***Screaming in the Void: Comment Sections in a Pandemic***

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**Introduction**

 The 2020 campaign changed dramatically, along with the rest of the country, as a result of the COVID-19 pandemic. Gone were the in-person events, fundraisers, debates and rallies that we have grown accustomed to during the course of an election season.

 Initially, this project was designed to address the following hypothesis:

*Conversations about the 2020 election in online comment sections will be more hostile and sexist relative to offline conversations.*

 This hypothesis is an extension of work that was performed in the late stages of the 2016 presidential election, that found that the conversations that occurred in these online spaces were more sexually explicit than their offline counterparts (Artime 2018). With the assistance of undergraduate students, we outlined a data collection process for March of 2020. The goal was to capture and analyze the ways individuals engaged with politics and political conversations in an election year.

However, the personal lives of commenters were upended as was the nature of the conversations that were going on in these forums. As a consequence of the change in the social, political, personal, and economic context, this paper can be viewed as a snapshot of the online conversations that were occurring in the midst of this transformative and devastating period in American history. This paper includes analyses that we would have conducted had the pandemic not occurred. However, it also contains analyses about the prevalence of comments related to health, jobs, and money. We also try to identify the ways in which online conversations changed after lockdowns were more widely instituted throughout the country.

**Literature Review**

 Work on comment sections has examined the commenters, the structure of the sites, and the nature of the conversations. In terms of commenters, earlier work has demonstrated that comment sections were once a place of refuge for socially isolated individuals. However, over time, commenting evolved into an activity practiced by the politically engaged and demographically privileged—wealthy, white, well-educated individuals (Artime 2016). Similarly, those who identify as men are more likely to post comments than their female or non-binary counterparts (Meyer et al. 2015). Correspondingly, young, wealthy, white men are more likely to report comments that they deem abusive—giving them even more of an outsized influence in the nature of the conversation on these sites (Watson et al. 2019). While it appears that men are generally more likely to make use of comment sections, it is somewhat dependent on the type of news topic being discussed. For example, it appears as if women are more likely to post a comment to a forum attached to a local news story (Van Duyn 2019).

In addition to demographic characteristics Wu and Atkins (2017) found that personality influences the propensity for someone to post. Specifically, they found that narcissism and agreeableness were positively related to commenting. Likewise, it appears as if individuals are more likely to engage online discussions if they feel a personal responsibility to speak up in the face of perceived incivility (Ziegele et al. 2020).

 In addition to the demographic or personality traits that make an individual more likely to post, there are also important design considerations faced by online news sites which shape the nature of comment sections (Peacock et al. 2019). With respect to The New York Times website, content moderation often leads to the rejection of comments that include swearing, but a mixed bag with respect to the policing of other types of language (Muddiman & Stroud (2017). The engagement of news sites in moderating comments seems likely to produce different types of discussions. For example, Miro (2020) examined comments on The New York Times site during the Kavanaugh hearings and found that journalists “favorited” comments that were different from those favorited by commenters. Specifically, commenters preferred comments that promoted conflict. Likewise, commenters can be encouraged to take part in moderation if they are encouraged to act (Naabm et al. 2018).

 Some sites have taken to allowing individuals to log into comment sections through their Facebook profile. The Washington Post allowed individuals to access their comment sections this way and Rowe (2014) identified that individuals who post through their Facebook profiles were “more polite and civil relative to those who simply use the Washington Post website.” This might also have a role in decreasing the overall number of comments because we have seen that decreased anonymity reduces the impulse to post comments (Wu & Atkin 2018). Likewise, changing how users can engage with individual comments can change behavior. For example, adding a “respect” or “recommend” button as opposed to “like” can shrink the amount of partisan behavior in online comment sections (Stroud et al. 2017).

 In addition to design features, the types of articles written by a news organization, can increase or decrease the likelihood that individuals engage with that content through comment sections. For example, users are more likely to comment when the subject of an article relates to a social group for which they are a part (Weber 2014). Likewise, Ziegel et al. (2020) examined the likelihood of individuals posting on Facebook pages in relation to news articles and found “that users predominantly engage in discussing issues that are unresolved, involve a certain amount of social conflict and diverging interests, and likely concern the users personally and/or regarding their social identity.” Taken together, the literature suggests that individuals are most likely to post when the article involves a controversy for which they consider themselves a part.

