	330		326.35	A



Generalized Bass Model (GBM)

Prediction accuracy evaluation

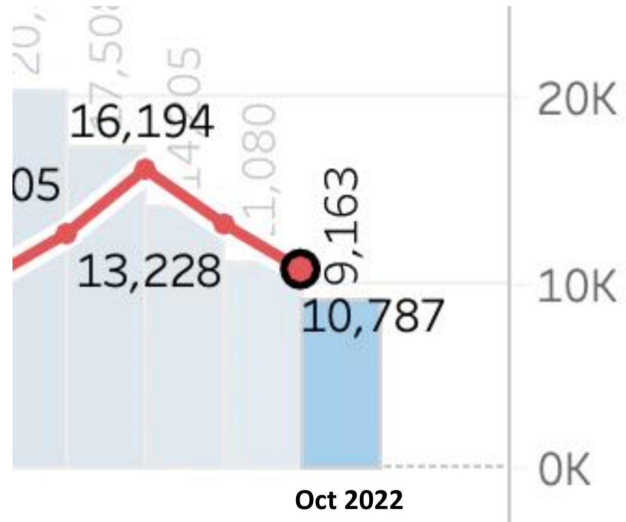


Predictive total death: October 1st-October 31st

9163 Blue Bar chart

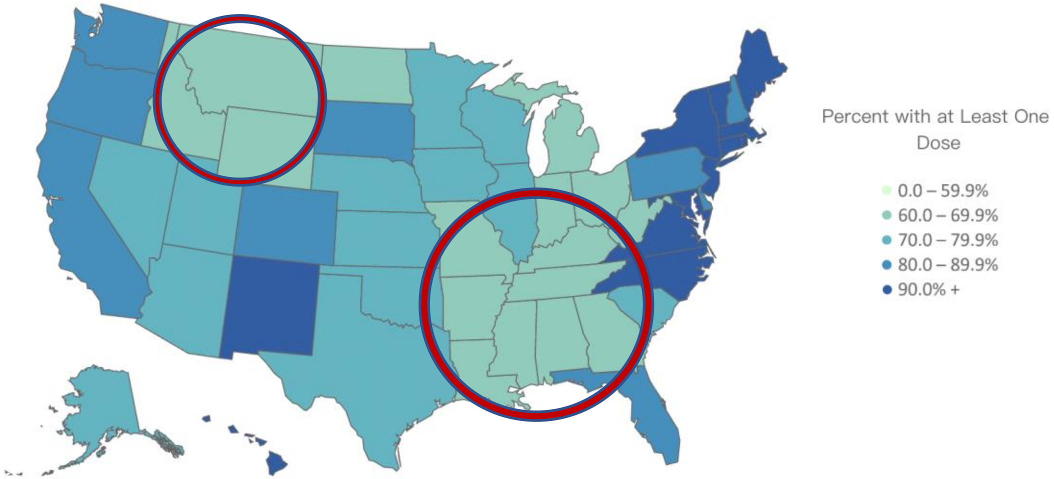
Actual total death:

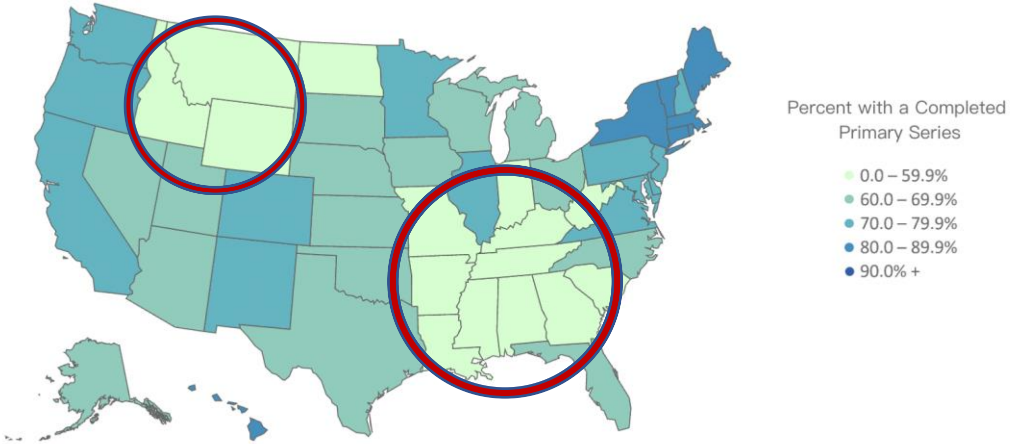
10787 Red Line chart

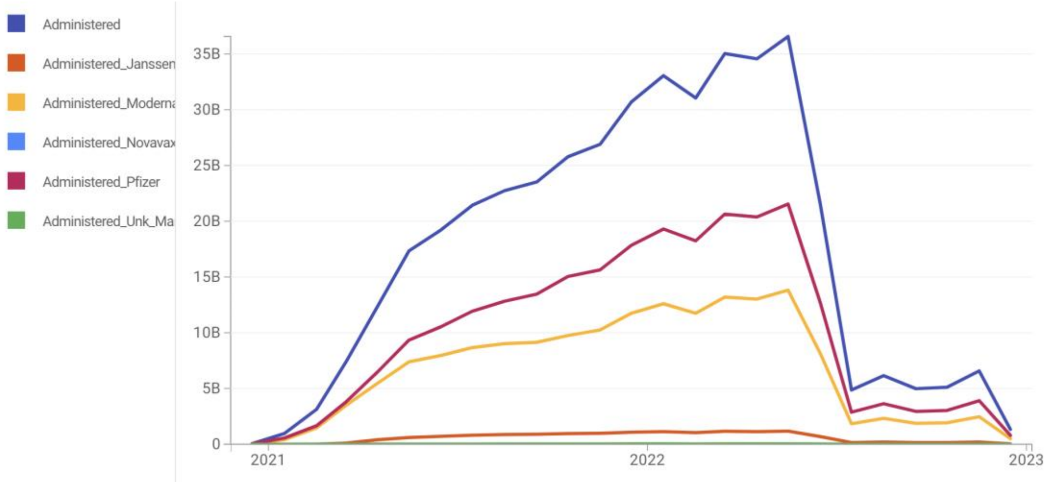


Generalized Bass Model (GBM)

Overview of Vaccines







Focus more on both the north and southeast areas since these areas have lower percentage of vaccine administered.

04 Recommendation

1 Focus on monthly/weekly forecast

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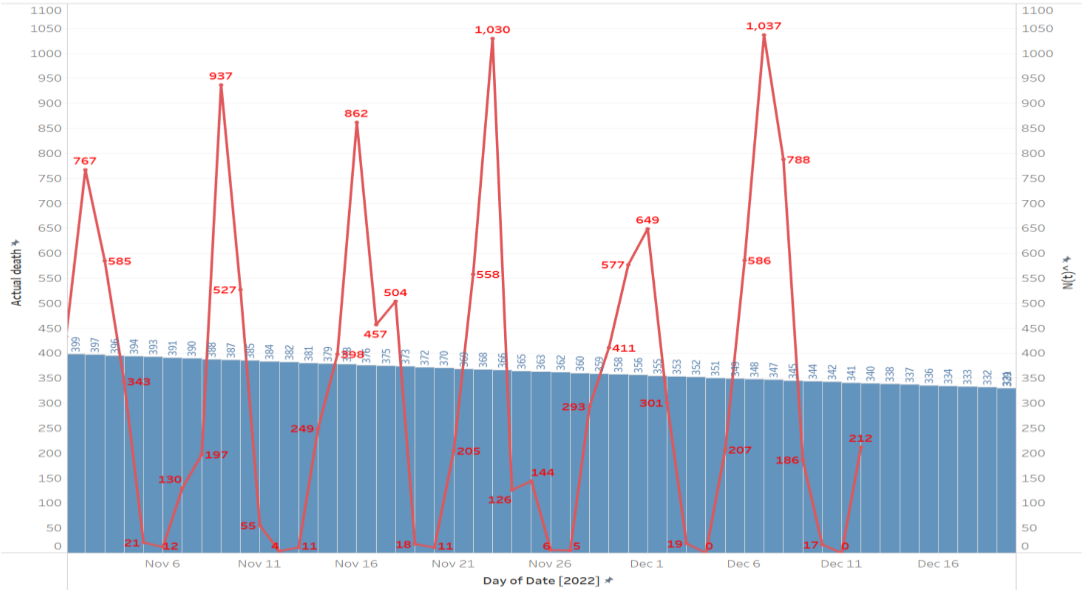
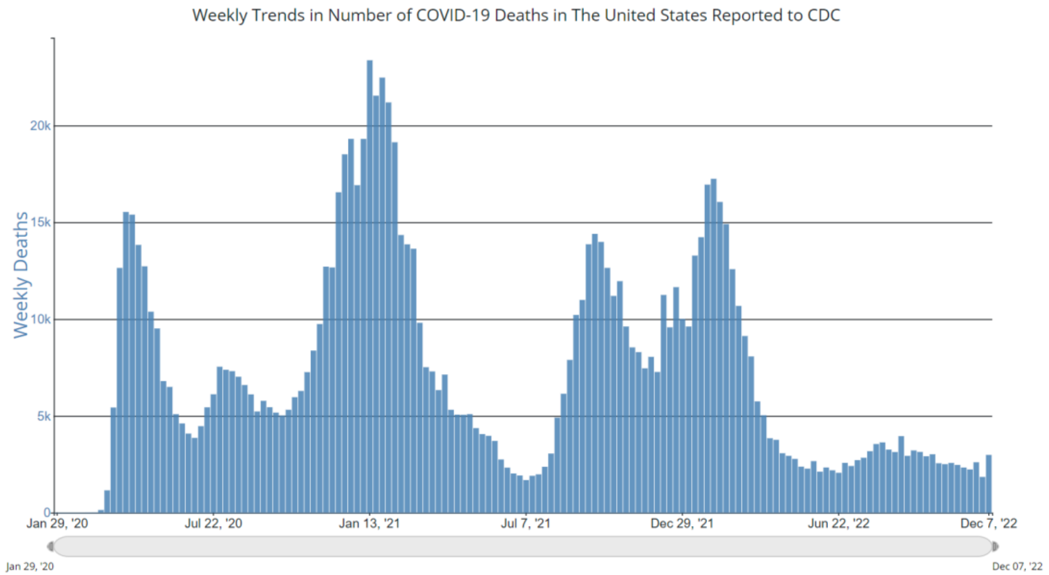


The data of daily deaths comes from JHU dashboard. The report of COVID deaths is more weekly based and fluctuating.



