Impact of the presence of people in photos

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Introduction

Humans are social creatures. Historically, we have relied on each other to survive in the wild. Cooperation and communication are the two integral differences between us and other species in the animal kingdom. With the rise of social media in the last decade and us getting more comfortable in isolation due to mandatory quarantine, is our tendency to seek out others for social interaction coming to an end?

Upon further research, scientific evidence suggests that we favor crowds in certain situations, especially when we can emotionally relate to the group. According to psychologist Robert Cialdini in his book Influence: The Psychology of Persuasion, we rely on signals such as popularity to gauge the value of a place or object. For example, if a baseball game sells out then one can say that it is worth giving attention to. Furthermore, University of Sussex psychologist John Drury found that the more someone associated themselves with a certain group, the less likely they will feel too crowded, both mentally and physically. The presence of like-minded people does not trigger the feeling of personal space invasion, since they are not considered "others", rather, they are "us".

Our team decided to conduct an experiment that would test the presence of people in a popular excursion site on a person's interest in going there. By asking this question, we are curious about whether or not people are turned away by large groups of people or if people think that typical leisure destinations are less attractive when they are full of people. In simpler terms, we wanted to see if people were turned away from crowds of people. Our alternative hypothesis is that there will be a difference in one's desire to visit a location based on the presence of people in the image shown. Contrarily, our null hypothesis is that there will be no difference in one's desire to visit a certain location, whether they see the photo with many people or virtually no people.

```
##    responseID            image treat rating age gender location free_time
## 1:          4            Beach     0      5   2      2        1         5
## 2:          4      Disney Land     0      2   2      2        1         5
## 3:          4    Movie Theater     0      4   2      2        1         5
## 4:          4       Restaurant     0      4   2      2        1         5
## 5:          4 Ice-Skating Rink     0      1   2      2        1         5
## 6:          4    Swimming Pool     1      5   2      2        1         5
##    enjoy_travelling group_activity leave_frequency
## 1:                5              5               3
## 2:                5              5               3
## 3:                5              5               3
## 4:                5              5               3
## 5:                5              5               3
## 6:                5              5               3
```

Experiment Design

We decided to survey our experiment respondents through Qualtrics. When creating the survey, we chose to have each treatment and control photo for a specific location in their own block so that we could randomize which photo each respondent received in each photo set. As a result, we used simple randomization, which is similar to flipping a coin for each photo that each person rated. The different locations we chose to use are as follows: a beach, Disneyland, a movie theater, a restaurant, an ice skating rink, a swimming pool, a sports stadium, the top of a mountain, an aquarium, and finally, an apple orchard. Each of these photos represents different activities people can do, especially as leisure activities. Rather than using well known places such as the Eiffel Tower or the Pyramids of Giza, we chose generalized locations so that there was no bias surrounding the location. Had we used well known places or landmarks, people might not respond to the treatment or control as we would hope. Instead, people might have seen the Eiffel Tower, recognized it, and might want to go there regardless of whether or not there were people in the photo. The subconscious would likely ignore the presence of people, or lack thereof. As a result, the photos we chose could be considered neutral so as to avoid this bias. Instead of having two separate surveys and randomly assigning respondents to either the treatment or control survey, we decided that randomly selecting each individual into either the treatment or control group per photo set would allow us to get a wider variety of data. For each individual location, the survey contained a treatment and a control photo. The treatment was the location with people in the photo, while the control was the same location without any people in the photo. By dividing each photo set into their own blocks on Qualtrics, respondents were randomly selected into either the treatment or control group for each photo set. In terms of sending out the survey to people, we were not interested in any specific age range or other demographics. Rather, we wanted to get results from a variety of ages and other demographics so that we could use them as covariates in future regressions to see if it had any impact on peoples' preferences towards larger groups of people. The survey link was sent out to family and friends who then passed the survey along to their friends and family. Sending the survey link out was primarily through text messaging and social media messaging. We were also able to post the link on Facebook, so people could click on in if they wanted to help out.

```
reg <- felm(rating ~ treat, data = project_data)
summary(reg)
```

```
##
## Call:
##    felm(formula = rating ~ treat, data = project_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.7919 -0.7919  0.2082  1.2082  1.3886
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.79185    0.05334  71.089   <2e-16 ***
## treat       -0.18046    0.07827  -2.305   0.0214 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.151 on 868 degrees of freedom
## Multiple R-squared(full model): 0.006086   Adjusted R-squared: 0.004941
## Multiple R-squared(proj model): 0.006086   Adjusted R-squared: 0.004941
## F-statistic(full model):5.315 on 1 and 868 DF, p-value: 0.02137
## F-statistic(proj model): 5.315 on 1 and 868 DF, p-value: 0.02137
```

