The Effects of the COVID-19 Pandemic on Happiness[1]

By Alvin Zhu

Negative emotions abound during the 2020 COVID-19 pandemic. People are stressed, anxious, and scared about the disease and its ramifications. Mandatory quarantine is one of its most impactful ramifications and this in particular is attributed to be a leading cause of such decrease in positive emotions. Thus, the goal of this paper is to empirically investigate this belief. By analyzing tweets from all 50 states of the United States within a two-month window of the start of mandatory quarantine, *I have determined that quarantine has a chronic, prolonged effect on the happiness of people living in America*. *This effect is on par with that of other factors such the number of COVID-19 cases, employment levels, consumer spending levels, and time spent outside the home. This suggests that quarantine is not the sole cause of unhappiness during this pandemic as economic and social factors are just as harmful.*

The 2020 COVID-19 pandemic is a monster that has disrupted modern life to unprecedented proportions. Since its detection in Wuhan, China in late 2019, this disease has killed more than 1.3 million people in more than 220 countries around the world.[2] In response to the deadly outbreak, many countries have implemented measures to curb infection and

[1] https://github.com/alvinzhu33/14.33/tree/master/14.33%20Final%20Paper
[2] (World Health Organization)

transmission. Social distancing is now vital, face masks are now mandatory, ritual hand and surface cleaning are now stressed, and most importantly, lockdowns have been enforced. Businesses and institutions had suddenly came to a stop, with some transitioning to online working environments but many others being forced to lay off their employees. These efforts are a necessity to save the lives of millions but have also created the worst recession since the 1930s Great Depression.[3]

From an individual's perspective, however, the impacts of recession are dwarfed by the impact of COVID-19 lockdowns. This includes curfews, stay-at-home orders, and self-quarantines. Under lockdown, life was suddenly a semblance of what it was just a few weeks back. Within a matter of days, everyone that was not an essential worker found themselves trapped at home. With all forms of social interaction forbidden, many relied on social media to connect and find solace with friends and family. There, they also expressed anger, anxiety, and stress while finding out that others are just as scared as they are. These drastic changes in daily life are coupled by media detailing how COVID-19 quarantine measures were negatively human emotions. For instance, according to the Houston Chronicle, 34% of women and 25% of men felt anxious nearly every day since the pandemic.[4] Moreover, the COVID Response Tracking Study by the NORC at the University of Chicago found that the amount of Americans who describe themselves as very happy dropped from 31% in 2018 to an all-time record low of 14% during the COVID-19 pandemic.[5] Even major organizations such as the Centers for Disease Control and Prevention[6], the U.S. Department of Veteran Affairs[7], and the American Psychological Association[8] have all published resources regarding emotional wellbeing under quarantine. This goes to show just how disruptive and unprecedented the COVID-19 lockdown measures are.

Yet, in time, the initial outpour of negative emotions seems to have eased. As early as the summer of 2020, stress and anxiety seemed to have become indifference despite how quarantine was still ongoing and the coronavirus still ravaged communities around the world. The irony in how there was so much negativity at the start of quarantine but not so much as quarantine

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[3] (Gopinath)
[4] (Gill)
[5] (NORC at the University of Chicago)
[6] (Centers for DIsease Control and Prevention)
[7] (U.S. Department of Veteran Affairs)
[8] (American Psychological Association)

progressed despite lockdown being blamed as the cause of unhappiness motivates the question at hand: how exactly does quarantine affect the happiness of those living in the United States? In fact, does quarantine even cause unhappiness or is it just a scapegoat for the fear of the virus and its byproducts like recession? Moreover, considering the shift in attitudes as COVID-19 progressed, are people just getting accustomed to life under lockdown? In this case, perhaps just the news of the lockdown and the novelty of it may be a factor.

Because the 2020 COVID-19 Pandemic has not been resolved, there have been few publications regarding quarantine and happiness. One study in China found that self-quarantine increased happiness whereas state-sanctioned quarantine decreased happiness. Moreover, they determined how reliable real-time updates on the disease and measures for its control increased happiness.[9] This seems counter to those living in the U.S., where self-quarantine is a burden and real-time coverage of COVID-19 raised fear and anxiety instead. In another study, researchers found that the perceived risk of COVID-19 reduced happiness.[10] Although these papers have found very interesting statistics, they do not address how the happiness of those living in the U.S. during lockdown is impacted by different factors relating to the pandemic. Thus, in this paper, I will consider the effects of a myriad of pandemic factors on happiness, which I will estimate via sentimental analysis of tweets on Twitter. These pandemic factors include the number of COVID-19 cases, change in spending habits, change in employment level, change in time spent outside the home, and enforcement of stay-at-home orders. I will use an event study model to explore the effects of lockdown on happiness by creating a two-month window around the date a state's stay-at-home order was first enacted, using the other pandemic factors as controls. These results will describe the empirical effects of lockdown on happiness in the U.S.