 Finally, a lot has been written about the nature of the dialogue that exists in these forums. Gonçalves (2018) posits that aggressive comments serve to spiral—leading others to respond in an aggressive manner. Likewise, these aggressive comments produce the same controversy that serves to drive engagement. In addition, these forums have served to spread dangerous, racist, and sexist rhetoric (Loke 2012; Artime 2018). The dialogue on comment sections can also spread misinformation about important policy topics. For example, Walter and Bruggemann (2018) demonstrate that climate change denialism spread on these forums even in instances in which climate change was an accepted scientific fact within the country more generally. The content of these forums also has the ability to shape the way that we understand the news more generally. For example, there is some evidence that negativity in comment sections can cause an attached article to be less persuasive (Heinbach et al. 2018). However, Krebs and Lischka (2019) made the case that comment sections did not damage the “brand” of online news sites and that audience perceptions were driven by “serious content.”

 The utility of the work being done in this paper is to consider the ways in which the demographic characteristics of commenters directly relates to the types of conversations which are occurring in online spaces. As we see from the previous research, these forums are largely populated, moderated, and consumed by men. In 2016, it was, consequently, unsurprising to find that these trends opened the door to hostile, sexist rhetoric. However, it is important to continue this work in 2020 to see whether or not this is a long-term trend or just a unique byproduct of having a woman as the head of a major party ticket in the 2016 race. Likewise, given the timing of the paper, we can examine the ways in which these forums change and adapt during mights of extraordinary crisis in the country.

**Research Design**

 Starting on March 1st of 2020, we identified the top political story on the Politics pages of the Huffington Post and The New York Times.[1] For that story, all comments made at the time of collection, were copied and pasted into a Word document. The time of collection alternated between morning, afternoon, and evening. The collection of comments occurred daily until April 4th—ending with a collection of 67 comment sections split evening between the two online news sources.

 The selection of The New York Times and the Huffington Post was made because they represented the most-frequented news sites with comment sections at the time.[2] The following table is from Statistica and includes the number of visitors to the most popular news sites in February of 2020:

[Insert Table 1 about here]

 Examination of the content in these online comment sections was performed using the Linguistic Inquiry and Word Count (LIWC) 2015 software. The software contains an expansive dictionary and allows for the analysis of the grammatical, psychological, and tonal properties of a given text. In conjunction with the release of this software program a document entitled “The Development and Psychometric Properties of LIWC2015” that provides a baseline for the analyses conducted by the software through the compilation of results from a variety of different texts (blogs, expressive writing, novels, natural speech, NY Times, and Twitter) was made available:

 The article also includes a description of how words are categorized in the LIWC software. For the variables being used in this particular study here are the descriptions:

|  |  |
| --- | --- |
| **Category** | **Example** |
| **Positive Emotion** | Love, nice, sweet |
| **Negative Emotion** | Hurt, ugly, nasty |
| **Anxiety** | Worried, fearful |
| **Anger** | Hate, kill, annoyed |
| **Certainty** | Always, never |
| **Sexual** | Horny, love, incest |
| **Work** | Job, majors, Xerox |
| **Money** | Audit, cash, owe |
| **Religion** | Altar, church |
| **Leisure** | Cook, chat, movie |
| **Death** | Bury, coffin, kill |

 The LIWC output for these categories represents the percentage of words in the text that fit these categorizations.