CDC only reports weekly deaths/cases on the official website now.

https://covid.cdc.gov/covid-data-tracker/#trends_weeklydeaths_select_00

Outcomes | Data Description | Model Construction | Recommendation | Q&A

2 Use SIRD/state level bass model as a prediction model

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Models	Next day (11.30)	7-days (11.21-11.27)	next month 11
US Level-Bass model	356	2728	11057
State Level-Bass model	184	1312 daily 1798 weekly	5755 daily 7525 weekly 8926 monthly
SIRD	384	2572	12191
Actual	577	2074	9985

- Next day — SIRD
- 7-days — State Level Bass model (Weekly basis)
- Next month — State Level Bass model (Monthly basis)

3

Focus on separating into smaller areas with bass prediction will yield a more accurate prediction (US level—State level—City level)

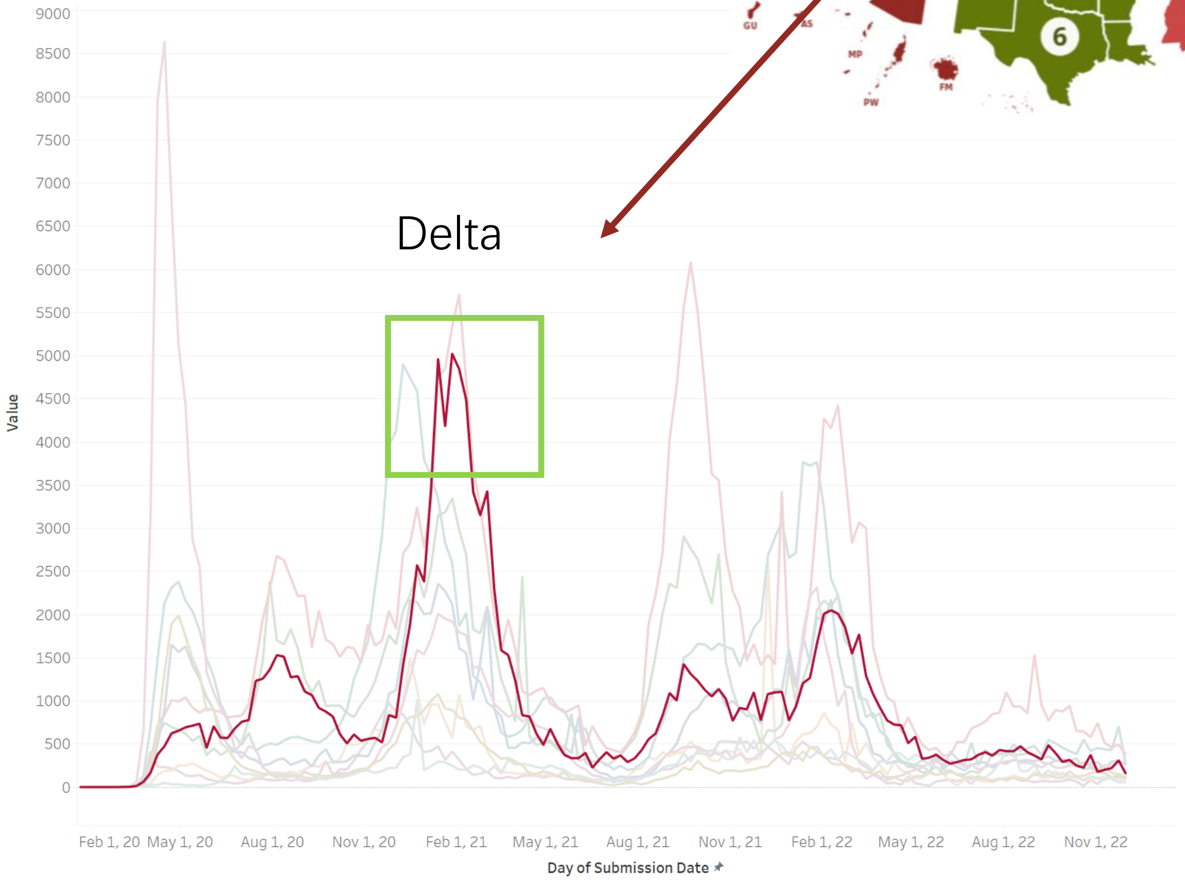
Models	Next day (11.30)	7-days (11.21-11.27)	next month 11
US Level-Bass model	356	2728	11057
State Level-Bass model	184	1312 daily 1798 weekly	5755 daily 7525 weekly 8926 monthly
SIRD	384	2572	12191
Actual	577	2074	9985

Overall, bass model in a state level yield a more accurate prediction. We could focus on city level in the future

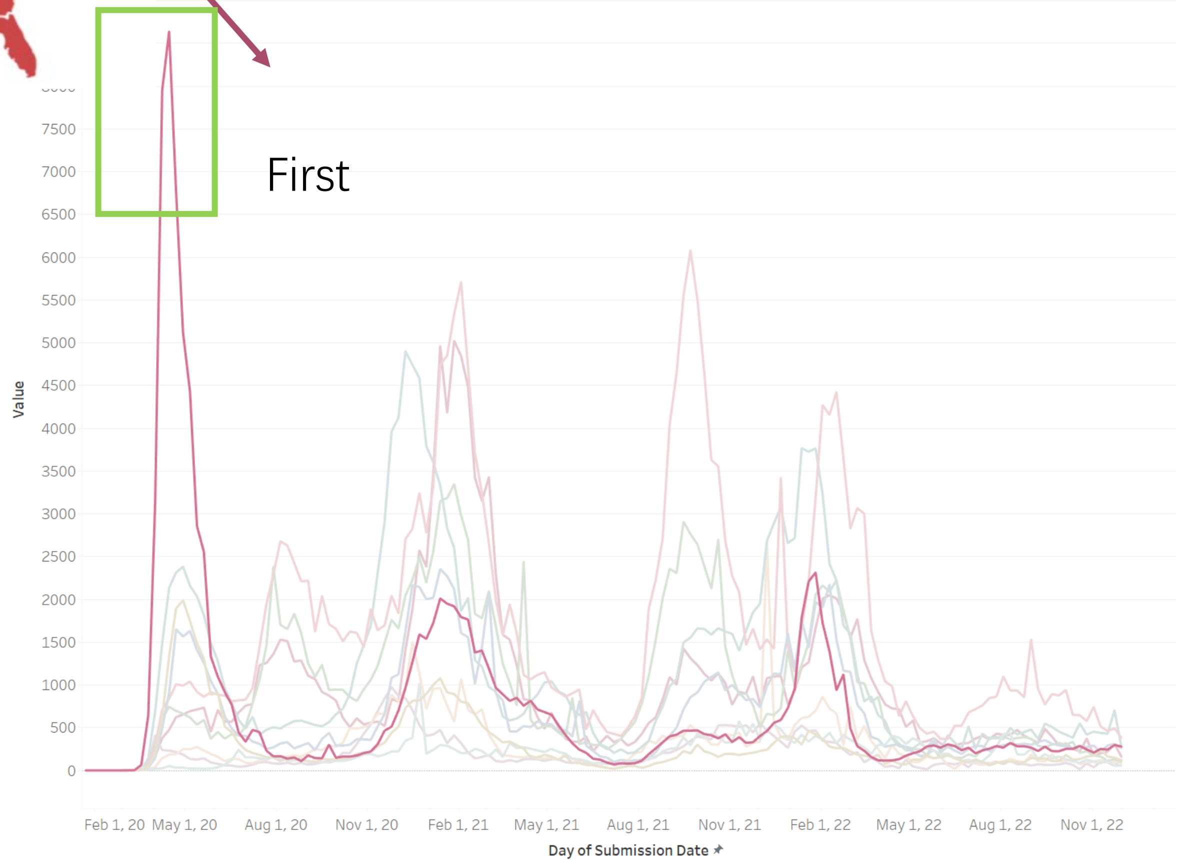
Running model in a regional level and then aggregate data together in a US level would be better.

