An Experiment on COVID-19 Data Visualizations

Tony Di Sera, Mahdieh Taher, Linda Yang

Abstract

As the COVID-19 continues to ravage the U.S. with mounting cases and death tolls, data visualizations play a vital role in informing the public. When done effectively, these visualizations can evoke an emotional response, change attitudes, and help alter behaviors to reduce the transmission of the virus. Yet even with the rich sources of data visualizations, a substantial portion of the population seems to underestimate the risks that this pandemic poses and the devastating magnitude of lives lost.

The most common COVID-19 data visualizations depict case and fatality counts and rates using choropleths (colored maps) and line charts. For the data savvy audience, these data visualizations are effective. Yet for the general public, these data visualizations seem to fall short in conveying the alarming rate of spread across vast portions of the U.S. and the enormous loss of life. We hypothesis that the use of animations and poignant comparisons best convey these key messages.

Our experiment measured two key emotional responses after exposure to the data visualization intervention: 1) concern over the spread of COVID-19 and 2) distress over the number of COVID-19 fatalities. We found a statistically significant effect for both outcomes and conclude that data visualizations that employ these targeted techniques can be effective in changing attitudes around the risks of the COVID-19 pandemic.

Research Question and Hypothesis

This study seeks to understand this basic question -- to what extent can novel data visualizations impact a person's emotional response to the COVID-19 crisis in the U.S? Answering this question is crucial at this time when the stakes are so high, when the spread of the virus largely depends on individuals following the public health guidelines.

During the planning phase of our study, we identified four key messages that needed to be conveyed by the data visualizations. These include: 1) the the alarming rate of spread across vast portions of the U.S., 2) the magnitude of the fatalities, 3) how the SARS-CoV-2 virus is far more deadly than the seasonal flu, and 4) how poorly the U.S. is responding to the public health crisis compared to other countries.

We evaluated the most widely used COVID-19 data visualization websites, including the Johns Hopkins COVID-19 and many prominent news organizations with a wide online audience. We observed that many sites use line charts for showing the rate of spread, and it was common to see cumulative case counts in log scale. While log transformation is useful for a scientific audience, it may be misinterpreted by the general public. Also, we observed that choropleths are the most common chart for showing cumulative case counts, change in daily case counts, and number of fatalities. Although colored maps ground the viewer in geography to provide important context around key statistics, these charts rely on color and value change to compare values, which is not as easy for the human eye to detect compared to length and volume.[1] Also, colored maps can give the false impression of stark delineations at state and county borders.

From this evaluation emerged two key data visualization factors that we hypothesized would be influential in conveying the critical messages and evoking an emotional response. First, animations are a powerful technique for conveying events over time that the general public can understand. There are a number of experiments that suggest animated visualizations outperformed static graphs and tables in their ability to help viewers in interpreting data, making comparisons among data points, and anticipating and understanding change and what happens next.[2]

Second, it is crucial that data visualizations put the COVID-19 health crisis in historical perspective to show the devastating loss of life over the last 6 months. Here, we employ stark comparisons of COVID-19 to other war-time fatalities. In addition, to clear up lingering misconceptions, we contrast COVID-19 deaths to those from past flu seasons in the U.S.

Formulating our experiment to measure emotional response is a key, albeit preliminary, step in assessing if novel data visualizations can indeed shift attitudes toward the public health crisis. We adopt the stages of concerns from Concerns-Based Adoption Model (CBAM)[3]. This model includes and describes seven categories. In the earlier stage of a change, individuals more likely have self-focused concerns. For example, in the case of pandemic, how this pandemic potentially changes their individual lifestyle. As individuals become more and more aware of the situation, their concerns shift to focus on broader impacts such as the interaction with other people and likelihood of death among other family members.

Experiment Design

We used the Qualtrics Survey platform to conduct our experiment. We anticipated that a treatment effect would be difficult to detect given the limitations of online surveys and self-reporting on emotional states. With this in mind, we expected that our experiment would require a large number of subjects.

COVID-19 has disproportionately impacted minorities and the elderly, and has caused enormous loss of life in particular cities and regions in the U.S. Furthermore, the current U.S. political environment has resulted in polarized responses to the pandemic based on political party affiliation. This necessitates capturing responses from a diverse pool of subjects. For these reasons, our experiment utilizes [Amazon Mechanical Turk]() prime workers vetted as high quality workers from the [CloudResearch]() survey panel company.

Our study employed between subject comparison with no clustering, using an RXO comparison. We randomize by subject (the survey taker) by utilizing Qualtrics "flow" with a 50/50 ratio of assignment to treatment and control using the following structure:

1. Gather covariates. Ask multiple choice (required) questions to gather the following covariates: location (state), age, gender, ethnicity, political party affiliation, and education level. In addition we asked three questions about personal experiences of COVID-19. ***(See Appendix, Figure 1)***

2. Randomized Intervention. Expose subjects to data visualizations. The control group was shown the Johns Hopkins COVID-19 dashboard[4]. The treatment group was shown three animated data visualizations.

3. Measure Outcome. Ask two questions to measure the emotional impact of data visualizations on COVID-19 in the U.S.

We considered using a difference-in-difference experiment design to increase power, but decided against it. First, we did not want to anchor the subject's sentiment before treatment and risk identical (or arbitrary) responses post-treatment. Second, since digital workers tend to rush through surveys; repeating the same questions risks arbitrary responses.