After running a regression of rating on the effects of the treatment, we found the coefficient to be -0.18 with a p-value of 0.05, meaning this coefficient was statistically significant. The result of -0.18 is very close to zero, but still leans towards the negative side. This means that, on average, the participants of the experiment preferred pictures that did not include people. However, the effect is so slight that it could have been ignored if not for the statistical significance. It is important to note here that our rating system went from one to five in terms of preference, with one being least preferred and five being most preferred. This puts in perspective how negligent the treatment effect of -0.18 is.

```r
reg2 <- felm(rating ~ treat + gender + age + location, data = project_data)
reg3 <- felm(rating ~ treat + age, data = project_data)
reg4 <- felm(rating ~ treat + location, data = project_data)
stargazer(reg2, reg3, reg4, type = 'text', dep.var.labels = c('Var 1', 'Var 2', 'Val 3')
          , covariate.labels = c('Treatment','Gender', 'Age', 'Location','Intercept'))
```

```
## 
## ======================================================================
##                                     Dependent variable:              
##                         ----------------------------------------------
##                                            Var 1                     
##                               (1)             (2)             (3)    
## ----------------------------------------------------------------------
## Treatment                  -0.172**        -0.182**        -0.176**  
##                            (0.078)         (0.078)         (0.078)   
##                                                                      
## Gender                      -0.110                                   
##                            (0.067)                                   
##                                                                      
## Age                         -0.023          -0.028                   
##                            (0.026)         (0.025)                   
##                                                                      
## Location                   -0.082*                         -0.087**  
##                            (0.044)                         (0.043)   
##                                                                      
## Intercept                  4.172***        3.873***        3.952***  
##                            (0.157)         (0.090)         (0.096)   
##                                                                      
## ----------------------------------------------------------------------
## Observations                 870             870             870     
## R2                          0.014           0.008           0.011    
## Adjusted R2                 0.010           0.005           0.008    
## Residual Std. Error 1.149 (df = 865) 1.151 (df = 867) 1.149 (df = 867)
## ======================================================================
## Note:                                      *p<0.1; **p<0.05; ***p<0.01
```

In regressions two, three, and four, we decided to include additional covariates to see how they would affect our outcomes. For all three of these regressions, we see a slightly negative coefficient for the treatment. Each outcome is also statistically significant with two stars, meaning that the p-value is less than 0.5 and we can be confident that 95% of the time, the treatment will have a negative effect on the ratings. In simpler terms, it is statistically significant that people are less inclined to go somewhere when there are many people pictured.

Looking deeper into regression two you can see that being male has a greater negative effect on the ratings. It also shows that as age increases, it has a greater negative effect on ratings as well. Unfortunately, both gender and age are not statistically significant, therefore we cannot make this claim confidently. When people live in rural or a mix of urban and rural areas, it decreases the rating for location as well. With one star of significance though, we cannot be completely confident in this result. Regression three also includes age, but similar to regression one, age is not statistically significant. While it does have a negative impact on the regression output, the lack of statistical significance means that we cannot say for certain that the impact of age on this regression is in fact negative.