4 Promote reinsurance in certain areas like Seattle and Florida

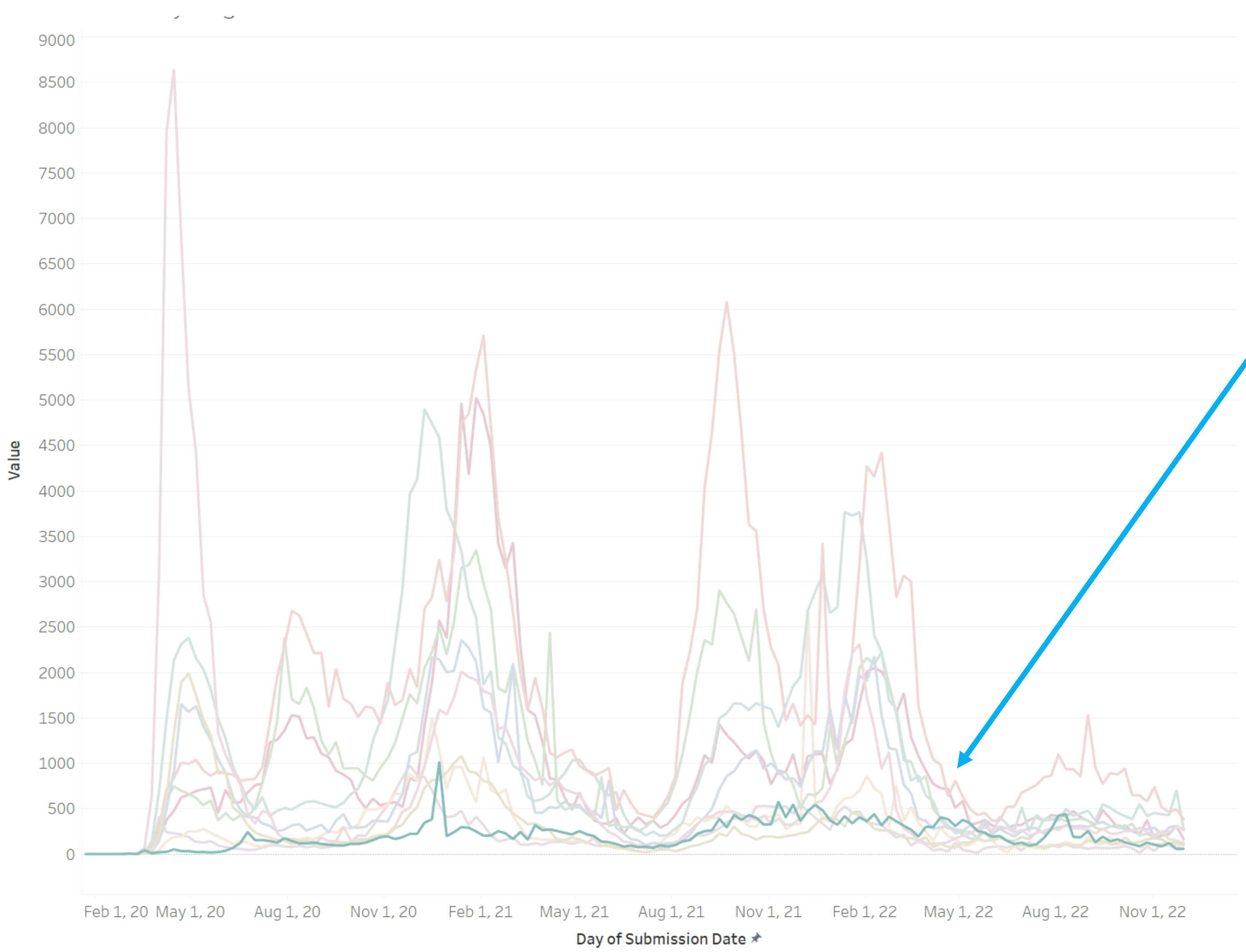
California



New York



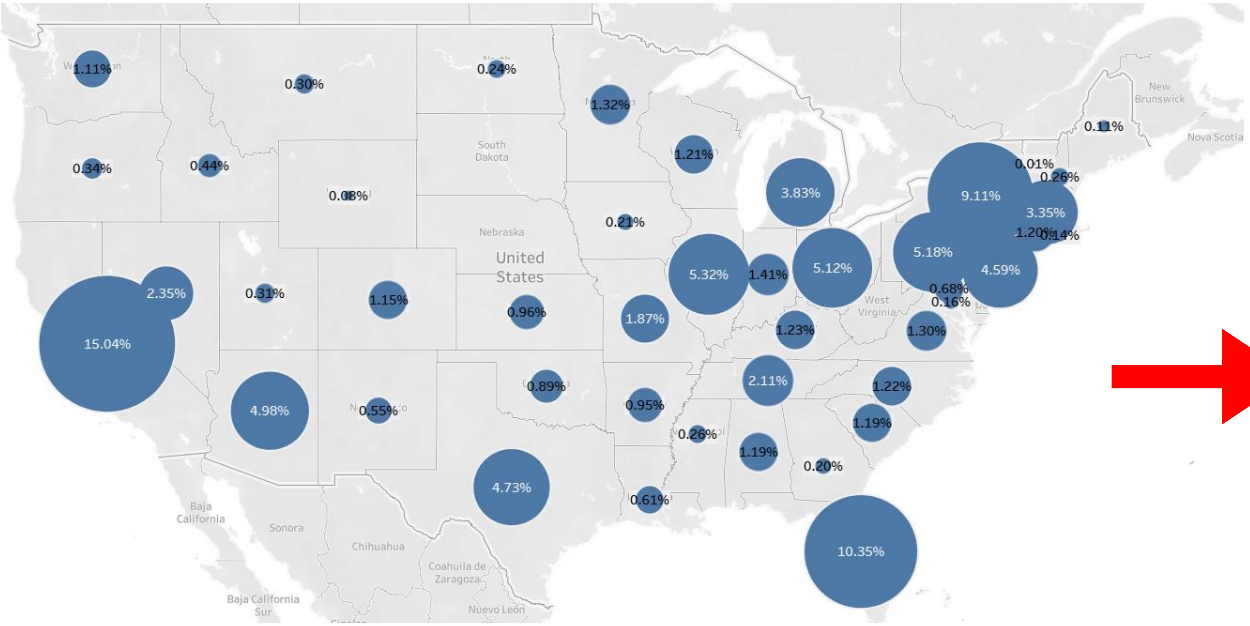
Promote reinsurance in certain areas like Seattle and Florida



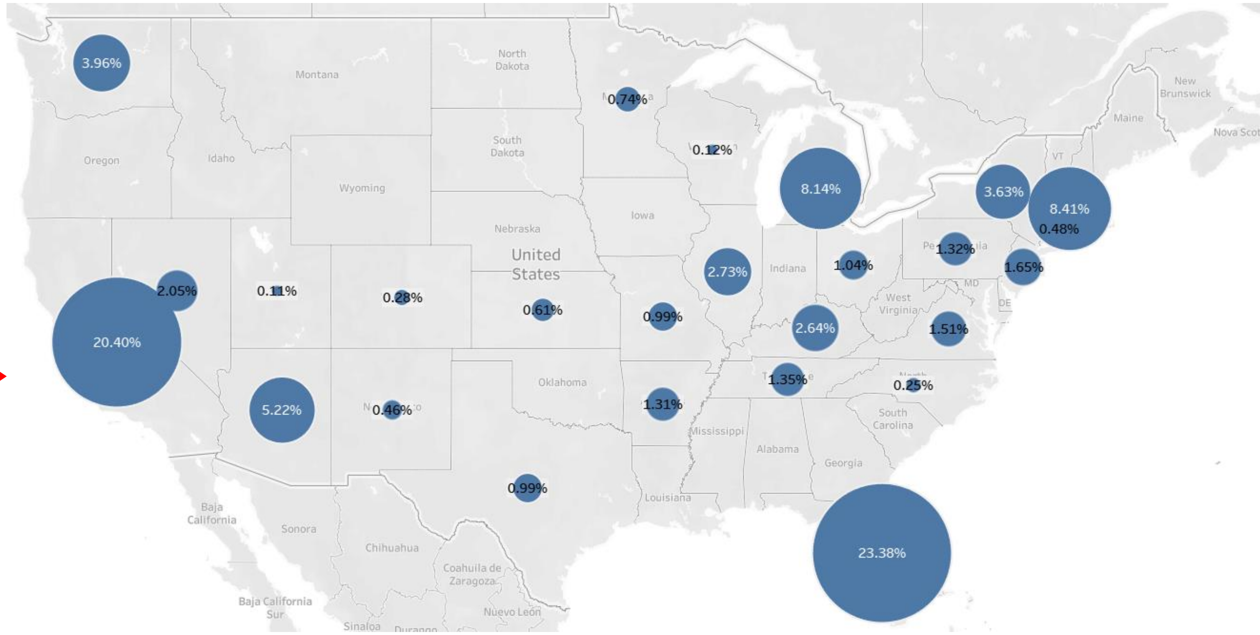
Regions that have suffered deaths from previous wave of COVID variant would have fewer deaths in the next wave

Seattle area may encounter a great loss of deaths if a new strong variant is introduced because it has never a huge wave of COVID breakout.

4 Promote reinsurance in certain areas like Seattle and Florida



Before June 2022



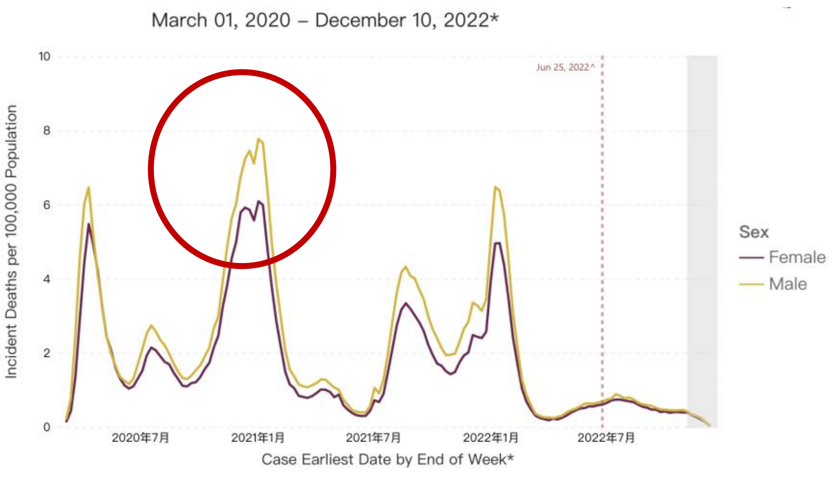
Last 6 Month

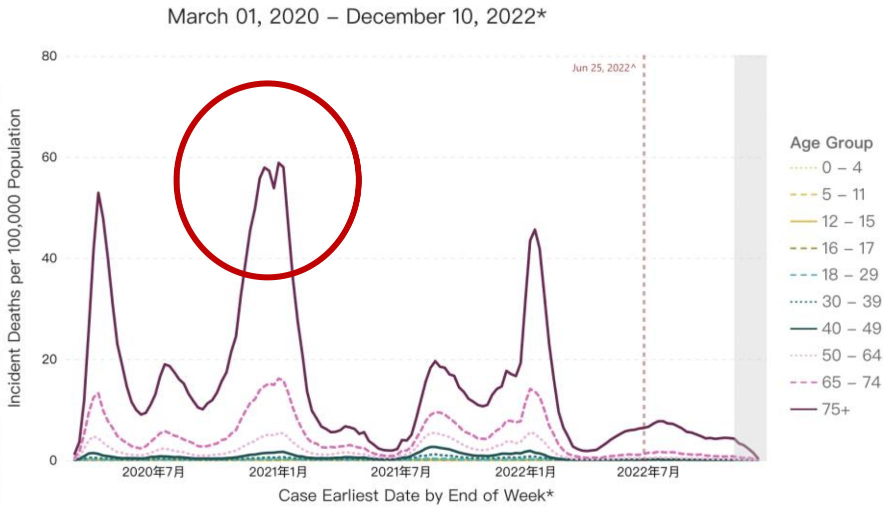
New York area and California have a high percentage of death contributed before.