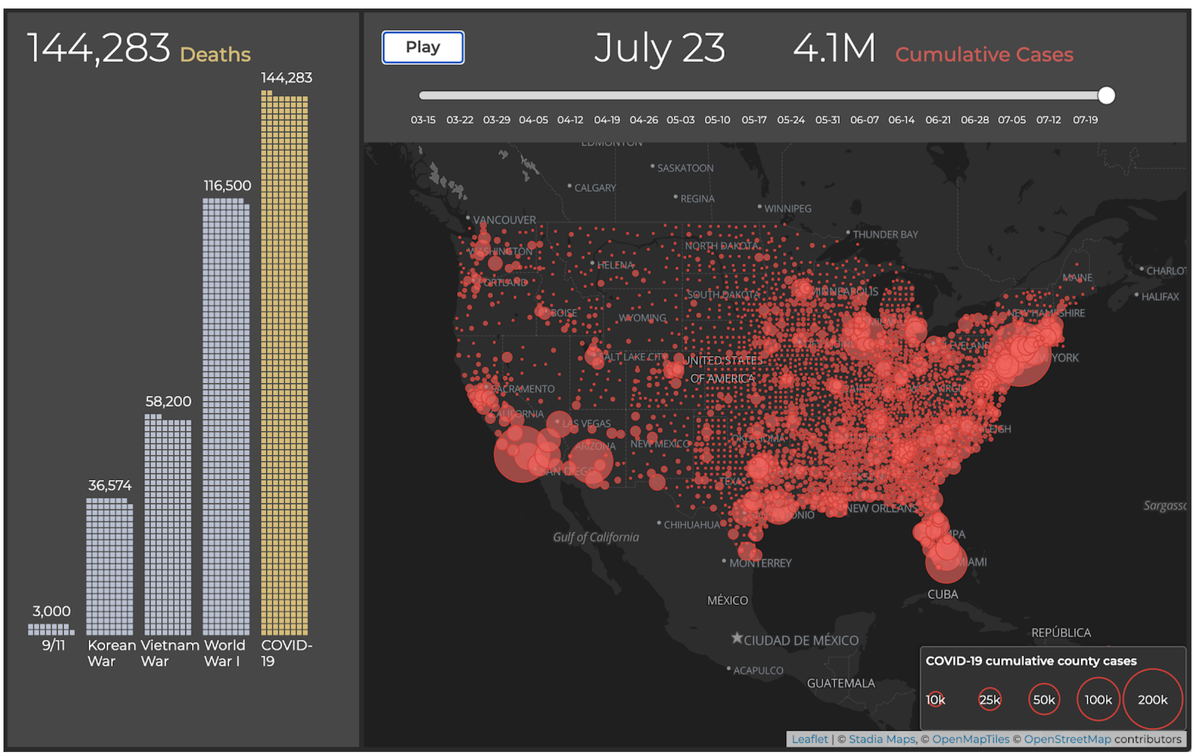
Treatment

We embedded the data visualizations as internal frames directly in the survey to minimize distraction and non-compliance. The control group saw the [Johns Hopkins COVID-19 dashboard for the U.S](). ***(See Appendix, Figure 2)*** The treatment group saw three novel data visualizations. After exposure to the data visualization(s), the respondents were asked if they trusted the information shown in the data visualizations.

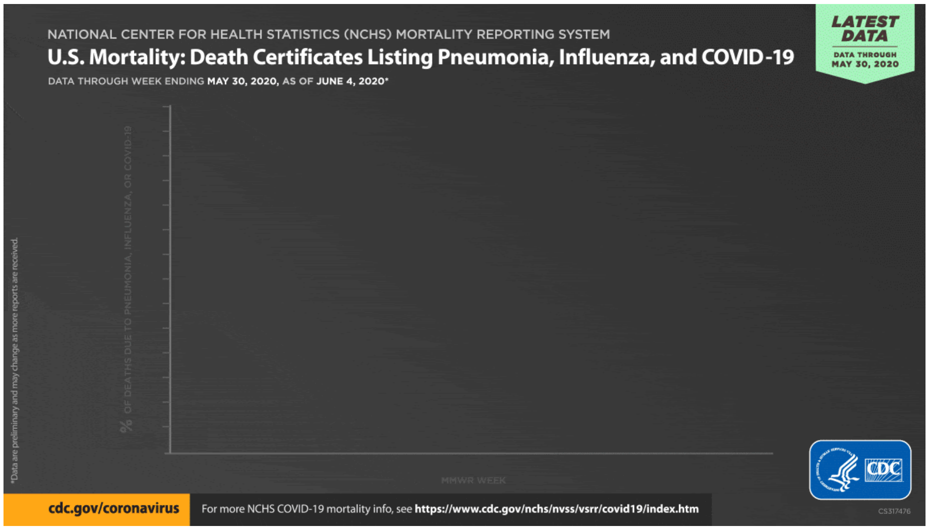
We chose to use the Johns Hopkins dashboard as our control intervention because we wanted a congruent experience between the treatment and control group; that is, subjects from both groups were shown COVID-19 data visualizations prior to being asked questions related to their current feelings about the COVID-19 spread and fatalities.

Finding a novel data visualization as informative, engaging, and comprehensive as the Johns Hopkins dashboard was challenging. It became apparent that we would require multiple data visualizations to convey the messages we deemed critical. The best candidates came from New York Times which has created an impressive repertoire of high quality, impactful COVID-19 data visualizations. But for the purposes of this study, none of these visualizations captured both how quickly the virus spread across the country and the enormity of the death toll over such a short period of time. So we developed our own [custom COVID-19 data visualization]() using D3 and Leaflet.js. *(The code is available at https://github.com/tonydisera/covid_impact_dashboard.)*

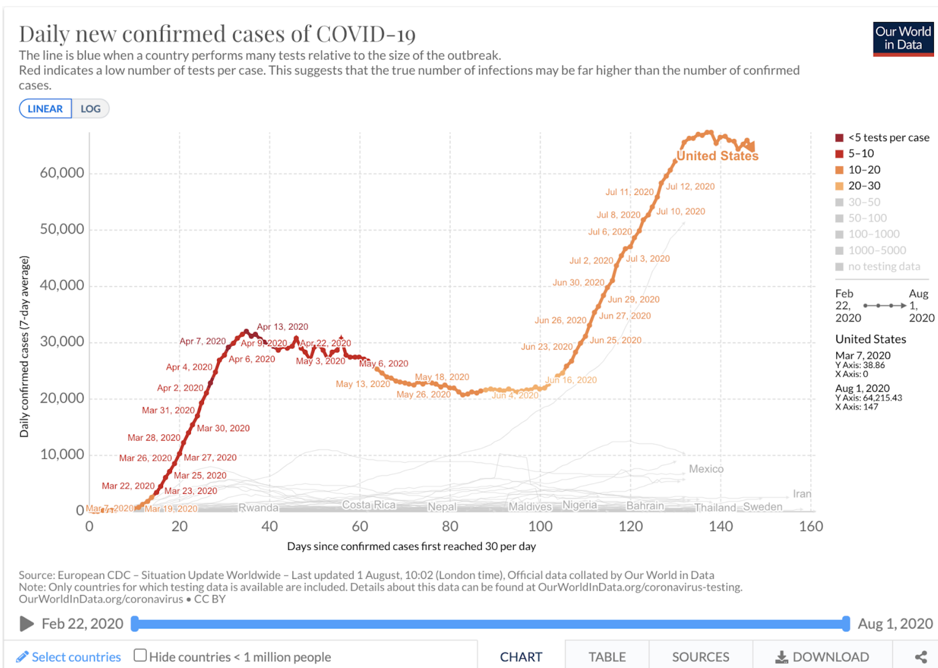
This data visualization uses animation to show the spread of the virus in the U.S. from mid March through the current date. The red circles on the map depict cumulative case counts. The left-side panel shows the rising fatalities in the same time frame as the case counts. When the animation completes on the last date, the left side-panel transitions to show U.S. COVID-19 fatalities compared to other U.S. wartime fatalities.