Data

I will be using seven different data sources for this project. Six of these datasets are pulled from the Opportunity Insight's Economic Tracker and will represent pandemic factors that may affect happiness.[11] These data sources are the Affinity, COVID, Employment, Mobility, Policy

[9] (Lu, Nie and Qian)
[10] (Yildirim and Güler)
[11] (Chetty, Friedman and Hendren) and https://tracktherecovery.org

Milestones, and GEOIDs datasets. The GEOIDs dataset helps translate Federal Information Processing Standard (FIPS) state codes into two-letter alphabetic codes (ex: “36” into “NY”). This translation facilitates the aggregation of the other five datasets.

The COVID dataset is adapted from the New York Times COVID-19 Data[12] and The COVID Tracking Project[13]. It records daily information pertaining to COVID-19 in every state from January 21, 2020 to October 29, 2020, including the daily case count of each state.

The Affinity dataset is adapted from Affinity Solutions.[14] It tracks debit and credit card spending in the U.S and then aggregates the data into daily spending rates. These spending rates are represented as the change in consumer spending relative to an indexing period of January 4, 2020 to January 31, 2020. From this dataset, we can extract the total change in spending habits within all industries in every state from January 1, 2020 to October 10, 2020.

The Employment dataset is adapted from Paychex’s and Intuit’s firm-level payroll data, Earnin’s employee-level data, and Krono’s employer-level data. Analogous to the Affinity dataset, this dataset measures via a 7-day moving average the change in employment levels relative to an indexing period from January 4, 2020 to January 31, 2020. From this dataset, we can extract the total percent change in employment levels from all demographics and industries in every state from January 1, 2020 to September 10, 2020.

The Mobility dataset is adapted from Google’s COVID-19 Community Mobility Reports[15] and the U.S. Bureau of Labor Statistics’ American Time Use Survey[16]. Through GPS tracking, this dataset measures the change in percent of time spent outside the home relative to the indexing period from January 3, 2020 to February 5, 2020. Data from February 24, 2020 to October 27, 2020 is available for every state.

Finally, the Policy Milestones dataset is created with information from the New York Times, Institute for Health Metrics and Evaluation, and local news sources. This dataset enumerates the dates for policy changes such as stay-at-home orders for each state that had

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[12] https://github.com/nytimes/covid-19-data
[13] https://covidtracking.com/
[14] https://www.affinity.solutions/dataforgood#dataforgood-content
[15] https://www.google.com/covid19/mobility/
[16] https://www.bls.gov/tus/

enforced COVID-19 lockdown. This dataset will be used to isolate the affects of lockdown apart from the other pandemic factors.

Aside from these six datasets, I will use a dataset of geo-tagged tweet IDs collected by researchers Yunhe Feng and Wenjun Zhou throughout the United States from January 25, 2020 to May 10, 2020. [17] This period of time not only encompasses when COVID-19 infections first began to accelerate in the U.S, but also when state governments had enacted stay-at-home orders. There are 650,563 tweets IDs in this dataset, all of which are already separated into states based on the tweets' geo-tagged locations. Note, however, that tweet IDs are not the tweets itself. Tweet IDs are unique identifiers for tweets that can be used to pull a specific tweet using Twitter's API. This caveat arises from how the sharing of datasets of tweets violate Twitter's Terms of Service while that for tweet IDs do not. Through sentiment analysis of the content of the tweets associated with these tweet IDs, I will gauge the happiness of Americans in response to COVID-19 lockdowns.

Data Processing

A substantial component of this project was dedicated towards processing the data that I had collected. Much of this time was devoted towards handing tweets. As mentioned earlier, Twitter's Terms and Services forbid the sharing of tweets. My tweets dataset is hence just a large collection of tweet IDs. These must undergo a process called hydration to extract the tweet's message as well as other meta-data such as the tweet's date of creation.