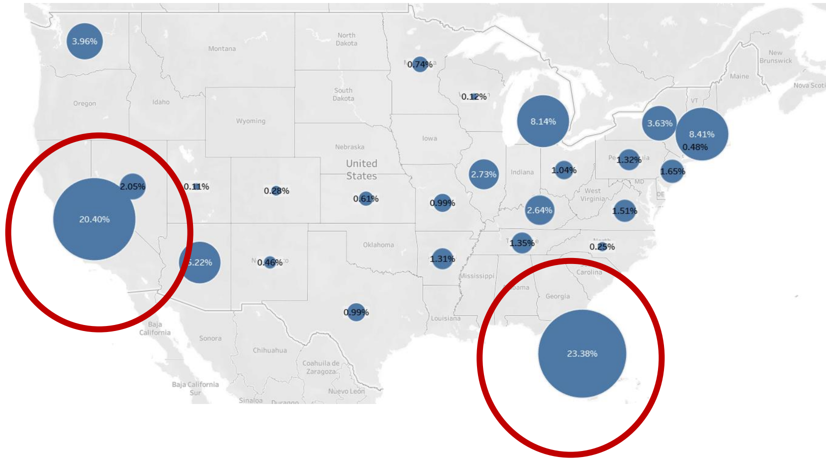
Florida has increasing percent of death in the last 6 month which may be due to a higher percentage of people over 65

5

Focus on the group of people who is male/75+/FL or CA





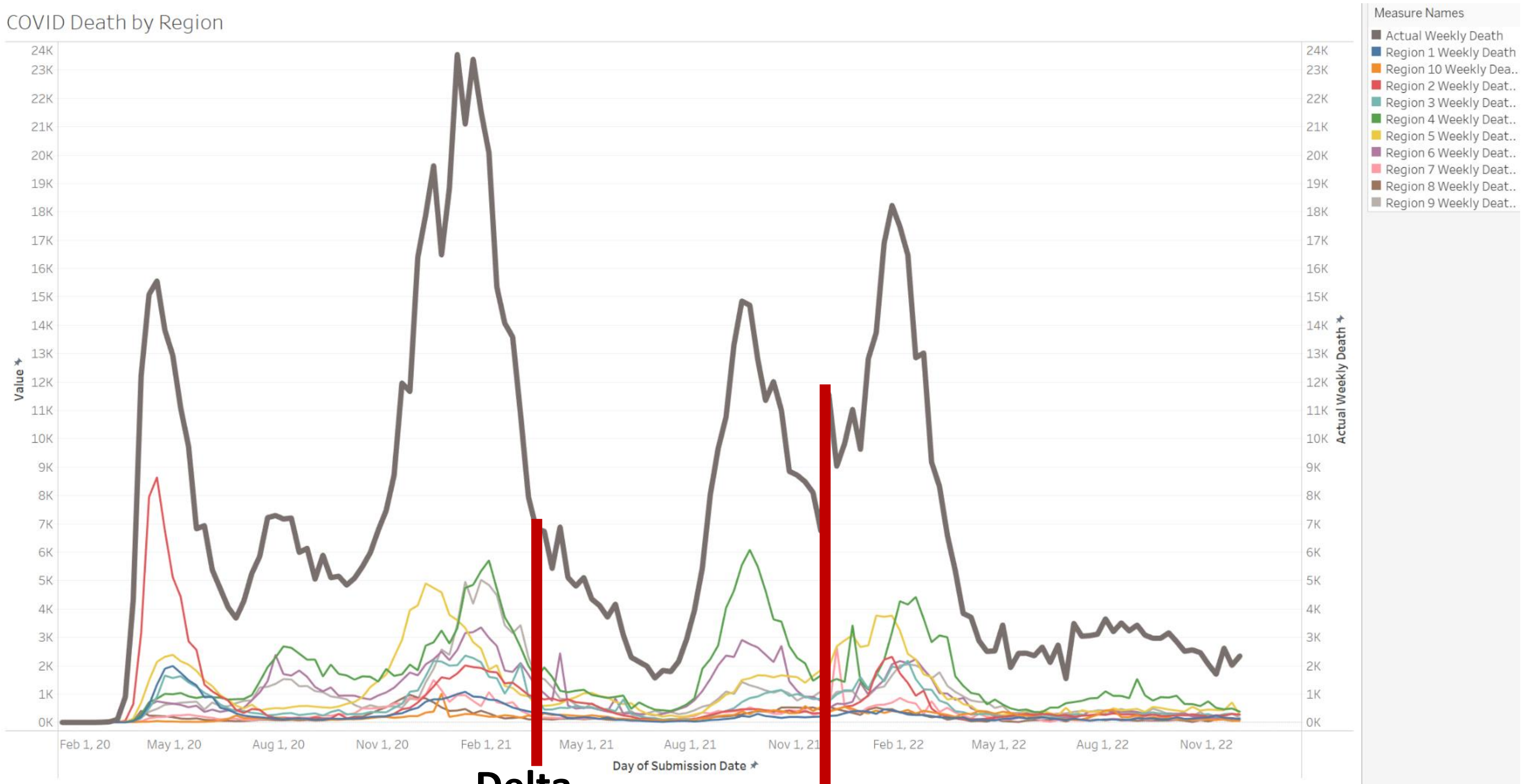


It is obvious that compared to females, males have a higher mortality rate due to Covid-19.

Among different age groups, people aged 75+ are the most vulnerable group.

Both FL and CA are experiencing a high percentage of the death rate.

6 Pay great attention to the new variant of covid virus entrance



Delta

The first detected case in the U.S. was in March 2021

Omicron

The first detected case in the U.S. was in November 2021

As soon as a new variant of COVID-19 virus enters U.S., an outbreak follows.

Targeting the north and southeast areas for business. (vaccine)

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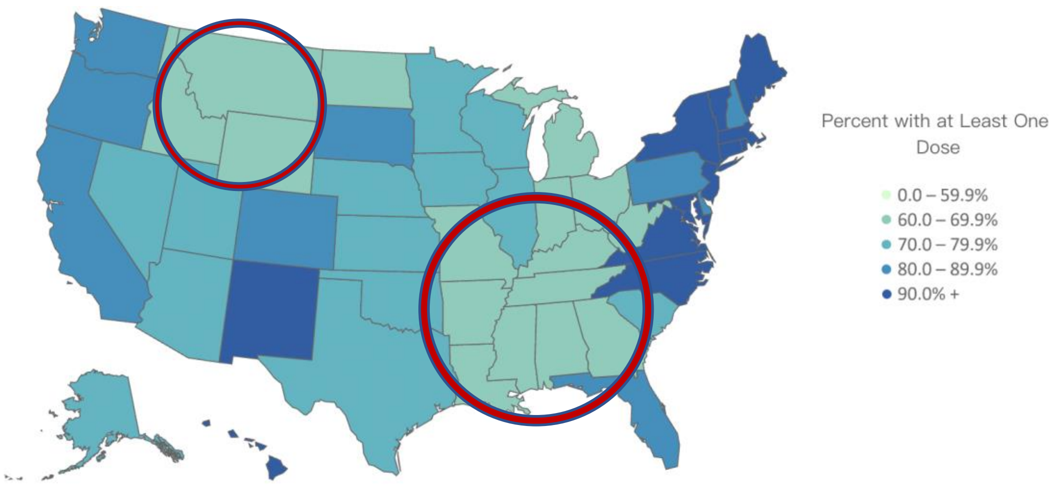
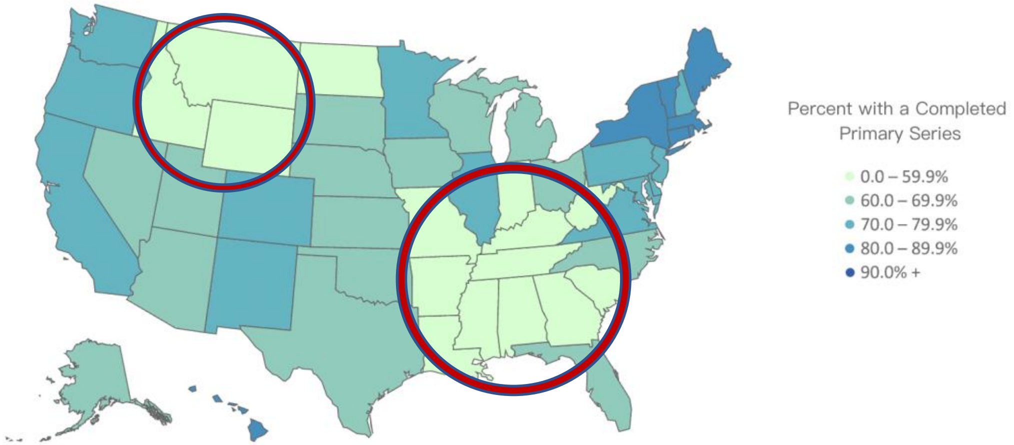
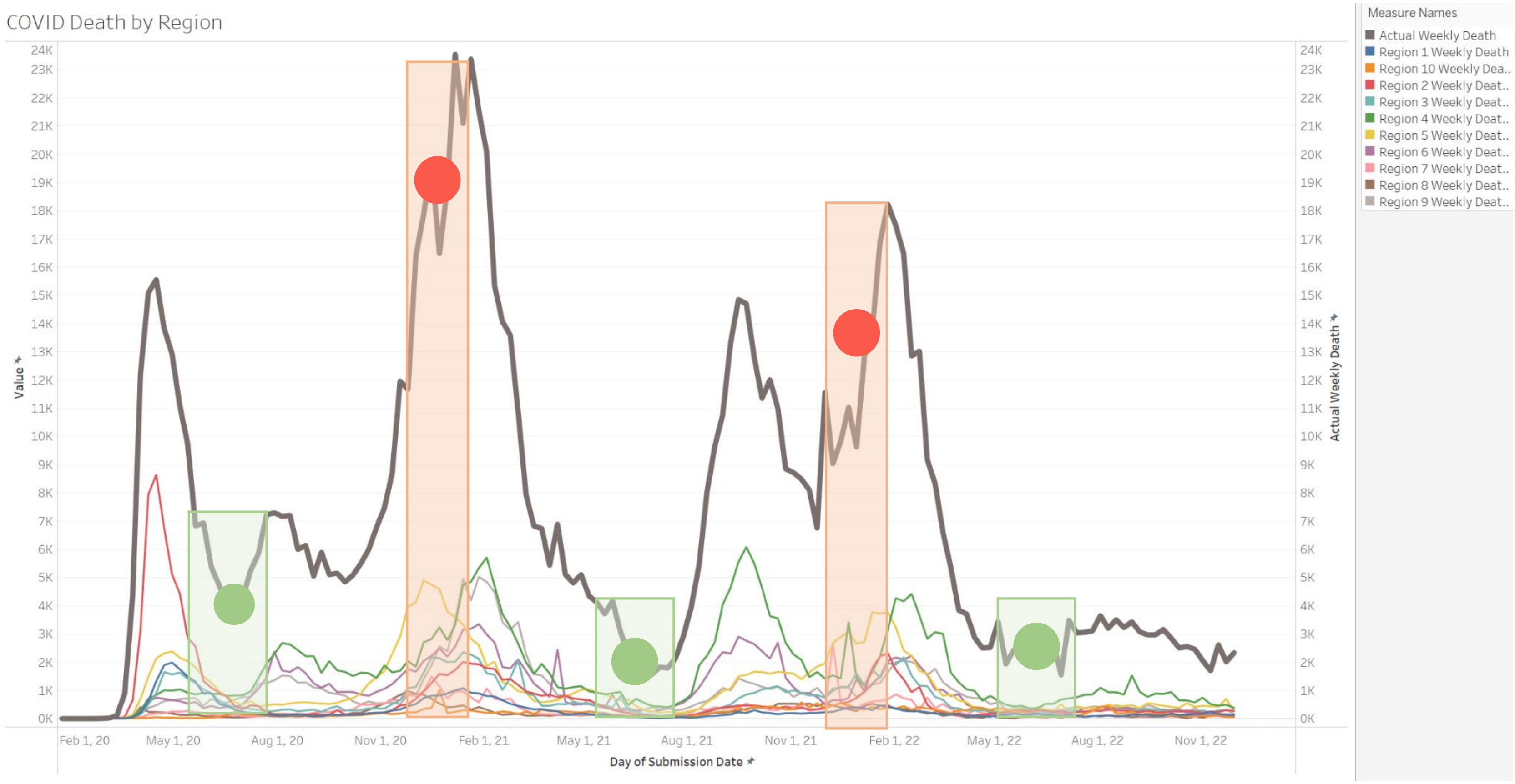