We included two other treatment visualizations. This [animated GIF from the CDC]()[5] shows how much more deadly the April/May 2020 outbreak of COVID-19 in the U.S. was compared to the last three flu seasons.

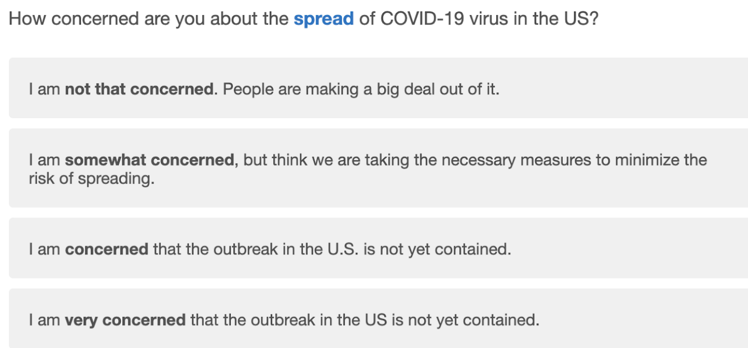


And finally, to contrast the COVID-19 crisis in the U.S. to other countries, we included this interactive data visualization from [Our World in Data](https://ourworldindata.org).[6]



Measurement of Potential Outcomes

After exposure to the data visualizations, the subject was asked two multiple choice questions, which comprise our two outcome measurements. We ask one question to gauge the subject's concern about the spread of COVID 19 in the U.S that is encoded as an output scale 1-4.



How concerned are you about the **spread** of COVID-19 virus in the US?

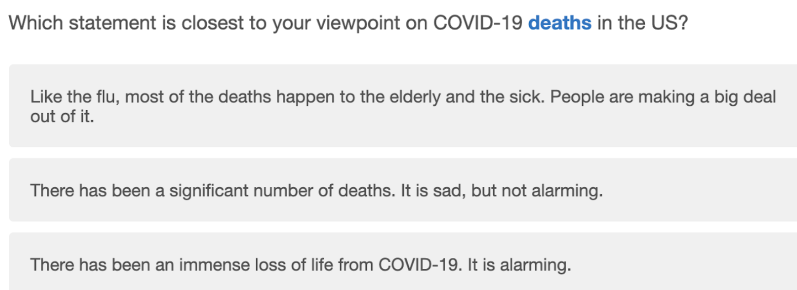
I am **not that concerned**. People are making a big deal out of it.

I am **somewhat concerned**, but think we are taking the necessary measures to minimize the risk of spreading.

I am **concerned** that the outbreak in the U.S. is not yet contained.

I am **very concerned** that the outbreak in the US is not yet contained.

Our second question is designed to appraise the level of distress over COVID-19 deaths in the U.S. This response is scaled 1-3.



Which statement is closest to your viewpoint on COVID-19 **deaths** in the US?

Like the flu, most of the deaths happen to the elderly and the sick. People are making a big deal out of it.

There has been a significant number of deaths. It is sad, but not alarming.

There has been an immense loss of life from COVID-19. It is alarming.

We employ multiple choice descriptive sentences instead of a scale for a few reasons. Using descriptive sentences risks introducing biased language that can sway responses, but this drawback is countered by the value of getting truthful responses. We expect that by embedding the emotional description in a sentence, participants are more likely to reflect how they relate to these feelings. Also, because our subjects are digital workers, we are concerned that a scale will prompt rushed responses rather than a measured, reflective engagement with the survey.

Pilot Study

We conducted a pilot run with 30 subjects and completed a preliminary analysis. We computed the ATE from the two outcome measures to estimate the sample size for our final run. We confirmed that we obtained reasonable distribution (both representative and random) which gave us confidence in the Mechanical Turk / CloudResearch platform to produce balanced covariate distribution between treatment and control.

Unexpectedly, the pilot study showed a negative average treatment effect for the response on the concern over the spread of COVID-19. We reviewed the survey and realized that the multiple choice wording was confusing. We re-ran another small pilot study to confirm that that the revised wording yielded a positive ATE.

We performed a statistical power calculation (set a .80) and estimated that the experiment would require 100 subjects in treatment and 100 subjects in control to detect a statistically significant average treatment effect. ***(See Appendix, Figure 3)***

Analysis and Results

Our first experiment, run on July 21, 2020, yielded 259 responses, 131 in treatment and 129 in control. As our analysis will show, we obtained a statistically significant ATE for both outcomes. Since we had a sufficient budget for a second run and we were interested in seeing if our results would replicate, we performed another run on July 25, 2020 on the identical survey. The second run resulted in 292 responses, 162 in treatment and 132 in the control group. (The 30 extra in treatment was expected. We combined a small batch of treatment-only observations performed on the prior evening with the results of the second run.)

After downloading, parsing, and validating the csv output from Qualtrics, we dropped a total of 11 records that were incomplete and had a duration under 10 seconds. (These dropped responses are survey takers on mobile devices that were sent to an error page.)

Covariate Balance

We did a covariate balance check against our final run to ensure that we captured a similar distribution for subjects in treatment and control. We examined location (state), gender, age, ethnicity, political party, education level, and COVID-19 experiences to ensure a balanced distribution and conducted formal t-tests We created histograms in Tableau to show distributions of treatment and control across all covariates were equivalent. ***(See Appendix, Figure 4a.)***

Based on the histograms and the t-tests, the covariates of *age* and *political party* show statistically significant differences in their distributions between treatment and control. ***(See Appendix, Figure 4b.)*** The *age* covariate is most imbalanced in the 20-29 age range. The *political party* imbalance is more pronounced with a .001 p-value on the t-test for the combined run observations. The histograms show that the number of *Republican* respondents were lower in the treatment group. In addition, we see a covariate imbalance for the response to ‘Do you know someone who has died from COVID-19?’. Since such few respondents answered yes to this question, we are not concerned with this imbalance.