To hydrate my tweet IDs, I used the Tweepy library on Python, which is an accessible way to access Twitter's API. The statuses_lookup function from Tweepy is the main method for hydration. This function takes in a list of up to 100 tweet IDs and returns a list of JSON objects containing all the information regarding that tweet, including tweet content and tweet creation date. Unfortunately, this function has two limitations. First, it can only take up to 100 tweet IDs at a time. Because I have 650,563 tweet IDs, I must subdivide these tweet IDs into at least 6,506 groups of 100 tweet IDs each. The larger issue, however, are the Twitter API's rate limits. The statuses_lookup function is capped at 900 executions every 15 minutes. Because I had at least 6,506 groups of tweet IDs, this process must then take a minimum of 1.5 hours to complete.

[17] (Feng and Zhou)

However, prolonged execution of Tweepy can cause the code to terminate or hang prematurely. Therefore, to play it safe, I hydrated my tweet IDs in smaller batches. First, I separated the 50 states into 10 batches of five states each. These 10 batches will contain a list of all the tweet IDs of the five designated states for that batch subdivided into mini lists of at most 100 tweet IDs. Each batch will be hydrated and saved individually. After processing all 10 batches, I will combine the 10 individual files into one master file of all the tweets in my dataset. This procedure addresses the rate limit driven time-intensive process of hydrating a large number of tweet IDs by processing and saving disjoint subsets that are smaller and more manageable. Therefore, if the code hangs before completion, I can run the code again starting off at the batch that was not complete. Although this procedure would take 45 minutes longer to complete, it eliminates the need to rerun the entire process if code fails.

After hydration, I perform sentiment analysis on each tweet's content. As mentioned above, I use the sentiments expressed through tweets as a substitute for happiness during the COVID-19 pandemic. Sentiment analysis was be done with the Natural Language Toolkit's Valence Aware Dictionary for sEntiment Reasoner (VADER) analyzer. Though a multiclass sentiment analysis algorithm, VADER can accurately calculate the polarity of a tweet, which is a measure from -1 to +1 of the sentiments expressed through a tweet (-1 being most negative and +1 being most positive). In other words, for the purposes of my study, happiness as expressed through tweets would range from a polarity of -1 (completely unhappy) to a polarity of +1 (completely happy). Aside from manually assigning the polarity score to every tweet, VADER is the best alternative as a recent study conducted by Shihab Elabagir and Jing Yang showed how VADER was not only fast at classifying huge amounts of text, but it was also effective and accurate.[18]

With sentiment analysis complete, I now combine all the data that I have collected into one file. This is accomplished via a left merge of the six pandemic factors datasets (number COVID-19 cases, spending levels, employment levels, time spent outside, and dates of lockdown) onto my newly created sentiments dataset, where state and date are the shared keys. This makes it so that data of the pandemic factors remain constant for each state and date pair while the sentiments change depending on the tweets in that state and date pair.

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[18] (Elbagir and Yang)

Empirical Design

With data about COVID-19 cases, consumer spending, employment levels, time spent outside, dates of policy changes, and tweet sentiments, I have all the factors I need for this study. Thus, to answer the question of how COVID-19 lockdowns have affected happiness, I will use an event study with a single policy timing of the day of lockdown enforcement for each state. I will create a two-month window around the date a state's stay-at-home order has been enforced (from a month prior to that date to a month afterwards), with the pandemic factors serving as controls. To create this window, I introduce 61 binary indicator variables that represent whether the date is *i* days from the date of lockdown enforcement, where *i* varies between -30 and 30. I then filter out the data that do not satisfy any of the 61 binary indictor variables. My event study model is thus:

$$\text{happiness} = \beta_0 + \beta_1\text{spending} + \beta_2\text{COVID} + \beta_3\text{employment} + \beta_4\text{outside} + \sum_{i=-30}^{30} \alpha_i \text{day}_i$$

By controlling for pandemic factors like a state's number of COVID-19 cases, change in consumer spending, change in employment levels, and change in time spent outside, this model would extract the impact of a stay-at-home order in and of itself. Out of the 61 coefficients for the 61-day window, I will focus my study on α_{-7} to α_{15} as I believe anything prior to a week before lockdown is irrelevant and anything after two weeks can be inferred by the trend from α_0 to α_{15}. As mentioned, an irony of the COVID-19 pandemic is that people do not seem as unhappy today as they were during early Spring. Therefore, I hypothesized that perhaps the sheer novelty and shock of a lockdown may be triggering negative emotions. If this were true, I expect a sudden and strong dip in the coefficients around α_0 that increases on both sides, making a V-shaped curve.