Since the number of deaths decreases with the vaccine effects, the company should target the north and southeast areas that have a lower percentage in both "completed primary series" and "with at least one dose" .

8 Focus on **seasonal** patterns (winter).



Winter Period:
Dec - Feb

Around peak time

Summer Period:
May - Aug

Slowing death rates

Q&A

- **Covid-19 Mortality Rate**
  - Background Info
    - Timelime
    - Situation
    - Company Infor
    - Define Problems
  - Key Findings
    - Model Comparison
    - Predictive Death numbers
  - Methods
    - U.S. Bass Model
    - State Bass Model
    - SIRD
    - GBM
  - Recommendation
    - Data aspects
    - Business aspects
    - Prediction aspects

Appendix—Bass Model Daily

t	Date	cul death	Actual death	A(t-1)	A(t-1)^2	N(t)^	A(t)^	A(t-1)^	Difference
1	1/22/2020	1	1	0	0	631.44856	631.44856	0	397465.3865
2	1/23/2020	1	0	1	1	633.607055	1265.05561	631.44856	401457.8999
3	1/24/2020	1	0	1	1	635.770214	1900.82583	1265.05561	404203.7646
4	1/25/2020	1	0	1	1	637.938024	2538.76385	1900.82583	406964.9231
5	1/26/2020	1	0	1	1	640.110475	3178.87433	2538.76385	409741.4204
6	1/27/2020	1	0	1	1	642.287553	3821.16188	3178.87433	412533.3011
7	1/28/2020	1	0	1	1	644.469246	4465.63113	3821.16188	415340.6096
8	1/29/2020	1	0	1	1	646.655542	5112.28667	4465.63113	418163.3898
9	1/30/2020	1	0	1	1	648.846427	5761.1331	5112.28667	421001.6852
10	1/31/2020	1	0	1	1	651.041887	6412.17498	5761.1331	423855.539
11	2/1/2020	1	0	1	1	653.241911	7065.41689	6412.17498	426724.9939
12	2/2/2020	1	0	1	1	655.446483	7720.86338	7065.41689	429610.0923
13	2/3/2020	1	0	1	1	657.655591	8378.51897	7720.86338	432510.8761
14	2/4/2020	1	0	1	1	659.86922	9038.38819	8378.51897	435427.3869
15	2/5/2020	1	0	1	1	662.087355	9700.47554	9038.38819	438359.6657
16	2/6/2020	1	0	1	1	664.309983	10364.7855	9700.47554	441307.7532
17	2/7/2020	1	0	1	1	666.537088	11031.3226	10364.7855	444271.6897
18	2/8/2020	1	0	1	1	668.768656	11700.0913	11031.3226	447251.5148
19	2/9/2020	1	0	1	1	671.004671	12371.0959	11700.0913	450247.2679
20	2/10/2020	1	0	1	1	673.245117	13044.3411	12371.0959	453258.9879
21	2/11/2020	1	0	1	1	675.48998	13719.831	13044.3411	456286.713
22	2/12/2020	1	0	1	1	677.739243	14397.5703	13719.831	459330.4813
23	2/13/2020	1	0	1	1	679.99289	15077.5632	14397.5703	462390.3301
24	2/14/2020	1	0	1	1	682.250904	15759.8141	15077.5632	465466.2962
25	2/15/2020	1	0	1	1	684.51327	16444.3273	15759.8141	468558.4162
26	2/16/2020	1	0	1	1	686.779969	17131.1073	16444.3273	471666.7258
27	2/17/2020	1	0	1	1	689.050985	17820.1583	17131.1073	474791.2604
28	2/18/2020	1	0	1	1	691.326301	18511.4846	17820.1583	477932.0548
29	2/19/2020	1	0	1	1	693.605899	19205.0905	18511.4846	481089.1433
30	2/20/2020	1	0	1	1	695.889761	19900.9803	19205.0905	484262.5597
31	2/21/2020	1	0	1	1	698.177869	20599.1581	19900.9803	487452.337

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.374145484
R Square	0.139984843
Adjusted R Squa	0.138298539
Standard Error	881.2170732
Observations	1023

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	128926112	64463056.1	83.0128044	3.9638E-34
Residual	1020	792074401	776543.53		
Total	1022	921000513			

	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	630.3708697	68.8752565	9.15235604	2.96E-19	495.217474	765.524266
A(t-1)	0.003416751	0.00030565	11.1786335	1.8959E-27	0.00281698	0.00401653
A(t-1)^2	-3.36944E-09	2.7108E-10	-12.429547	3.9581E-33	-3.901E-09	-2.837E-09

p	0.000537185
q	0.003953936
M	1,173,470.77
M	1,173,470.77
p	0.000537185
q	0.003953936
799462755.2	

Appendix—Bass Model Weekly

Week #	Week	Actual Weekly Death	A(t-1)	A(t-1)^2	N(t)^	A(t)^	A(t-1)^	Difference between actual and estimated
1	1/22/2020	1	0	0	4532.9865	4532.98649	0	20538901.55
2	1/29/2020	0	1	1	4636.85	9169.83646	4532.986491	21500377.68
3	2/5/2020	0	1	1	4742.1042	13911.9406	9169.836464	22487551.99
4	2/12/2020	0	1	1	4848.7133	18760.6539	13911.94064	23510020.77
5	2/19/2020	0	1	1	4956.6381	23717.292	18760.65395	24568261.25
6	2/26/2020	7	1	1	5065.8356	28783.1277	23717.29205	25591818.08
7	3/4/2020	21	8	64	5176.2593	33959.387	28783.12769	26576698.92
8	3/11/2020	104	29	841	5287.8588	39247.2458	33959.38704	26872392.17
9	3/18/2020	900	133	17689	5400.5798	44647.8256	39247.24585	20255218.22
10	3/25/2020	4326	1033	1067089	5514.364	50162.1896	44647.82562	1412208.952
11	4/1/2020	12226	5359	28718881	5629.1492	55791.3388	50162.1896	43518440.43
12	4/8/2020	15091	17585	309232225	5744.8691	61536.2079	55791.3388	87350162.96
13	4/15/2020	15563	32676	1067720976	5861.4532	67397.6611	61536.20789	94120011.01
14	4/22/2020	13830	48239	2327001121	5978.8268	73376.4878	67397.66106	61640921.18
15	4/29/2020	12941	62069	3852560761	6096.911	79473.3988	73376.48782	46841553.95
16	5/6/2020	11086	75010	5626500100	6215.6228	85689.0217	79473.39884	23720573.67
17	5/13/2020	9726	86096	7412521216	6334.8749	92023.8966	85689.02168	11499729.49
18	5/20/2020	6826	95822	9181855684	6454.5756	98478.4722	92023.89658	137956.0664
19	5/27/2020	6936	102648	10536611904	6574.6293	105053.101	98478.4722	130588.7983
20	6/3/2020	5377	109584	12008653056	6694.9359	111748.037	105053.1015	1736955.126
21	6/10/2020	4720	114961	13216031521	6815.3916	118563.429	111748.0374	4390665.789
22	6/17/2020	4060	119681	14323541761	6935.8881	125499.317	118563.429	8270732.279
23	6/24/2020	3677	123741	15311835081	7056.3135	132555.631	125499.3171	11419759.64
24	7/1/2020	4282	127418	16235346724	7176.5519	139732.182	132555.6305	8378430.658
25	7/8/2020	5251	131700	17344890000	7296.4837	147028.666	139732.1824	4184003.613
26	7/15/2020	5855	136951	18755576401	7415.9858	154444.652	147028.6661	2436676.575
27	7/22/2020	7220	142806	20393553636	7534.9315	161979.583	154444.6519	99181.83715
28	7/29/2020	7295	150026	22507800676	7653.191	169632.774	161979.5834	128300.8037
29	8/5/2020	7170	157321	24749897041	7770.6315	177403.406	169632.7744	360758.2208
30	8/12/2020	7205	164491	27057289081	7887.1173	185290.523	177403.4059	465284.0334
31	8/19/2020	5997	171696	29479516416	8002.5102	193293.033	185290.5233	4022071.031