Although we would prefer to have balanced distributions across all covariates, we still can sufficiently demonstrate that randomization was indeed working as expected and has sufficiently distributed hidden covariates.

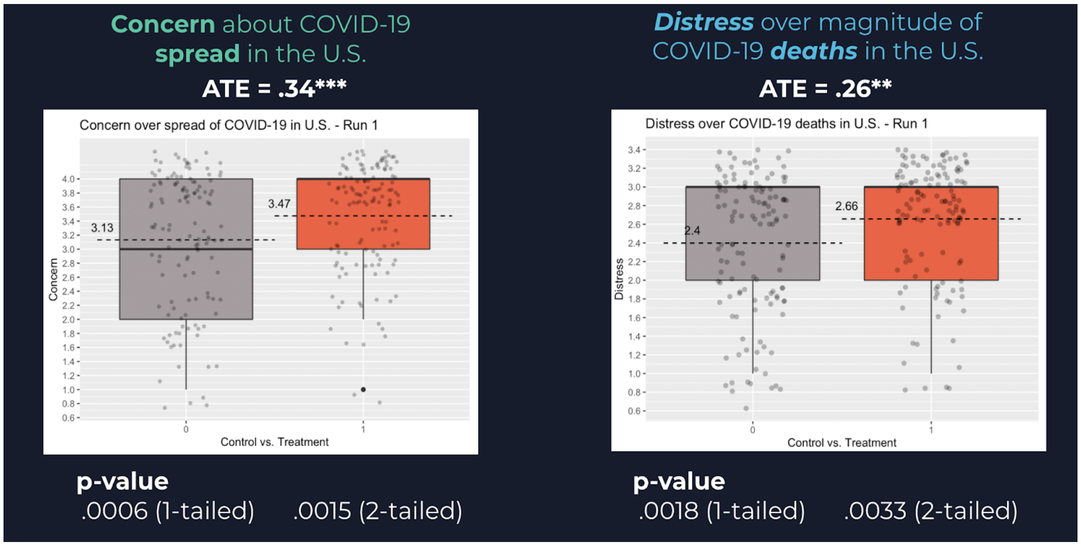
Modeling Choices

Our key assumption is that the multiple-choice questions are scaled linearly, so that each unit increase measures an equivalent uptick in emotional response. Our primary independent variable is assignment to treatment (0=assigned to control, 1=assigned to treatment). We use randomization inference with 10,000 simulations to estimate the ATE for our two outcomes.

In addition, we use linear regression to examine the causal relationship of the novel data visualizations to subjects’ emotional responses to COVID-19. We include location (state), age, gender, ethnicity, political party, education level and personal experiences with COVID-19 in our model. By including these covariates in the regression, we can estimate concern over COVID-19 and distress over COVID-19 fatalities across these factors, all of which we anticipate to exert some degree of influence.

Findings

Using randomization inference on the results for the first experiment run (N=259), we estimate a statistically significant ATE for both outcomes: We estimate an ATE of .34 (p-value .0006) on level of concern over the spread of COVID-19. We estimate an ATE of .26 (p-value .0018) and level of distress regarding COVID-19 deaths. ***(See Appendix Figure 5 for histograms of outcomes).***



When comparing ATE across the two experiment runs, it is clear that the second run (N=292) did not yield statistically significant results. However, the same upward average treatment effect is consistent with the first run. ***(See Appendix, Figure 6).***

We ran a series of linear regressions that show a statistically significant ATE for both outcomes. Here we show the regression results on concern over the spread of COVID-19 in the U.S. We show regression results for experiment run as well as the results when combining the observations from both dates. For the combined observations (across both runs), we observe a treatment coefficient of 0.205 with a robust standard error of 0.07 and a p-value of .0004.

	Concerned over COVID-19 Spread in U.S.			
	21-Jul-20	21-Jul-20	25-Jul-20	Both dates
treatment_assignment	0.34	0.334	0.146	0.205
	0.107	*0.104*	*0.096*	*0.07*
	p = 0.002***	p = 0.002***	p = 0.128	p = 0.004***
run				-0.125
				-0.07
				p = 0.074*
gender_female		-0.091	0.166	0.058
		0.105	*0.106*	*0.073*
gender_other		0.645	0.93	0.788
		-0.214	-0.248	-0.147
		p = 0.003***	p = 0.0002***	p = 0.00000***
age_40_60		0.143	0.232	0.198
		0.125	*0.112*	*0.084*
		p = 0.254	p = 0.040**	p = 0.018**
age_over_60		0.94	0.017	0.307
		0.221	*0.259*	*0.204*
		p = 0.00003***	p = 0.947	p = 0.132
party_democrat		0.681	1.053	0.879
		0.133	*0.132*	*0.093*
		p = 0.00000***	p = 0.000***	p = 0.000***
party_other		0.261	0.438	0.347
		0.167	*0.156*	*0.112*
		p = 0.118	p = 0.006***	p = 0.002***
not_caucasian		0.171	-0.052	0.048
		0.104	*0.109*	*0.075*
college_educated		0.153	0.071	0.097
		0.102	*0.102*	*0.073*
region_south		0.054	0.044	0.033
		0.137	*0.141*	*0.097*
region_midwest		0.098	-0.206	-0.071
		-0.147	*-0.175*	*-0.113*
region_west		0.28	0.077	0.152
		0.139	*0.166*	*0.109*
covid_sick		-0.225	-0.176	-0.196
		0.12	*0.118*	*0.085*
		p = 0.062*	p = 0.137	p = 0.022**
covid_hospitalized		-0.186	-0.07	-0.121
		0.155	*0.156*	*0.107*
covid_died		0.051	-0.117	-0.066
		0.153	*0.16*	*0.105*
Constant	3.133	3.057	2.922	3.137
	0.085	*0.283*	*0.306*	*0.206*
	p = 0.000***	p = 0.000***	p = 0.000***	p = 0.000***
Observations	259	259	292	551
R^2	0.038	0.263	0.291	0.254
Adjusted R^2	0.034	0.218	0.252	0.232
Residual Std. Error	0.858 (df = 257)	0.773 (df = 243)	0.812 (df = 276)	0.797 (df = 534)
F Statistic	10.183*** (df = 1; 257)	5.782*** (df = 15; 243)	7.541*** (df = 15; 276)	11.367*** (df = 16; 534)
Note:				*p**p***p<0.01

Next we ran the same series of regressions on our second outcome variable, the level of distress over the COVID-19 deaths in the U.S. We observe a positive ATE for the first and second run, as well as the observations in the combined runs. For the combined observations (from both runs), we observe a treatment coefficient of 0.142 with a robust standard error of 0.054 and a p-value of 0.01.