Results

Factor	Estimated Effect	p-value
Number of COVID-19 cases	$-6.411 * 10^{-8}$	0.0036
Change in credit card spending	$2.364 * 10^{-4}$	0.0917
Change in employment levels	$2.075 * 10^{-4}$	0.3071
Change in time spent outside	$-1.641 * 10^{-3}$	0

Table 1. Effects of COVID-19 factors on emotions as expressed through Twitter

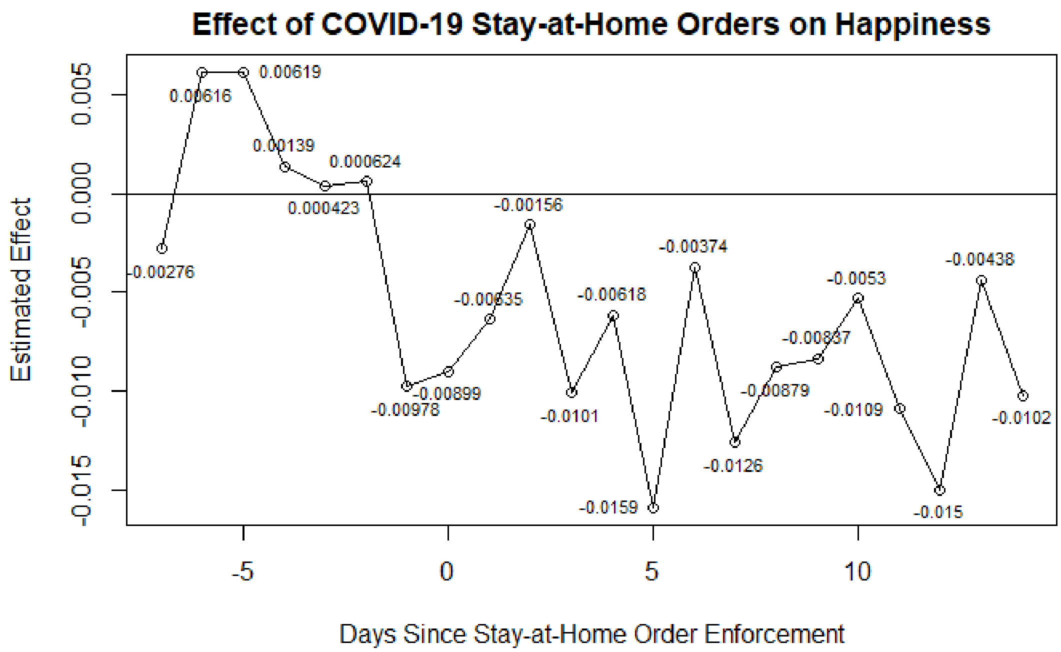

Figure 1. Effects of COVID-19 stay-at-home orders on emotions as expressed through Twitter

As we can see in Table 1, human emotions are undoubtedly affected by the number of COVID-19 cases, spending habits, employment levels, and amount of time spent outside. For every extra case of COVID-19 within a state, the average happiness goes down by $-6.411 * 10^{-8}$. This magnitude is quite small, but considering how the average number of COVID-19 cases on October 29, 2020 per state was 175,498 cases, happiness on a scale of -1 to 1 decreased by $-1.125 * 10^{-2}$! This tells us that the mere knowledge of the number of COVID-19 cases in one's locality causes worry. This makes sense as the prevalence of COVID-19 cases is tied to the likelihood that the person will catch COVID-19. COVID-19 is a deadly disease, so the thought of catching it will naturally be a stressor.

Aside from the effect of the number of COVID-19 cases on happiness, we see that for every percent increase in spending habits, people are happier by $2.364 * 10^{-4}$. The greatest change in spending for every state is -33.237% on average, which means that people could be less happy by as much as $7.857 * 10^{-3}$ from spending less during the pandemic. This positive correlation between spending rates and happiness agrees with researchers Elizabeth Dunn and Michael Norton's book *Happy Money; The Science of Happier Spending*, wherein the pair argue that happiness can be derived from how people spend money.[19]

We also see from our regression that higher employment levels are correlated with more positive sentiments. For every percent increase in employment levels, happiness increases by $2.075 * 10^{-4}$. This effect is not as large as that of spending, but it is still notable. The largest change in employment levels for the 50 states is -33.237% on average, thus people can be less happy by up to $4.792 * 10^{-3}$. Although the positive correlation between employment levels and happiness is as expected, the magnitude is not as high as I would have thought. I hypothesize that this magnitude may be quite small because most Twitter users are affluent millennials[20], a demographic that is less likely to be affected by COVID-19 related unemployment.