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.453803603
R Square	0.20593771
Adjusted R Square	0.194909067
Standard Error	4975.41458
Observations	147

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	924490277.8	462245138.9	18.67298738	6.15927E-08
Residual	144	3564684034	24754750.24		
Total	146	4489174312			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	4526.817725	1018.762038	4.443449556	1.75388E-05	2513.158083	6540.4773
A(t-1)	0.023637532	0.00453254	5.215074251	6.27086E-07	0.014678627	0.0325964
A(t-1)^2	-2.35286E-08	4.02309E-09	-5.848382037	3.19747E-08	-3.14805E-08	-1.55766E-

p	0.003871766
q	0.027509298
M	1,169,186.84

M	1,184,725.24
p	0.003782756
q	0.026641666

3606013932

Appendix—Bass Model Monthly

	A	B	C	D	E	F	G	H	I	J	K
1	time	t	N(t)	A(t)	A(t-1)	p-N(t)	p-A(t)	p-A(t-1)	difference		
2	1/1/2020	1	0	0	0	18242.22	18242.221	0	3.33E+08		
3	2/1/2020	2	1	1	0	20243.7	38485.924	18242.22	4.1E+08		
4	3/1/2020	3	3326	3327	1	22368.31	60854.238	38485.92	3.63E+08		
5	4/1/2020	4	57134	60461	3327	24598.69	85452.927	60854.24	1.06E+09		
6	5/1/2020	5	44864	105325	60461	26910.44	112363.36	85452.93	3.22E+08		
7	6/1/2020	6	22925	128250	105325	29271.63	141634.99	112363.4	40279686		
8	7/1/2020	7	28717	156967	128250	31642.68	173277.67	141635	8559581		
9	8/1/2020	8	31831	188798	156967	33976.75	207254.41	173277.7	4604225		
10	9/1/2020	9	21361	210159	188798	36220.81	243475.22	207254.4	2.21E+08		
11	10/1/2020	10	23448	233607	210159	38317.42	281792.64	243475.2	2.21E+08		
12	11/1/2020	11	41105	274712	233607	40207.18	321999.82	281792.6	806087.9		
13	12/1/2020	12	77292	352004	274712	41831.82	363831.64	321999.8	1.26E+09	p	0.014924983
14	1/1/2021	13	100119	452123	352004	43137.69	406969.33	363831.6	3.25E+09	q	0.122974788
15	2/1/2021	14	67730	519853	452123	44079.24	451048.56	406969.3	5.59E+08	m	1158164.508
16	3/1/2021	15	33397	553250	519853	44622.31	495670.88	451048.6	1.26E+08		
17	4/1/2021	16	20768	574018	553250	44746.72	540417.59	495670.9	5.75E+08		
18	5/1/2021	17	17442	591460	574018	44447.76	584865.35	540417.6	7.29E+08	Sum-difference	15170206754
19	6/1/2021	18	9459	600919	591460	43736.66	628602.01	584865.4	1.17E+09		
20	7/1/2021	19	9045	609964	600919	42639.64	671241.66	628602	1.13E+09		
21	8/1/2021	20	31496	641460	609964	41195.93	712437.59	671241.7	94088673		
22	9/1/2021	21	54691	696151	641460	39454.84	751892.43	712437.6	2.32E+08		
23	10/1/2021	22	48578	744729	696151	37472.36	789364.79	751892.4	1.23E+08		
24	11/1/2021	23	31309	776038	744729	35307.64	824672.43	789364.8	15989152		
25	12/1/2021	24	43017	819055	776038	33019.61	857692.04	824672.4	99947800		
26	1/1/2022	25	65001	884056	819055	30664.15	888356.19	857692	1.18E+09		
27	2/1/2022	26	63682	947738	884056	28291.89	916648.08	888356.2	1.25E+09		
28	3/1/2022	27	27637	975375	947738	25946.77	942594.85	916648.1	2856863		
29	4/1/2022	28	13263	988638	975375	23665.23	966260.09	942594.9	1.08E+08		
30	5/1/2022	29	9953	998591	988638	21476.04	987736.13	966260.1	1.33E+08		
31	6/1/2022	30	9885	1008476	998591	19400.6	1007136.7	987736.1	90546646		
32	7/1/2022	31	13117	1021593	1008476	17453.59	1024590.3	1007137	18806055		
33	8/1/2022	32	13716	1035309	1021593	15643.82	1040234.1	1024590	3716490		
34	9/1/2022	33	12795	1048104	1035309	13975.13	1054209.3	1040234	1392700		

Appendix—Bass Model State Level

```
url = "https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_covid19_deaths_US.
df = pd.read_csv(url,index_col=0)
df.head()
```

UID	iso2	iso3	code3	FIPS	Admin2	Province_State	Country_Region	Lat	
84001001	US	USA	840	1001.0	Autauga	Alabama	US	32.539527	-86.6
84001003	US	USA	840	1003.0	Baldwin	Alabama	US	30.727750	-87.7
84001005	US	USA	840	1005.0	Barbour	Alabama	US	31.868263	-85.3
84001007	US	USA	840	1007.0	Bibb	Alabama	US	32.996421	-87.1
84001009	US	USA	840	1009.0	Blount	Alabama	US	33.982109	-86.5

5 rows × 1059 columns

```
death_by_state = df.groupby('Province_State')[df.columns[11:]].sum()
death_by_state.head(10)
```

Province_State	1/22/20	1/23/20	1/24/20	1/25/20	1/26/20	1/27/20	1/28/20	1/29/20	1/30/
Alabama	0	0	0	0	0	0	0	0	
Alaska	0	0	0	0	0	0	0	0	
American Samoa	0	0	0	0	0	0	0	0	
Arizona	0	0	0	0	0	0	0	0	
Arkansas	0	0	0	0	0	0	0	0	
California	0	0	0	0	0	0	0	0	
Colorado	0	0	0	0	0	0	0	0	
Connecticut	0	0	0	0	0	0	0	0	
Delaware	0	0	0	0	0	0	0	0	
Diamond Princess	0	0	0	0	0	0	0	0	

```
test = pd.DataFrame(death_by_state.iloc[1])
current_state = test.columns[0]
current_state
##### WARNING: is the data already counting cumulative or is it daily cases?
test.columns=['cum_death']
test['new_death']=test['cum_death'].diff().fillna(test['cum_death'])
#print(df)
#test.reset_index()
#test.head()
```

```
from math import exp
def model(params, time_step):
  p,q,m = params
  N=[]
  for t in range(1,time_step):
```

Appendix—Bass Model State Level

```
    current=m*(1-exp(-(p+q)*t))/(1+(q/p)*exp(-(p+q)*t))
    last=m*(1-exp(-(p+q)*(t-1)))/(1+(q/p)*exp(-(p+q)*(t-1)))
    N.append(current-last)
  return N


def error(params, time_step, actual_N):
  pred_N = model(params,time_step)
  N_error = []
  for t in range(0,time_step-1):
    N_error.append((actual_N[t+1]-pred_N[t])**2)
  total_error = sum(N_error)
  return total_error



import numpy as np
from scipy.optimize import minimize
import pandas as pd


initial_value = [0.027,0.003,0.03]
bnds = [(0, None), (0, None), (0, None)]
res = minimize(error,initial_value, args = (1028,test.new_death), bounds = bnds, tol=1e-8, method = 'Powell')
```

```
print(res)

        direc: array([[-1.20012006e-05,  7.47837393e-04,  9.60104503e+01],
            [-3.04291749e-05,  1.12323411e-03, -1.39193406e+02],
            [-4.78326155e-06,  5.60700835e-04, -6.38933555e+01]])
          fun: 28422.787858961932
      message: 'Optimization terminated successfully.'
         nfev: 1198
          nit: 16
       status: 0
      success: True
            x: array([1.08686633e-04, 6.25513198e-03, 1.75989179e+03])

def prediction(params,current_time, time_range):
  p,q,m = params
  N_t = []
  for t in range(current_time,current_time+time_range):
    current=m*(1-exp(-(p+q)*t))/(1+(q/p)*exp(-(p+q)*t))
    last=m*(1-exp(-(p+q)*(t-1)))/(1+(q/p)*exp(-(p+q)*(t-1)))
    N_t.append(current-last)
  return N_t



len(death_by_state)

     58
```

Appendix—Bass Model State Level

```
final_prediction_df = pd.DataFrame()
for state in range(0,58):
  test = pd.DataFrame(death_by_state.iloc[state])
  current_state = test.columns[0]
  ##### WARNING: is the data already counting cumulative or is it daily cases?
  test.columns=['cum_death']
  test['new_death']=test['cum_death'].diff().fillna(test['cum_death'])
  initial_value = [0.027,0.03,100]
  bnds = [(0, None), (0, None), (10, None)]
  res = minimize(error,initial_value, args = (1028,test.new_death), bounds = bnds, tol=1e-8, method = 'Powell')
  print(res.x)
  final_prediction_df[current_state] = prediction(res.x,1018,30)
```

```
[6.85348468e-05 7.45512874e-02 7.15048376e+02]
[1.95890521e-06 1.32754303e-02 1.19923394e+03]
[4.74359040e-05 5.64467686e-03 6.25494210e+01]
[4.93288970e-04 4.34575555e-03 3.43540333e+04]
[1.73888509e-04 1.01622182e-01 4.71895508e+01]
[4.80542406e-06 2.29601548e-02 6.39887423e+04]
[2.93835533e-03 2.68151079e-02 2.15148859e+03]
[2.12348097e-03 2.85751395e-02 5.42844123e+03]
[1.71509248e-03 2.69908748e-02 7.61501051e+02]
[1.51278758e-17 5.02591791e-09 1.00000000e+01]
[1.68958999e-03 2.78090743e-02 7.32408180e+02]
```

```
final_prediction_df.sum(axis = 1)
```

```
0     276.415553
1     275.252001
2     274.092548
3     272.937188
4     271.785914
5     270.638720
6     269.495599
7     268.356543
8     267.221547
9     266.090604
10    264.963706
11    263.840846
12    262.722018
13    261.607214
14    260.496427
15    259.389649
16    258.286874
17    257.188094
18    256.093301
19    255.002488
20    253.915648
21    252.832772
22    251.753853
23    250.678883
24    249.607854
25    248.540759
26    247.477589
27    246.418336
28    245.362993
29    244.311552
dtype: float64
```

```
weekly_df = death_by_state[death_by_state.columns[::7]]
weekly_df.head()
```