In testing the original, pre-pandemic hypothesis, we are looking at the “sexual” variable and determining the extent to which sexual language appears in comment sections relative to other forms of speech gathered by the contributors to the LIWC article. If there is a significant difference in the direction of more sexual content in comment sections that would be a reason to review the context in which this language occurred to determine whether or not it is indeed a sign of gendered or sexually violent imagery and/or language. I have also included a conversation about the other items above because I think that they help to elucidate some interesting trends that we found during our analysis. In addition to the evaluation of the original hypothesis, we make an effort to detail how these forums changed in tone and content as a result of the imposition of various lockdowns throughout the country.[[1]](#footnote-1)

 Finally, we should mention that there are important differences between the structure of the comment sections on The New York Times website and those housed on the Huffington Post site. The New York Times has individuals log-in in order to post. However, when you log-in you can use a pseudonym and refuse to provide your real name and/or location. The New York Times curates comments in several ways. First, when you open a comment section there are three threads—a thread with moderator favorites, one with reader favorites, and one that contains all of the comments without curating. For the purposes of our research, we collected the comments that had not been curated by moderators or readers. Additionally, moderators evaluate comments to ensure “civility.” For The New York Times incivility includes “name-calling, personal attacks, obscenity, vulgarity, profanity (including expletives and letters followed by dashes), commercial promotion, impersonations, incoherence, and SHOUTING.” Users can also take part in this moderation by “flagging” posts that they believe violate the civility policy as outlined by the rules of the Times.

 For the Huffington Post, you need to create either a free or paid account on the site before you’re permitted to post. You can use a name that is not your own but do have to connect your account to an email address (although that address is not shared with readers/posters on the comment thread). This is a change to their earlier approach which required individuals to sign in via their Twitter or Facebook profiles. The site claims that this change was made because users were uncomfortable with using their social media profiles to post on the site. Moderation of the comment section occurs through the use of a content filter that is applied to all comments before they appear on the site. On the site, they outline the types of dialogue that are prohibited on these threads:

“Above all, we strongly believe that the HuffPost community should be a safe and welcoming space for all individuals, groups and their ideas. Using purposefully insulting or hostile language and making personal threats are not welcome. If you directly or indirectly threaten the physical or mental well-being of a member of this community, or an individual or group, you may be removed immediately. If a credible threat is made against an individual or group, it may also be reported to law enforcement, and we will cooperate with them. Personally identifiable information should never be posted to HuffPost comments sections, for the privacy and protection of all community members. This includes but is not limited to full names, addresses, phone numbers, or email addresses. Any comments that contain such information will be deleted. (Personally identifiable information excludes your displayed name as it appears on HuffPost comments; HuffPost highly discourages anonymous usernames and pseudonyms).”

 The site allows users to report comments that violate these directives which may lead to the post being removed. Likewise, they establish the bounds of civility by stating that “HuffPost does not tolerate direct or indirect attacks, name-calling or insults, nor does it tolerate intentional attempts to derail, hijack, troll or bait others. We reserve the right to remove such comments whenever warranted. Individuals who consistently or intentionally post these types of comments may lose their ability to comment and, if necessary, may be permanently excluded from the platform.” Unlike The New York Times, moderators do not highlight comments that they believe to be important to the dialogue. However, users can “favorite” or “dislike” (by giving a thumb up or a thumb down) when reviewing comments.

**Results**

 The results indicate that the hypothesis cannot be confirmed. Specifically, there does appear to be a statistically significant difference between the amount of sexual content in comment sections relative to the sample provided by LIWC. However, the relationship is not in the direction hypothesized. In other words, the amount of sexually explicit content seems significantly less in comment sections relative to other types of communication. This is distinct from the results that we saw in 2016, in which we saw the reverse of this relationship.

[Insert Table 2 about here]

 Even though the amount of sexually explicit content was less than the mean of the LIWC sample, there was still a distinction between this content when comparing news sources.

[Insert Tables 4 and 5 about here]

 Comments collected through the New York Times website were significantly more sexually explicit relative to the comments collected through Huffington Post. However, even if you isolate the comments from the New York Times, the amount of sexually explicit content is still significantly less than in the content gathered for the LIWC mean. Interestingly, this was not the only difference between the content from the New York Times and Huffington Post.

[Insert Tables 8. 11, 13, and 16]

 The New York Times sample was significantly less positive, more negative, agrier, and more certain than the Huffington Post sample. The data that we have does not allow us to make a definitive argument about why these differences exist. Perhaps the results are shaped by the audiences of the respective online news sites. Likewise, it is possible that the differences in content moderation outlined above translated into differences in the type of content allowed on their respective forums.

While the hypothesis was not correct, there were interesting results from our analysis that deserve some discussion. First, consistent with other research, the comments were less positive, more negative, and angrier than other forms of speech.