Regression four shows a negative impact of location on rating. Contrary to gender in regression two and age in regressions two and three, location is statistically significant in regression four. With two stars significance, we can be 95% confident that location has a negative impact on rating. For people who live in urban areas, the impact is only 1 x (-0.087). For people in rural areas, the impact is 2 x (-0.087), and for people living in a mix of urban and rural areas, the impact is 3 x (-0.087). Therefore, living in a mix of urban and rural areas has the greatest negative impact, though it still is not that large.

```r
reg5 <- felm(rating ~ treat + free_time| 0 | 0 | responseID, data = project_data )
reg6 <- felm(rating ~ treat + group_activity| 0 | 0 | responseID, data = project_data )
stargazer(reg5,reg6, type = "text")
```

```
##
## ============================================================
##                                   Dependent variable:
##                               ----------------------------
##                                          rating
##                                    (1)            (2)
## ------------------------------------------------------------
## treat                           -0.179**      -0.181**
##                                 (0.077)        (0.076)
##
## free_time                        -0.062
##                                 (0.046)
##
## group_activity                                 -0.045
##                                                (0.063)
##
## Constant                        4.011***      3.961***
##                                 (0.169)        (0.251)
##
## ------------------------------------------------------------
## Observations                       870            870
## R2                                0.009          0.007
## Adjusted R2                       0.007          0.005
## Residual Std. Error (df = 867)    1.150          1.152
## ============================================================
## Note:                           *p<0.1; **p<0.05; ***p<0.01
```

In regressions five and six we included fixed effects, specifically controlling for the average differences among each individual. These differences include age, location, gender, and other characteristics we asked for in the survey. After including the fixed effect for response ID, the effect on the treatment on rating remained the same. The covariates we tested were free_time and group_activity. Although both were positive, they showed no signs of significance because the p-values were small.

```r
reg7 <- felm(rating ~ treat*age| 0 | 0 | responseID, data = project_data )
reg8 <- felm(rating ~ treat*location| 0 | 0 | responseID, data = project_data )
reg9 <- felm(rating ~ treat*free_time| 0 | 0 | responseID, data = project_data )
stargazer(reg7,reg8,reg9, type = "text")
```

```
##
## =============================================================
##                                     Dependent variable:
##                               -----------------------------
##                                          rating
##                                  (1)        (2)       (3)
## -------------------------------------------------------------
## treat                         -0.417***  -0.542***  -0.219
##                                (0.149)    (0.168)   (0.264)
##
## age                            -0.065*
```

```
##                                (0.034)
##
## treat:age                        0.082*
##                                (0.044)
##
## location                                   -0.179***
##                                             (0.069)
##
## treat:location                              0.195**
##                                             (0.077)
##
## free_time                                             -0.068
##                                                       (0.058)
##
## treat:free_time                                        0.012
##                                                       (0.076)
##
## Constant                      3.981***  4.123***  4.030***
##                               (0.132)    (0.144)  (0.204)
##
## ------------------------------------------------------------
## Observations                    870        870      870
## R2                             0.011      0.017    0.009
## Adjusted R2                    0.007      0.013    0.006
## Residual Std. Error (df = 866)  1.150      1.147    1.151
## ============================================================
## Note:                          *p<0.1; **p<0.05; ***p<0.01
```

The summary for regressions seven, eight, and nine shows us the different interactions in the regressions of the ratings of the images and the treatment alongside other covariates. The second interaction that provides statistically significant evidence is the interaction between location and treatment in regards to ratings. This was deemed more significant than the first interaction shown, and has a larger effect of 0.195. Considering our data ranged from one to five with higher ratings corresponding to likelihood, this is still a minimal effect, but an effect nonetheless. For some people, seeing a crowded amount of people in a location may be commonplace, especially when someone is from an urban area. On the other side of the coin, when someone is from a rural area, the treatment might have a greater effect on them because seeing a crowd of people may be more significant to them.