Province_State	1/22/20	1/29/20	2/5/20	2/12/20	2/19/20	2/26/20	3/4/20	3/11/20	3/18/20
Alabama	0	0	0	0	0	0	0	0	0
Alaska	0	0	0	0	0	0	0	0	0
American Samoa	0	0	0	0	0	0	0	0	0
Arizona	0	0	0	0	0	0	0	0	0
Arkansas	0	0	0	0	0	0	0	0	0

5 rows × 150 columns

Appendix—Bass Model State Level

```
weekly_final_prediction_df = pd.DataFrame()
for state in range(0,58):
  test = pd.DataFrame(weekly_df.iloc[state])
  current_state = test.columns[0]
  ##### WARNING: is the data already counting cumulative or is it daily cases?
  test.columns=['cum_death']
  test['new_death']=test['cum_death'].diff().fillna(test['cum_death'])
```

```
initial_value = [0.027,0.03,500]
bnds = [(0, None), (0, None), (0, None)]
res = minimize(error,initial_value, args = (149,test.new_death), bounds = bnds, tol=1e-8, method = 'Powell')
print(res.x)
weekly_final_prediction_df[current_state] = prediction(res.x,147,4)
```

```
[2.53662352e-03 3.92312856e-02 2.17136281e+04]
[4.52641064e-04 5.09960391e-02 1.47285756e+03]
[3.57395004e-03 1.33183661e-02 4.48146283e+01]
[3.43372743e-03 3.05269579e-02 3.43702057e+04]
[2.66275774e-03 3.12050306e-02 1.38800931e+04]
[2.06263090e-04 1.21178910e-01 7.24063712e+04]
```

```
weekly_final_prediction_df
```

	Alabama	Alaska	American Samoa	Arizona	Arkansas	California	Colorado	Connecticut	Del
0	30.737555	4.084786	0.174536	70.778633	35.755428	0.097930	1.543645	0.0	0.2
1	29.559719	3.902083	0.172993	68.680416	34.739994	0.086736	1.494937	0.0	0.2
2	28.423980	3.726545	0.171447	66.636268	33.748125	0.076822	1.447766	0.0	0.2
3	27.329070	3.557984	0.169897	64.645307	32.779600	0.068041	1.402083	0.0	0.2

4 rows × 58 columns

```
weekly_final_prediction_df.sum(axis=1)
```

```
0    1966.177380
1    1908.668365
2    1852.592750
3    1797.931651
dtype: float64
```

```
monthly_df = death_by_state[death_by_state.columns[::30]]
monthly_df.head()
```

	1/22/20	2/21/20	3/22/20	4/21/20	5/21/20	6/20/20	7/20/20	8/19/20	9/18/
Province_State									
Alabama	0	0	0	183	529	838	1291	1944	24
Alaska	0	0	0	9	10	12	18	29	
American Samoa	0	0	0	0	0	0	0	0	
Arizona	0	0	2	208	764	1346	2784	4634	54
Arkansas	0	0	0	42	110	224	363	631	11

5 rows × 35 columns

```
monthly_final_prediction_df = pd.DataFrame()
for state in range(0,58):
  test = pd.DataFrame(monthly_df.iloc[state])
  current_state = test.columns[0]
  ##### WARNING: is the data already counting cumulative or is it daily cases?
  test.columns=['cum_death']
  test['new_death']=test['cum_death'].diff().fillna(test['cum_death'])
  initial_value = [0.027,0.03,500]
  bnds = [(0, None), (0, None), (0, None)]
  res = minimize(error,initial_value, args = (34,test.new_death), bounds = bnds, tol=1e-8, method = 'Powell')
  print(res.x)
  monthly_final_prediction_df[current_state] = prediction(res.x,33,2)
```

```
[1.09724254e-02 1.66298404e-01 2.17996097e+04]
[ 0.02684564  1.71448828 14.37953792]
[1.19940817e-03 1.68337786e-01 7.01835424e+01]
[1.48915765e-02 1.27672369e-01 3.46636125e+04]
[1.14451831e-02 1.34034738e-01 1.38623322e+04]
[5.35237879e-02 1.04530323e+00 7.39875900e+03]
[1.20972417e-01 9.13257263e-10 6.07894933e+03]
[4.10707613e-02 1.01075066e+00 6.31964760e+03]
[1.34604120e-08 2.12809506e+01 1.14047808e+02]
```

Appendix--SIRD

```
import pandas as pd

url = "https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_covid19_deaths_US.
df = pd.read_csv(url,index_col=0)
df.head()
```

UID	iso2	iso3	code3	FIPS	Admin2	Province_State	Country_Region	Lat
84001001	US	USA	840	1001.0	Autauga	Alabama	US	32.539527 -86.6
84001003	US	USA	840	1003.0	Baldwin	Alabama	US	30.727750 -87.7
84001005	US	USA	840	1005.0	Barbour	Alabama	US	31.868263 -85.3
84001007	US	USA	840	1007.0	Bibb	Alabama	US	32.996421 -87.1
84001009	US	USA	840	1009.0	Blount	Alabama	US	33.982109 -86.5

5 rows × 1064 columns

```
daily_death = pd.DataFrame(df[df.columns[11:]].sum())
daily_death.columns=['cum_death']
daily_death['new_death']=daily_death['cum_death'].diff().fillna(daily_death['cum_death'])

df_cases = pd.read_csv("https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_c
df_cases.head()
```


```
import pandas as pd

url = "https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_covid19_deaths_US.
df = pd.read_csv(url,index_col=0)
df.head()
```

UID	iso2	iso3	code3	FIPS	Admin2	Province_State	Country_Region	Lat
84001001	US	USA	840	1001.0	Autauga	Alabama	US	32.539527 -86.6
84001003	US	USA	840	1003.0	Baldwin	Alabama	US	30.727750 -87.7
84001005	US	USA	840	1005.0	Barbour	Alabama	US	31.868263 -85.3
84001007	US	USA	840	1007.0	Bibb	Alabama	US	32.996421 -87.1
84001009	US	USA	840	1009.0	Blount	Alabama	US	33.982109 -86.5

5 rows × 1064 columns

```
daily_death = pd.DataFrame(df[df.columns[11:]].sum())
daily_death.columns=['cum_death']
daily_death['new_death']=daily_death['cum_death'].diff().fillna(daily_death['cum_death'])

df_cases = pd.read_csv("https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_c
df_cases.head()
```

Appendix--SIRD

```
daily_cases = pd.DataFrame(df_cases[df_cases.columns[11:]].sum())
daily_cases.columns=['cum_cases']
daily_cases['new_cases']=daily_cases['cum_cases'].diff().fillna(daily_cases['cum_cases'])
daily_cases.head(10)
```

	cum_cases	new_cases
1/23/20	1	1.0
1/24/20	2	1.0
1/25/20	2	0.0
1/26/20	5	3.0
1/27/20	5	0.0
1/28/20	5	0.0
1/29/20	6	1.0
1/30/20	6	0.0
1/31/20	8	2.0
2/1/20	8	0.0

```
import numpy as np
from scipy.optimize import minimize, curve_fit
from scipy import integrate, optimize
import pandas as pd
from scipy.integrate import odeint
import matplotlib.pyplot as plt


def model(params, time_step):
  beta, gamma, S0, I0, d = params
  N = S0 + I0
  S = [S0]
  I = [I0]
  R = [0]
  D = [0]
  dS =[]
  dI = []
  dR = []
  dD = []
  for t in range(0,time_step):
    dS.append(-beta*I[t]*S[t]/N)
    dI.append(beta*I[t]*S[t]/N- gamma*I[t] - d*I[t])
    dR.append(gamma*I[t])
    dD.append(d*I[t])
    S.append(S[t] + dS[t])
    I.append(I[t] + dI[t])
    R.append(R[t] + dR[t])
    D.append(D[t] + dD[t])
  return I, D

def error(params, time_step, actual_I, actual_D):
  I_pred, D_pred = model(params, time_step)
  beta, gamma, S0, I0, d = params
  I_error = 0
  D_error = 0
  for t in range(0,time_step):
    I_error+=abs(I_pred[t]-actual_I[t])
    D_error+=abs(D_pred[t]-actual_D[t])
  total_error = I_error + D_error
  return total_error
```