[Insert Tables 6, 9, and 12 about here]

 As noted in previous research, this type of negativity can serve to possibly undercut the intent of the article and can serve to spiral into even more negative, hostile content. While these findings are not new, they are confirmation that, even with moderation, there is still a tonal difference between comment sections and other forms of communication.

[Insert Table 14 about here]

In addition to being negative and angry, commenters also displayed a high degree of confidence as evidenced by the results in Table 6. This level of certainty does not seem to be conducive to a cooperative, thoughtful conversation. Likewise, these conversations seem to be centered on very personal topics.

[Insert Tables 17, 19, and 21 about here]

According to the results depicted in the preceding tables, these conversations were populated with more discussion of work, money, and death than would be found in other forms of written material. It is important to note that many of these conversations were occurring in the context of the COVID-19 pandemic and that it is reasonable to assume that individuals were more concerned with the potential loss of work and money as well as the health of themselves and their family. In these areas, it seems as if the conversations in these comment sections mirrored the ones that many were having offline.

 Indeed, if we breakdown the results into the period prior to significant lockdowns and the period during which those lockdowns were in effect, we can see the direct changes in the nature of the online conversations likely due to the COVID-19 pandemic. Table 7 demonstrates that online conversations became significantly less positive after the lockdowns. Likewise, in Tables 18, 20, and 22 it is apparent that the dialogue taking place on comment sections during the lockdown were more focused on questions of work (Table 18) and death (Table 22).

**Discussion**

 The results suggest that individuals were engaged in negative and hostile conversations about topics of a deeply personal nature. Ultimately, the hypothesis could not be confirmed and there are a variety of reasons why this could be the case. First, it could simply be an indication that sexism and gender-based discrimination is not as prevalent on these comment sections as we thought. Second, it could be the unique nature of the time period during which comments were collected. In other words, perhaps the focus on the pandemic shifted the conversation away from the typical targets of hostile, negative rhetoric. Thirdly, because both the Democratic and Republican candidates identify as male in the 2020 presidential election, the level of sexism is not as pronounced as it was when Hillary Clinton was the Democratic nominee in 2016.

 We do feel that the data provides some perspective regarding the thoughts and concerns of users before and after lockdowns were instituted throughout the United States. While it is unsurprising that many were increasingly concerned about work and issues related to mortality, confirmation of this helps us to better understand the political climate that existed in spring of 2020.

 It should be noted that there are inherent limitations with this type of content analysis. For example, we can only identify trends in the nature of the discussion that is occurring in these forums, but we cannot speak directly to the individual characteristics of those who post or those who read the comments. In addition, we have selected to analyze only two sources and, while we feel this is defensible, it means that we do not have a representative sample of all comments from all news sites—something you would ideally want if you are going to make generalizable conclusions about the nature of comment sections.

 As we continue this research, we hope that it provides some useful contributions to our knowledge about how these forums of political conversation function.

**Appendix A: References**

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Appendix B: Tables

Table 1: Most Popular Online News Sites

*These numbers represent readership as of February 20, 2020 and each unit represents one million (for example, Yahoo News had approximately 175 million monthly users at the time that this data was collected)*

Data from Statista, “Most popular news websites in the United States as of February 2020, by unique monthly visitors” 2020

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**Table 2. T-Test for mean versus the sample value of sexual content.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Observations | Mean | Standard error | Standard deviation | 95% conf. interval (lower bound) | 95% conf. interval (upper bound) |
| 67 | 0.04 | 0.00 | 0.03 | 0.03 | 0.05 |

t= -23.47

Ha: mean < 0.13 Ha: mean ! = 0.13 Ha: mean > 0.13

Pr(T < t) = 0.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 1.00

 **Table 3. Difference between sexual content before and after lockdown.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| **Pre** | **21** | **0.04** | **0.01** | **0.03** | **0.03** | **0.06** |  |
| **Post** | **46** | **0.04** | **0.00** | **0.03** | **0.03** | **0.05** |  |

t= 0.35

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.64 Pr(ITI > ItI) = 0.73 Pr(T > t) = 0.37