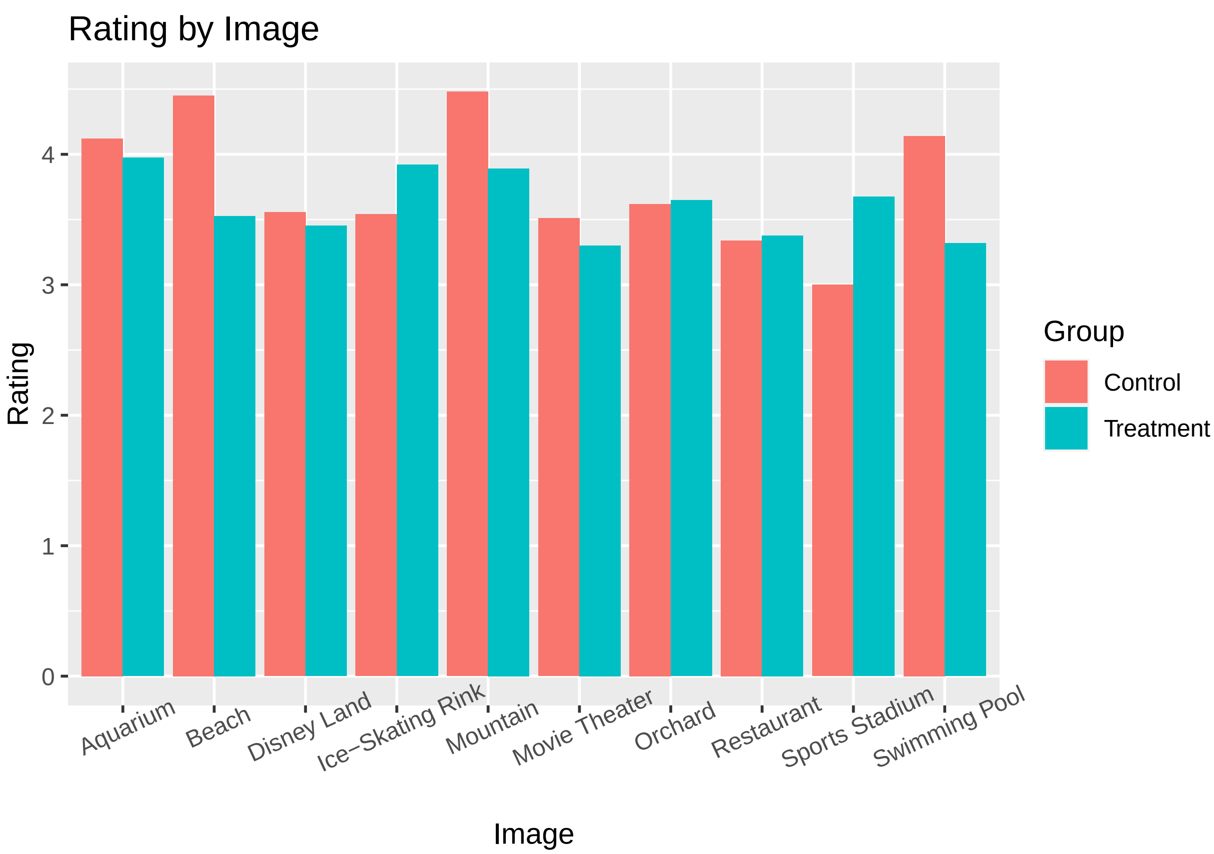
```r
#Separating Data by Treatment
treat_data <- project_data[project_data$treat ==1, ]
control_data <- project_data[project_data$treat ==0, ]


#Aggregating Data by Image
agg_data_image <- aggregate(rating~image,treat_data,mean)
agg_data_image_control <- aggregate(rating~image,control_data,mean)
setDT(agg_data_image)
setDT(agg_data_image_control)
agg_data_image_control[,Group:="Control"]
agg_data_image[,Group:="Treatment"]
agg_data_both <- rbind(agg_data_image_control,agg_data_image)
```

Potential Limitations and Errors

Since we are in a pandemic, that might have an effect on the respondents' answers; maybe people are less willing to be in groups of people. The fact that we are in a pandemic means our results do not necessarily represent the population in normal times. External validity might be present since our sample does not represent the entire population, rather it represents our friends and family and maybe a few more people. Since we had a smaller group of respondents, we might not have gotten enough variety for certain covariates (ex. location because we are in a city school, primarily reaching out to friends, so maybe the respondents prefer urban life and more people). The effect of people in photos could have opposite effects on the places they are at. If someone is at a beach, they might prefer less people to be there, whereas if you see a lot of people at a stadium you might be more inclined to go there because you associate a full crowd at a sports game with fun. Since people have these internal biases, they had differentiating opinions on places. The data would reflect this as it balances itself out, which is why we do not see a strong leaning in either direction (some people do not like sports anyway, so they would not want to go to a stadium regardless of whether or not there are people there).

```
ggplot(agg_data_both, aes(x = image, y = rating, fill=Group))+
  geom_bar(stat = 'identity', position = "dodge") +
  ggtitle("Rating by Image")+theme(axis.text.x=element_text(angle=25))+
  xlab("Image")+ylab("Rating")
```