Appendix--SIRD

```
actual_cum_cases = daily_cases["cum_cases"]
actual_cum_death = daily_death["cum_death"]
actual_cum_case = [i/10000000 for i in actual_cum_cases.values.tolist()]
actual_cum_death = [i/10000000 for i in actual_cum_death.values.tolist()]


initial_value = [8.63e-1,1.53e-4,18.3,6.78e-5,8.6e-1]
bnds = [(0, 1), (0, 1), (9, 50), (0, 1), (0, 1)]
res = minimize(error,initial_value, args = (1028, actual_cum_cases, actual_cum_death), bounds = bnds, tol=1e-7, method = 'Nelder-Mead', options={'m


print(res)

      final_simplex: (array([[8.63201345e-01, 2.48787398e-04, 1.26890726e+01, 6.77213074e-05,
             8.59425852e-01],
            [8.63201345e-01, 2.48787396e-04, 1.26890726e+01, 6.77213074e-05,
             8.59425852e-01],
            [8.63201345e-01, 2.48787397e-04, 1.26890726e+01, 6.77213073e-05,
             8.59425852e-01],
            [8.63201345e-01, 2.48787395e-04, 1.26890727e+01, 6.77213075e-05,
             8.59425852e-01],
            [8.63201345e-01, 2.48787397e-04, 1.26890726e+01, 6.77213076e-05,
             8.59425852e-01],
            [8.63201345e-01, 2.48787398e-04, 1.26890726e+01, 6.77213074e-05,
             8.59425852e-01]]), array([4.22762574e+10, 4.22762574e+10, 4.22762574e+10, 4.22762574e+10,
            4.22762574e+10, 4.22762574e+10]))
                fun: 42276257373.543175
            message: 'Optimization terminated successfully.'
               nfev: 361
                nit: 157
             status: 0
            success: True
```

```
                 x: array([8.63201345e-01, 2.48787398e-04, 1.26890726e+01, 6.77213074e-05,
            8.59425852e-01])


from scipy.optimize import brute


grid = ((8.63e-1,8.63e-1),(1.53e-4,1.53e-4),slice(1,40, 0.1),(6.78e-5, 6.78e-5),(0.86,0.86))
resbrute = brute(error, grid, args = (1028, actual_cum_cases, actual_cum_death), Ns = 1,full_output=True, disp=True, finish=None)
print("Best coeffs: {}".format(resbrute[0]))
print("Score with best coeffs: {}".format(resbrute[1]))
print("Grid: {}".format(resbrute[2].tolist()))
print("Scores for grid: {}".format(resbrute[3].tolist()))

     Best coeffs: [8.63e-01 1.53e-04 1.83e+01 6.78e-05 8.60e-01]
     Score with best coeffs: 42276257374.381165
     Grid: [[[[[[0.863]], [[0.863]], [[0.863]], [[0.863]], [[0.863]], [[0.863]], [[0.863]], [[0.863]], [[0.863]], [[0.863]], [[0.863]], [[0.863]],
     Scores for grid: [[[[[42276257416.69559]], [[42276257415.98136]], [[42276257415.295685]], [[42276257414.63543]], [[42276257413.99786]], [[422


params = res.x
#params = np.array([0.022,0.00165,33,1e-7,7.5e-6])
```

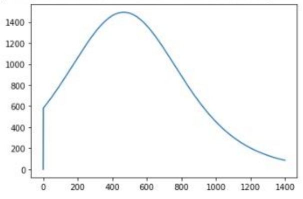
Appendix--SIRD

```
# predictions
I, D = model(params, 1450)
D = pd.DataFrame(D)
D.columns = ['cum_death']
D['new_death']=D['cum_death'].diff().fillna(D['cum_death'])
new_death = [i*10000000 for i in D['new_death']]
print(new_death[1018:])
```

```
[422.90521110488476, 421.29197393270255, 419.6836837216944, 418.08033540688405, 416.48192383322845, 414.88844375742184, 413.29988984761815, 4
```

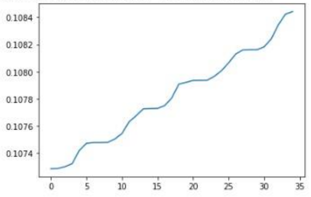
```
plt.plot(new_death)
```

```
[<matplotlib.lines.Line2D at 0x7fcf9aee9e80>]
```



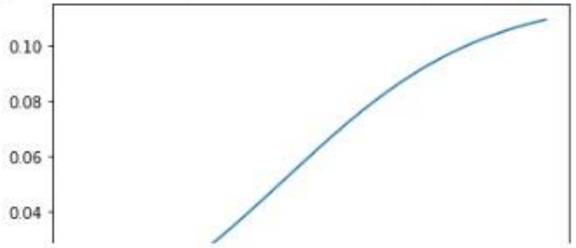

```
plt.plot(actual_cum_death[1018:])
```

```
[<matplotlib.lines.Line2D at 0x7fcf9aeff550>]
```




```
plt.plot(D['cum_death'])
```

```
[<matplotlib.lines.Line2D at 0x7fcf9afb8af0>]
```




```
D.to_csv('SIRD_death.csv')
```

```
daily_death.to_csv("actual death.csv")
```

```
beta, gamma, S0, I0, d = params
beta * S0/gamma
```

```
44026.44433003097
```

Appendix--GBM

M	N	O	P	Q
t*	Ahat(t)	Ahat(t-1)	Nhat(t)	SE(t)
A2	$K$3*(1-EXP(-($K$1+$K$2)*D2))/(1+($K$2/$K$1)*EXP(-($K$1+$K$2)*D2))	$K$3*(1-EXP(-($K$1+$K$2)*(D2-1)))/(1+($K$2/$K$1)*EXP(-(K	E2-F2	(B2-G2)^2

t	Death	Vaccine Administered	t*	Ahat(t)	Ahat(t-1)	Nhat(t)	SE(t)	Date	p	0.000652209
1.00	1.00	0.00	1.0000	437.8806478	0	437.8806478	190864.7004	2020/1/22	q	0.007680922
2.00	0.00	0.00	2.0000	878.8454359	437.8806478	440.9647881	194449.9444	2020/1/23	M	669025.1021
3.00	0.00	0.00	3.0000	1322.911591	878.8454359	444.0661547	197194.7498	2020/1/24	b	-34.63850985
4.00	0.00	0.00	4.0000	1770.096365	1322.911591	447.1847739	199974.222	2020/1/25		
5.00	0.00	0.00	5.0000	2220.417035	1770.096365	450.3206708	202788.7066	2020/1/26		
6.00	0.00	0.00	6.0000	2673.890905	2220.417035	453.4738693	205638.5501	2020/1/27		
7.00	0.00	0.00	7.0000	3130.535297	2673.890905	456.644392	208524.1007	2020/1/28		
8.00	0.00	0.00	8.0000	3590.367557	3130.535297	459.8322603	211445.7076	2020/1/29		
9.00	0.00	0.00	9.0000	4053.405051	3590.367557	463.0374943	214403.7211	2020/1/30	762167676	
10.00	0.00	0.00	10.0000	4519.665164	4053.405051	466.2601129	217398.4929	2020/1/31		
11.00	0.00	0.00	11.0000	4989.165298	4519.665164	469.5001335	220430.3753	2020/2/1		
12.00	0.00	0.00	12.0000	5461.92287	4989.165298	472.7575722	223499.7221	2020/2/2		
13.00	0.00	0.00	13.0000	5937.955314	5461.92287	476.0324439	226606.8876	2020/2/3		
14.00	0.00	0.00	14.0000	6417.280076	5937.955314	479.3247619	229752.2273	2020/2/4		
15.00	0.00	0.00	15.0000	6899.914614	6417.280076	482.6345381	232936.0974	2020/2/5		

Appendix--GBM

1	990.00	400.00	226560190.00	637.3096	629134.5341	628819.2221	315.3120337	7172.051632	2022/10/7					
2	991.00	50.00	226590460.00	638.3050	629446.073	629133.0803	312.9927096	69165.16533	2022/10/8					
3	992.00	9.00	226607620.00	639.3023	629755.9387	629445.2551	310.6836076		2022/10/9	9.00				
4	993.00	134.00	226660597.00	640.2943	630061.8342	629753.4323	308.4019033		2022/10/10	134.00				
5	994.00	608.00	226714380.00	641.2860	630365.4442	630059.3091	306.1350996		2022/10/11	608.00				
6	995.00	769.00	226772393.00	642.2772	630666.6254	630362.7411	303.8843143		2022/10/12	769.00			9162.91599	
7	996.00	659.00	226827925.00	643.2687	630965.7047	630664.0576	301.6471524		2022/10/13	659.00				
8	997.00	262.00	226891622.00	644.2590	631262.209	630962.7818	299.4272021		2022/10/14	262.00				
9	998.00	41.00	226919762.00	645.2547	631558.1371	631260.9275	297.2095308		2022/10/15	41.00			10787.00	
)0	999.00	9.00	226935897.00	646.2522	631852.4101	631557.4078	295.002246		2022/10/16	9.00				
)1	1000.00	335.00	226989536.00	647.2440	632142.826	631850.004	292.821921		2022/10/17	335.00				
)2	1001.00	434.00	227041882.00	648.2360	632431.1512	632140.4958	290.6553544		2022/10/18	434.00				
)3	1002.00	757.00	227097267.00	649.2276	632717.2086	632428.7046	288.5039217		2022/10/19	757.00				
)4	1003.00	557.00	227150610.00	650.2194	633001.2361	632714.8702	286.3658754		2022/10/20	557.00				
)5	1004.00	577.00	227210823.00	651.2103	633282.8609	632998.6168	284.2440664		2022/10/21	577.00				
)6	1005.00	22.00	227238204.00	652.2061	633563.8044	633281.6788	282.1255548		2022/10/22	22.00				
)7	1006.00	8.00	227253469.00	653.2038	633843.1676	633563.1504	280.0171431		2022/10/23	8.00				
)8	1007.00	204.00	227304956.00	654.1959	634118.9127	633840.9785	277.9342595		2022/10/24	204.00				
)9	1008.00	429.00	227356976.00	655.1880	634392.5833	634116.718	275.8653014		2022/10/25	429.00				
.0	1009.00	1127.00	227413256.00	656.1794	634664.0384	634390.227	273.8113738		2022/10/26	1127.00				
.1	1010.00	549.00	227465632.00	657.1714	634933.6322	634661.8624	271.7698352		2022/10/27	549.00				
.2	1011.00	187.00	227524078.00	658.1625	635200.9665	634931.2228	269.743741		2022/10/28	187.00				
.3	1012.00	33.00	227549600.00	659.1587	635467.6434	635199.9224	267.7209755		2022/10/29	33.00				
.4	1013.00	5.00	227562998.00	660.1566	635732.8075	635467.0995	265.7080471		2022/10/30	5.00				
.5	1014.00	127.00	227600597.00	661.1509	635995.0087	635731.2927	263.7160055		2022/10/31	127.00				