	Distressed by COVID-19 Deaths in U.S.			
	21-Jul-20	**21-Jul-20**	**25-Jul-20**	**Both dates**
treatment_assignment	0.34	0.235	0.095	0.142
	0.107	*0.085*	*0.072*	*0.054*
	p = 0.002***	p = 0.006***	p = 0.185	p = 0.010***
run				-0.017
				0.054
gender_female		0.023	0.105	0.067
		0.085	*0.074*	*0.055*
gender_other		0.486	0.586	0.526
		0.137	*0.174*	*0.102*
		p = 0.0004***	p = 0.001***	p = 0.00000***
age_40_60		0.11	0.2	0.161
		0.091	*0.087*	*0.063*
		p = 0.227	p = 0.022**	p = 0.011**
age_over_60		0.57	-0.268	0.011
		0.181	*0.253*	*0.197*
		p = 0.002***	p = 0.289	p = 0.954
party_democrat		0.559	0.769	0.663
		0.11	*0.105*	*0.076*
		p = 0.00000***	p = 0.000***	p = 0.000***
party_other		0.274	0.344	0.294
		0.129	*0.127*	*0.091*
		p = 0.035**	p = 0.007***	p = 0.002***
not_caucasian		0.116	0.034	0.058
		0.089	*0.077*	*0.058*
college_educated		-0.082	-0.013	-0.055
		0.081	*0.07*	*0.054*
region_south		0.006	0.102	0.051
		0.108	*0.099*	*0.072*
region_midwest		0.052	-0.174	-0.068
		0.111	*0.137*	*0.087*
region_west		0.03	0.076	0.049
		0.12	*0.123*	*0.086*
covid_sick		-0.093	-0.11	-0.111
		0.096	*0.082*	*0.062*
		p = 0.330	p = 0.181	p = 0.075*
covid_hospitalized		-0.111	0.031	-0.024
		0.114	*0.112*	*0.077*
covid_died		0.054	-0.106	-0.056
		0.123	*0.119*	*0.082*
Constant	3.133	2.255	2.192	2.31
	0.085	*0.242*	*0.225*	*0.165*
Observations	259	259	292	551
R^2	0.038	0.198	0.295	0.228
Adjusted R^2	0.034	0.149	0.257	0.204
Residual Std. Error	0.858 (df = 257)	0.631 (df = 243)	0.589 (df = 276)	0.609 (df = 534)
F Statistic	10.183*** (df = 1; 257)	4.004*** (df = 15; 243)	7.698*** (df = 15; 276)	9.834*** (df = 16; 534)
Note:				*p**p***p<0.01

We see a somewhat larger ATE with tighter confidence intervals for concern over the spread of COVID-19 than we do for the second outcome measuring the level of distress over COVID-19 deaths. Given the different scales (outcome with a scale 1-4, outcome 2 with a scale 1-3) and the different wording, no clear conclusions can be drawn from this difference. In addition, we see a much smaller ATE for both outcomes on the second run. When including *run* as a variable in the regression, we see a negative coefficient, but this lacks precision to draw any conclusions. Indeed, the most likely explanation for the difference between runs is due to variance alone.

We suspected a possible heterogeneous treatment effect based on political party affiliation. Because attitudes about COVID-19 are entrenched along partisan lines, we speculated that those subjects who identified as neither Republican or Democrat would be more amenable to being influenced by the novel data visualizations. After including the interaction term of *treatment:party_other*, we did not observe a statistically significant heterogeneous treatment effect. Of note, we observed a more significant HTE for the outcome regarding distress over COVID-19 deaths with a p-value of 0.16. ***(See Appendix, Figure 7).***

Limitations and Future Directions

Emotional responses that are self-reported from a survey are known to be problematic.[6] This reporting modality lacks reliability because respondents may not be able to identify or distinguish between emotional states or may report based on perceived expectations. So we must be careful to not interpret our findings too literally. Also, the relationship between emotional response, attitude shifts, and behavior changes is complicated. Although our analysis indicates that novel data visualizations can evoke emotional responses, this may not translate into behavioral changes that improve public health response to the pandemic.

It was noteworthy that the second experiment run, only 4 days after the first run, yielded a smaller ATE. Attitudes toward COVID-19 are likely to change over time as new outbreaks emerge and people are confronted with the stark reality that the pandemic is far from over. Given this situation, it is tempting to speculate that and that the average treatment effect would lessen over time. But indeed, two small experiment runs are insufficient to substantiate this claim. Rather, a longer running experiment where overall trends could be measured would be necessary to determine if the treatment effect would diminish over the coming months.

The findings from this experiment pose another interesting question regarding which data visualizations had the largest impact and whether a treatment effect could be detected without multiple visualizations that communicate specific information and convey targeted messages. To deconstruct this further, it would be interesting to not only isolate treatment data visualizations in an experiment, but also devise an experiment that used different visualization techniques to portray the same information.

Conclusion

When evaluating the value of visualizations, researchers traditionally focus on efficiency, comprehension, or insight. Based on our findings, we would like to highlight that the value of visualization is not only from the technical perspective but also from a broader point of view that includes evoking emotional responses such as concern. Arguably, data visualizations that inform the general public are most effective when they engage the audience, and elicit emotion, interest and insight.

As this public health crisis continues to unfold in the U.S., it is imperative that citizens stay informed. Our experiment demonstrates that targeted data visualizations can play an important role in communicating key information to the public.

References

1. Tufte, Edward R. The Visual Display of Quantitative Information. 2nd edition. Cheshire Connecticut: Graphics Press; 2001.

2. http://libres.uncg.edu/ir/uncc/f/Harrison_uncc_0694D_10516.pdf

3. HALL, GENE E. "The Concerns-Based Approach to Facilitating Change." *Educational Horizons*, vol. 57, no. 4, 1979, pp. 202–208. *JSTOR*, www.jstor.org/stable/42924345. Accessed 8 Aug. 2020.