**Table 4. Difference between sexual content by source.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| HuffPo | 34 | 0.03 | 0.00 | 0.02 | 0.02 | 0.04 |  |
| NYT | 33 | 0.04 | 0.00 | 0.03 | 0.04 | 0.07 |  |

t= -3.80

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 1.00

**Table 5. T-Test for mean versus the sample value of sexual content in the NY Times.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Observations | Mean | Standard error | Standard deviation | 95% conf. interval (lower bound) | 95% conf. interval (upper bound) |
| 33 | 0.05 | 0.01 | 0.03 | 0.04 | 0.07 |

t= -13.85

Ha: mean < 0.13 Ha: mean ! = 0.13 Ha: mean > 0.13

Pr(T < t) = 0.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 1.00

**Table 6. T-Test for mean versus the sample value of positive emotion.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Observations | Mean | Standard error | Standard deviation | 95% conf. interval (lower bound) | 95% conf. interval (upper bound) |
| 67 | 3.29 | 0.09 | 0.73 | 3.12 | 3.47 |

t= -4.26

Ha: mean < 3.67 Ha: mean ! = 3.67 Ha: mean > 3.67

Pr(T < t) = 0.01 Pr(ITI > ItI) = 0.00 Pr(T > t) = 1.00

**Table 7. Difference between positive emotion in comments before and after lockdown.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| Pre | 21 | 3.78 | 0.14 | 0.66 | 3.48 | 4.08 |  |
| Post | 46 | 3.07 | 0.09 | 0.64 | 2.88 | 3.26 |  |

t= 4.13

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 1.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 0.00

 **Table 8. Difference between positive emotion by source.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| HuffPo | 34 | 3.37 | 0.13 | 0.76 | 3.11 | 3.63 |  |
| NYT | 33 | 3.21 | 0.12 | 0.70 | 2.97 | 3.46 |  |

t= 0.88

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.81 Pr(ITI > ItI) = 0.38 Pr(T > t) = 0.19

**Table 9. T-Test for mean versus the sample value for negative emotion.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Observations | Mean | Standard error | Standard deviation | 95% conf. interval (lower bound) | 95% conf. interval (upper bound) |
| 67 | 2.48 | 0.07 | 0.58 | 2.33 | 2.62 |

t= 8.97

Ha: mean < 1.84 Ha: mean ! = 1.84 Ha: mean > 1.84

Pr(T < t) = 1.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 0.00

**Table 10. Difference between negative emotion in comments before and after lockdown.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| Pre | 21 | 2.46 | 0.14 | 0.63 | 2.17 | 2.74 |  |
| Post | 46 | 2.48 | 0.08 | 0.56 | 2.32 | 2.65 |  |

t= -0.17

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.43 Pr(ITI > ItI) = 0.87 Pr(T > t) = 0.57

**Table 11. Difference between negative emotion by source.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| HuffPo | 34 | 2.22 | 0.09 | 0.51 | 2.04 | 2.39 |  |
| NYT | 33 | 2.74 | 0.09 | 0.53 | 2.55 | 2.93 |  |

t= -4.15

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 1.00

**Table 12. T-Test for mean versus the sample value for anger.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Observations | Mean | Standard error | Standard deviation | 95% conf. interval (lower bound) | 95% conf. interval (upper bound) |
| 67 | 0.82 | 0.04 | 0.36 | 0.73 | 0.91 |

t= 6.31

Ha: mean < 0.54 Ha: mean ! = 0.54 Ha: mean > 0.54

Pr(T < t) = 1.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 0.00

**Table 13. Difference between anger by source.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| HuffPo | 34 | 0.63 | 0.04 | 0.26 | 0.54 | 0.72 |  |
| NYT | 33 | 1.02 | 0.06 | 0.36 | 0.89 | 1.14 |  |

t= -5.08

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 1.00

**Table 14. T-Test for mean versus the sample value for certainty.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Observations | Mean | Standard error | Standard deviation | 95% conf. interval (lower bound) | 95% conf. interval (upper bound) |
| 67 | 1.89 | 0.03 | 0.24 | 1.83 | 1.94 |

t= 18.27

Ha: mean < 1.35 Ha: mean ! = 1.35 Ha: mean > 1.35

Pr(T < t) = 1.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 0.00

**Table 15. Difference between certainty in comments before and after lockdown.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| Pre | 21 | 1.88 | 0.06 | 0.28 | 1.75 | 2.01 |  |
| Post | 46 | 1.89 | 0.03 | 0.22 | 1.82 | 1.95 |  |

t= -0.10

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.46 Pr(ITI > ItI) = 0.92 Pr(T > t) = 0.54