Finally, we see that for every increase in percent of time spent outside, happiness decreases by $1.641 * 10^{-3}$. This effect is much greater than that of changes in spending and employment levels. Moreover, the greatest change in the time spent outside for the 50 states is -22.696% on average, meaning that the people are more happy by as much as $3.724 * 10^{-2}$. However, as opposed to the effects of the number of COVID-19 cases, consumer spending levels, and employment levels, the correlation between time spent outside and happiness seem to be antithetical. Contrary to popular belief, this tells us that leaving the home makes people more upset than if they stayed inside! However, it is important to note that the data I have used corresponds to a two-month window around the time when a state's stay-at-home order was enforced—a time period when COVID-19 cases were rapidly increasing and paranoia was rampant. Thus, leaving home not only increased the likelihood of catching the disease, but it was also an opportunity to observe how others may not have been following COVID-19 protocol, how grocery stores were running out of stock, how masks were uncomfortable to wear, and etc. Therefore, this seemingly antithetical impact is not so strange after all because people were negatively reacting to the outside world in comparison to their safe inside bubble. Moreover, during that time, lockdown had just started. Very few people believed that the pandemic would last as long as it did. Hence, the adage

[19] (Dunn and Norton)
[20] (Omnicore)

that spending time outside improves mood may still be true, it is just that the paranoia of leaving the house is stronger.

In Figure 1, we see the effects of a stay-at-home order on happiness. Depending on the x-values, interpretation of the cause behind the estimated effects are quite different. For days before a stay-at-home order (negative x-values), I like to think of these numbers as the effect of the anticipation of a lockdown. On the other hand, for days after a stay-at-home order (positive x-values), I like to think of the numbers as the effects of living under lockdown. We previously predicted a V-shaped curve for these values, but it turns out to not have been the case. There is indeed a particularly sharp decrease in the period from two days before lockdown to the day before lockdown. This corresponds to how just knowing that there will be a lockdown very soon is upsetting. From then on, however, the effects of living under lockdown have been negative, which tells us that lockdown has indeed eroded happiness. It is not an acute effect as I had hypothesized, but a prolonged and persistent stressor. In fact, these magnitudes are on par with that of the other four pandemic factors. Therefore, by controlling these other pandemic factors, we know that life under lockdown is negatively impacting the happiness of U.S. residents and that it is not just the news of it that is damaging.

Conclusions

COVID-19 has, without a doubt, negatively impacted the emotions of people under lockdown. The number of COVID-19 cases in one's state, the changes in spending habits of Americans, the changes in employment levels within the U.S., and life under a stay-at-home order have all made U.S. residents less happy. The only respite is the increase in amount of time one spends at home. This is particularly interesting because the belief that spending time outside improves mood was turned on its head. Now, we see that leaving the house is a major cause of unhappiness!

There are, of course, limitations to my study of the effects of COVID-19 quarantine on happiness. The most glaring point is that I had used the sentiments expressed through tweets as a substitute for human happiness. Tweets cannot express the full emotional range of happiness—they are just a tiny window into what the Twitter user felt in the moment. However, studying the polarity of tweets may be the most optimal solution outside of spending huge amounts of resources on mass surveys and tracking programs throughout the entire U.S. Other than that, however, even the best algorithms today cannot fully interpret the intricacies of human language and internet slang. This means that VADER, the sentiment analysis tool I used, may not correctly classify the polarity of every tweet correctly. To address this issue, I have also ran my regression with TextBlob's polarity scores, which is another popular Python text processor. These regression coefficients have stayed largely the same, thus I am confident that my results using VADER are as legitimate as can be. Furthermore, all the factors I have considered may have some cofounding variables that I have not considered. For instance, an accelerating number of COVID-19 cases may be why consumer spending, employment levels, and time spent outside have all lowered.

Notwithstanding, the COVID-19 pandemic is an unprecedented event rich in data. It has taken an undeniable toll on the happiness and wellbeing of Americans, but what comes next is anybody's guess. I have showed through an event study that the number of COVID-19 cases in one's state, decreases in spending and employment levels, and living under a stay-at-home order have all negatively affected the happiness of U.S. residents. On the flip side, the decrease in time spent outside have positive effects on happiness. As this pandemic rages on, there has been little to no publications regarding the effects of quarantine on happiness in the U.S. I am thus working in new waters. However, one question I am particularly interested in is the effects of lockdown lifts on happiness. This paper studies the effects of quarantine stay-at-home orders on happiness, but what are the effects of quarantine lifts? Will the two be equal in magnitude but negatives of each other? Will quarantine lifts even have an effect at all? I unfortunately do not have the resources to conduct this study but moving forward, I hope to jumpstart the discussion into how exactly the COVID-19 pandemic have impacted the wellbeing of Americans and American society.

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