4. https://coronavirus.jhu.edu/us-map

5. https://www.cdc.gov/coronavirus/2019-ncov/covid-data/data-visualization.htm

6. https://ourworldindata.org/grapher/daily-new-confirmed-cases-of-covid-19-tests-per-case

7. Mauss IB, Robinson MD. Measures of emotion: A review. *Cogn Emot*. 2009;23(2):209-237. doi:10.1080/02699930802204677

Appendix

Figure 1. Questions about personal experiences of COVID-19.

Have you or anyone you know been **sick** from COVID-19?

Yes | No

Have you or anyone you know been **hospitalized** due to COVID-19?

Yes | No

Has anyone you know **died** from COVID-19?

Yes | No

Figure 2. Johns Hopkins COVID-19 Dashboard for the U.S.

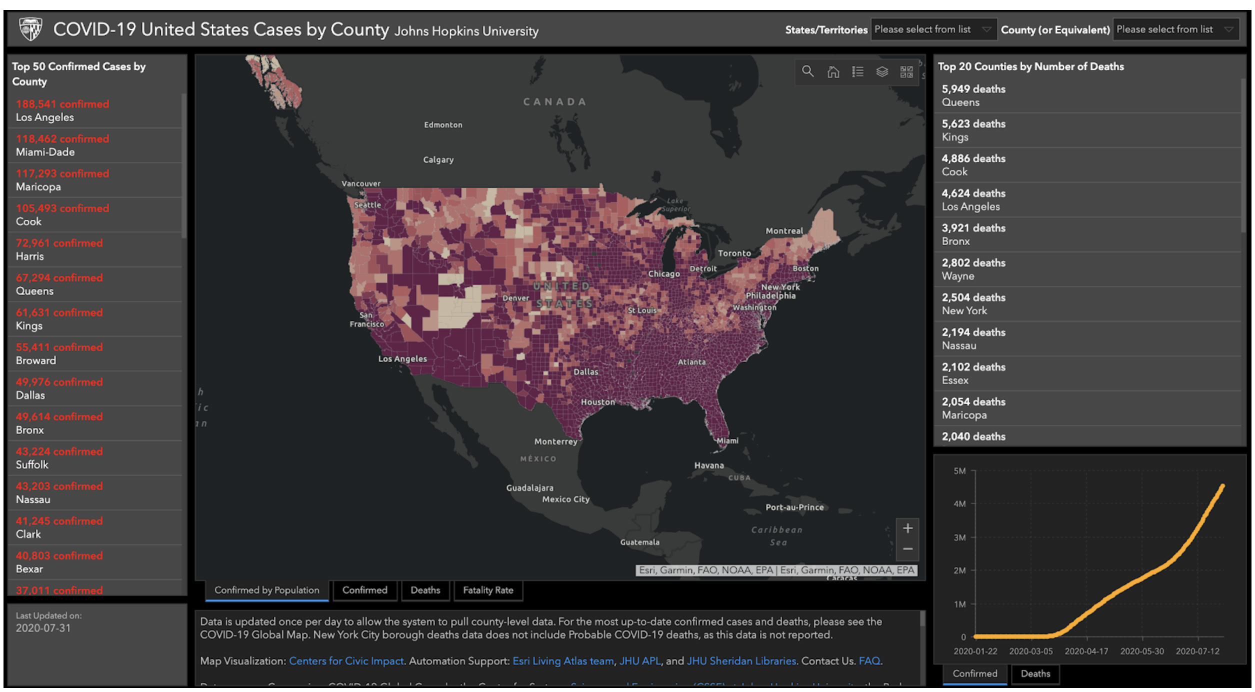


Figure 3. Power Calculation

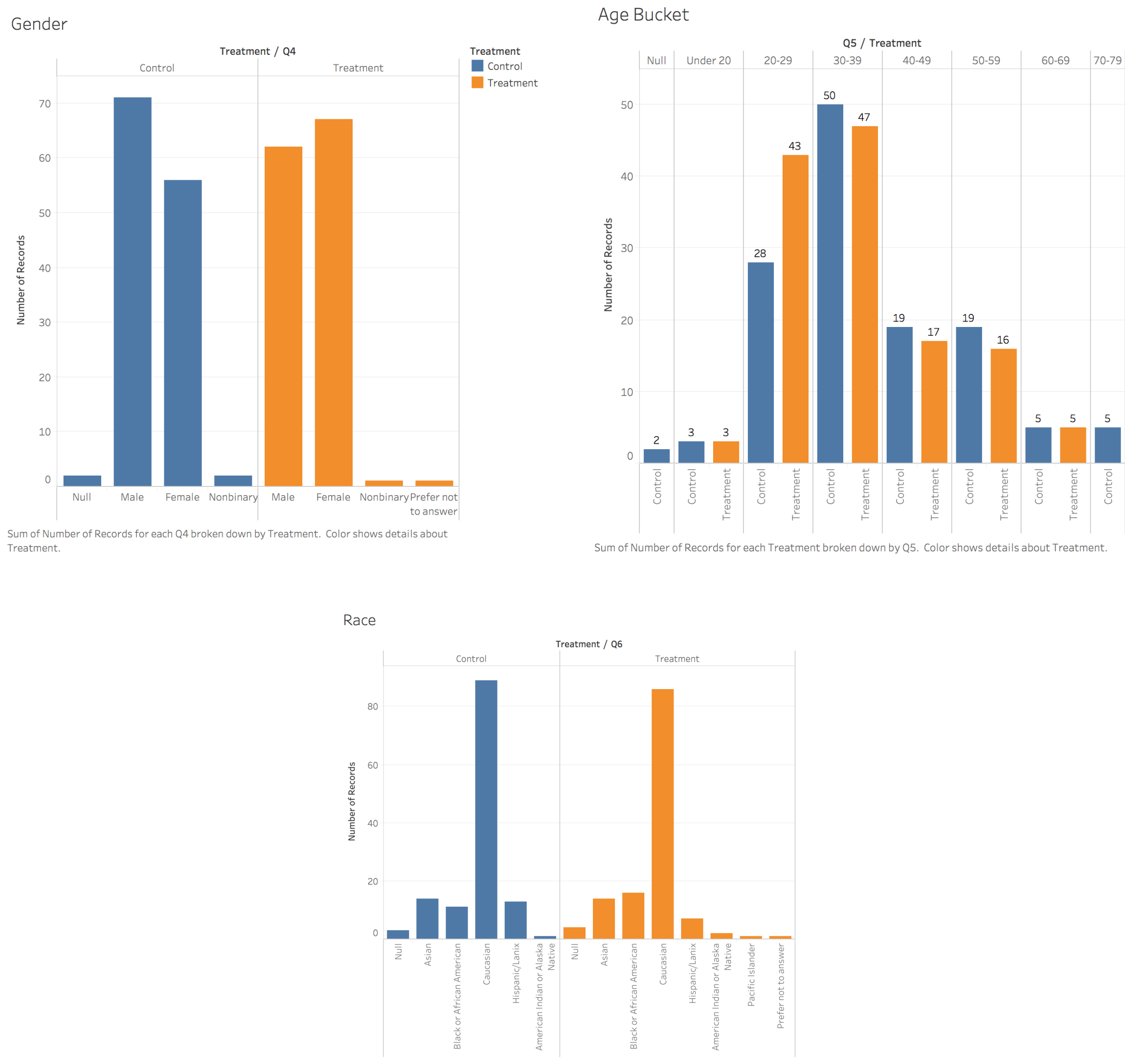
```
Power
```{r}
library(pwr)
pwr.t2n.test(n1=100,n2=100,0.4,sig.level=.05,power=NULL)
```

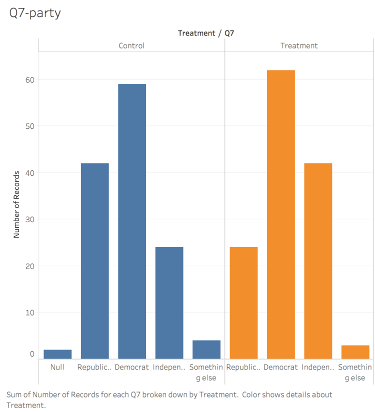

     t test power calculation

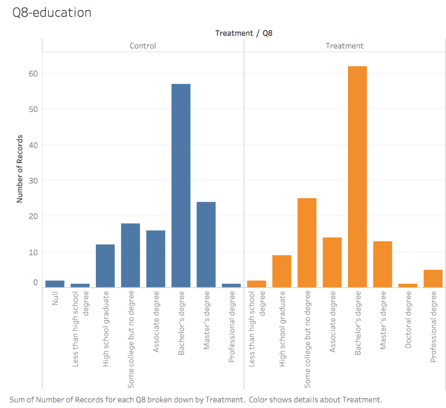
             n1 = 100
             n2 = 100