This graph of the average rating shows the treatment effect of our experiment for each image. We decided to graph this data because of how we randomized our experiment to allow every respondent to be randomly selected into either the treatment or control group for each photo. We wanted to see if some images were more susceptible to treatment effects than others, and speculate as to why that might be the case. One of the first things that stood out is that the difference between control and treatment ratings are some of the largest differences between ratings for each image. In particular the beach, swimming pool, and mountain showcased the largest differences in ratings between the two groups. A potential reason for this could be that the amount of people was indicative of how popular the location was. Since beaches are fairly common, respondents might be more likely to choose a beach that has people in it versus one that does not since they expect there to be people at a beach. Compare this to an image with a small difference between the groups like Disneyland, where there are very few Disneyland in the world, so people know of its popularity even when there are no people in the photos.

Conclusion

We were able to derive multiple conclusions about the experiment results with the help of the various regressions we ran. First and foremost, it is worthwhile to mention that "failure to treat" was not a relevant aspect to consider for our experiment because every response that we intended to treat was successfully treated. Since we had not pooled participants into treatment or control groups before sending them the survey, it did not matter if someone did not take the survey. The treatment or control was assigned randomly through Qualtrics after a participant clicked a button to view the next image.

To elaborate further on the treatment and control groups, it is important to note that these groups were assigned based on the picture type that is shown to a person. Every time a new picture is shown to a participant, that is recorded as being either in the treatment or in the control group. Hence, each participant received a completely randomized 10-question survey. This was very helpful to increase the power of the experiment and is probably what helped us achieve statistical significance for many of the regression results. However, this made it relatively difficult for us to melt and process the data.

It would be interesting to run this experiment again in the future. In doing so, there are a few changes we would make. Given more time and a higher budget, we would first want to include a much larger number of participants in our experiment. This would not only improve the power of our experiment, but also lead to a better representation of the U.S. population in our data. Second, we would like to avoid the "COVID bias" that was unfortunately a limitation of our current experiment. It would help to get an idea of how people react to different pictures in general, and not just during a pandemic. Lastly, we would want to include a more diverse set of pictures in our survey, so that we can minimize any effects or bias based on particular places shown in the images.

Appendix

FOR ALL PHOTO QUESTIONS:	Very Uninterested	Uninterested	Neutral	Interested	Very Interested		
	1	2	3	4	5		
On the average week, how much free time do you have?	0 Hours	1-3 Hours	4-7 Hours	8-10 Hours	11+ Hours		
	1	2	3	4	5		
Please rate your level of agreement with the following statement: "I enjoy travelling"	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree		
	1	2	3	4	5		
When you do leisure activities, do you prefer to be with other people or alone?	Never with people	Rarely with people	Sometimes with people	Mostly with people	Always with people		
	1	2	3	4	5		
On average in 2019, how often did you leave your house for leisure activities per week?	0 times	1-3 times	4-6 times	7+ times			
	1	2	3	4			
What is your age?	Under 18	18-24	25-34	35-44	45-54	55-64	65 or older
	1	2	3	4	5	6	7
What gender do you identify with?	Female	Male	Other	Prefer not to answer			
	1	2	3	4			
Which of the following best describes the town/city where you currently live?	Urban	Rural	A mix of urban and rural				
	1	2	3				

Figure 1: Variable keys

Works Cited

Henderson, Rob. “The Science Behind Why People Follow the Crowd.” Psychology Today, 24 May, 2017, https://www.psychologytoday.com/us/blog/after-service/201705/ the-science-behind-why-people-follow-the-crowd. Accessed 30 Nov. 2020. “Why Some of Us Love Being in Crowds.” Independent.ie, 13, Nov. 2013, https://www.indepen dent.ie/world-news/and-finally/why-some-of-us-love-being-in-crowds-29752776.html#:~:text=Researchers%20said%20their%20findings%20explained,of%20the%20attraction%2C%20they%20added.&text=Dr%20Drury%20argued%20that%20the%20findings%20have%20important%20impications%20for%20psychology. Accessed 30 Nov. 2020.