**Table 16. Difference between certainty by source.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| HuffPo | 34 | 1.82 | 0.05 | 0.28 | 1.72 | 1.92 |  |
| NYT | 33 | 1.96 | 0.03 | 0.17 | 1.90 | 2.02 |  |

t= -2.46

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.01 Pr(ITI > ItI) = 0.02 Pr(T > t) = 1.00

**Table 17. T-Test for mean versus the sample value for work.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Observations | Mean | Standard error | Standard deviation | 95% conf. interval (lower bound) | 95% conf. interval (upper bound) |
| 67 | 3.42 | 0.15 | 1.22 | 3.12 | 3.72 |

t= 5.78

Ha: mean < 2.56 Ha: mean ! = 2.56 Ha: mean > 2.56

Pr(T < t) = 1.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 0.00

**Table 18. Difference between work-related comments before and after lockdown.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| Pre | 21 | 2.89 | 0.17 | 0.80 | 2.53 | 3.26 |  |
| Post | 46 | 3.66 | 0.19 | 1.31 | 3.28 | 4.05 |  |

t= -2.50

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.01 Pr(ITI > ItI) = 0.02 Pr(T > t) = 1.00

**Table 19. T-Test for mean versus the sample value for money.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Observations | Mean | Standard error | Standard deviation | 95% conf. interval (lower bound) | 95% conf. interval (upper bound) |
| 67 | 1.40 | 0.14 | 1.16 | 1.11 | 1.68 |

t= 5.06

Ha: mean < 0.68 Ha: mean ! = 0.68 Ha: mean > 0.68

Pr(T < t) = 1.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 0.00

**Table 20. Difference between money-related comments before and after lockdown.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| Pre | 21 | 1.19 | 0.13 | 0.59 | 0.92 | 1.45 |  |
| Post | 46 | 1.50 | 0.20 | 1.34 | 1.10 | 1.89 |  |

t= -1.01

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.16 Pr(ITI > ItI) = 0.32 Pr(T > t) = 0.84

Pr(T < t) = 0.86 Pr(ITI > ItI) = 0.27 Pr(T > t) = 0.14

**Table 21. T-Test for mean versus the sample value for focus on death.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Observations | Mean | Standard error | Standard deviation | 95% conf. interval (lower bound) | 95% conf. interval (upper bound) |
| 67 | 0.29 | 0.02 | 0.20 | 0.24 | 0.34 |

t= 5.36

Ha: mean < 0.16 Ha: mean ! = 0.16 Ha: mean > 0.16

Pr(T < t) = 1.00 Pr(ITI > ItI) = 0.00 Pr(T > t) = 0.00

**Table 22. Difference between death-related comments before and after lockdown.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Group | Observations | Mean | Standard Error | Standard Deviation | 95% conf. Interval (lower bound) | 95% conf. Interval (upper bound) |  |
| Pre | 21 | 0.20 | 0.03 | 0.16 | 0.12 | 0.27 |  |
| Post | 46 | 0.33 | 0.03 | 0.20 | 0.27 | 0.39 |  |

t= -2.69

Ha: diff < 0 Ha: diff ! = 0 Ha: diff > 0

Pr(T < t) = 0.00 Pr(ITI > ItI) = 0.01 Pr(T > t) = 0.99

[1] The top story was defined as the literal top story on the page. This means that it is not necessarily the story that has generated the most engagement but, rather, it was the article that the news site had made their premiere story for the moment that the comments were being collected.

[2] Yahoo News and Google News are not news sites but rather are news aggregators. CNN was not selected because their website does not allow users to comment.

1. [↑](#footnote-ref-1)