              d = 0.4
      sig.level = 0.05
          power = 0.8036475
    alternative = two.sided
```

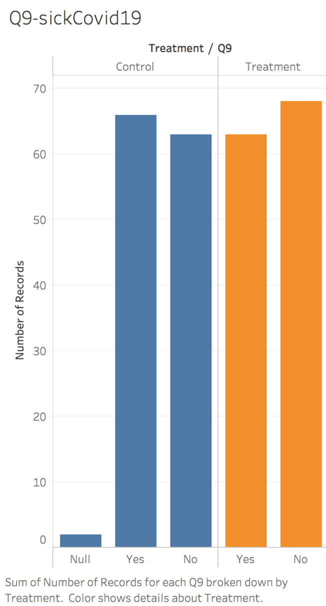
Using the ATE from our pilot study, we estimated that the experiment would require 100 subjects in treatment and 100 subjects in control to detect a statistically significant ATE.

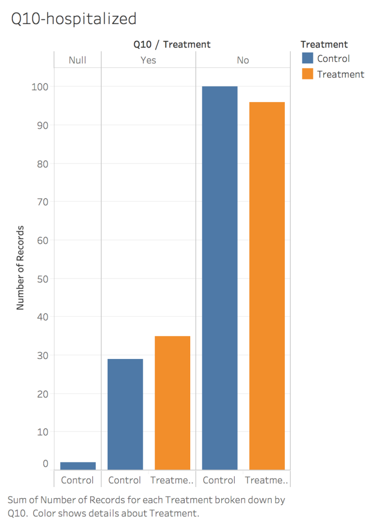
Figure 4a. Covariate Balance Histograms











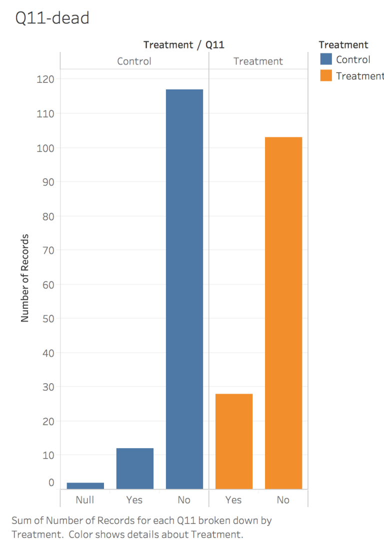


Figure 4b. T-test to Check for Covariate Balance.

Covariate	**p-value from Welch Two Sample t-test**		
	Run 1	Run 2	Combined
Gender	0.2333	0.6255	0.5722
Age	0.03286	0.1658	0.01833
Political party	0.007243	0.06321	0.001277
Ethnicity	0.5962	0.5934	0.4709
State	0.8281	0.3596	0.5942
College educated	0.8105	0.8082	0.9949
COVID-19 sick	0.5782	0.7379	0.9221
COVID-19 hospitalized	0.4503	0.6059	0.3824
COVID-19 death	0.007243	0.7113	0.03226
Political Party			
Republican	0.007478	0.152	0.003492
Democrat	0.7461	0.8499	0.9145
Other	0.02544	0.1185	0.007321

Figure 5. Histograms of Outcomes

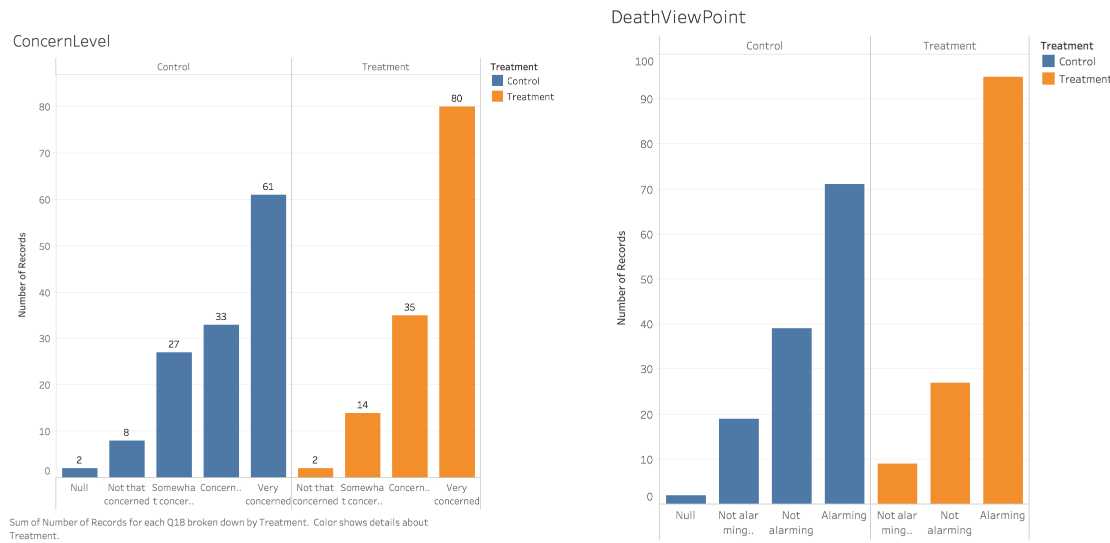


Figure 6. Results from randomization inference for two experiment runs

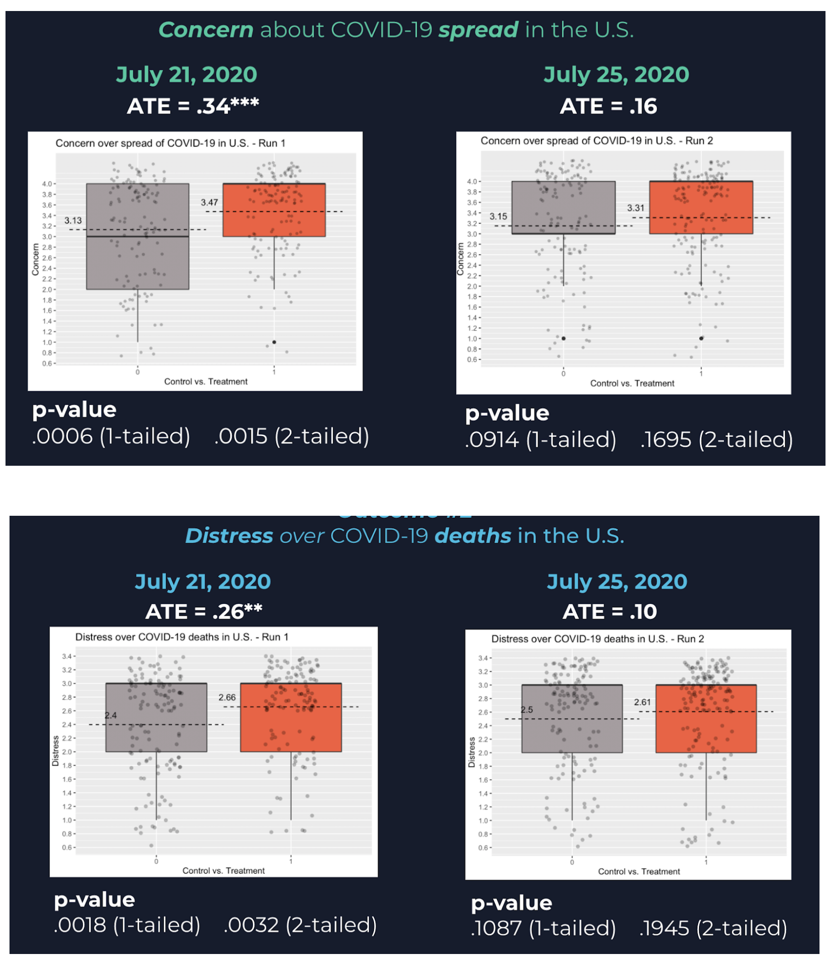


Figure 7. Regression for HTE

Concerned over COVID-19 Spread in U.S. - HTE

	Combined Runs
treatment_assignment	0.152 *0.078* p = 0.053*
gender_female	0.043 *0.072*
gender_other	0.802 *0.149* p = 0.00000***
age_40_60	0.188 *0.084* p = 0.025**
age_over_60	0.297 *0.204*
party_democrat	0.881 *0.094* p = 0.000***
party_other	0.244 *0.153*
not_caucasian	0.048 *0.075*
college_educated	0.093 *0.073*
region_south	0.032 *0.097*
region_midwest	-0.059 *0.113*
region_west	0.148 *0.11*
covid_sick	-0.185 *0.085* p = 0.030**
covid_hospitalized	-0.127 *0.106*
covid_died	-0.067 *0.103*
treatment_assignment:party_other	0.172 *0.166* p = 0.302
Constant	3.104 *0.205* p = 0.000***
Observations	551
R^2	0.251
Adjusted R^2	0.229
Residual Std. Error	0.798 (df = 534)
F Statistic	11.194*** (df = 16; 534)
Note:	*p**p***p<0.01

Distressed by COVID-19 Death in U.S. - HTE

	Combined Runs
treatment_assignment	0.073 *0.061* p = 0.227
gender_female	0.064 *0.055*
gender_other	0.553 *0.106* p = 0.00000***
age_40_60	0.154 *0.063* p = 0.015**
age_over_60	0.011 *0.188*
party_democrat	0.671 *0.076* p = 0.000***
party_other	0.153 *0.123*
not_caucasian	0.057 *0.058*
college_educated	-0.062 *0.054*
region_south	0.052 *0.072*
region_midwest	-0.065 *0.087*
region_west	0.046 0.086
covid_sick	-0.108 *0.061* p = 0.080*
covid_hospitalized	-0.025 *0.076*
covid_died	-0.048 *0.081*
treatment_assignment:party_other	0.247 *0.13* p = 0.059*
Constant	2.318 -0.164 p = 0.000***
Observations	551
R^2	0.234
Adjusted R^2	0.211
Residual Std. Error	0.607 (df = 534)
F Statistic	10.180*** (df = 16; 534)
Note:	*p**p***p<0.01