

protest legitimacy

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This is the first pass at the analyses registered on the OSF (<https://osf.io/sd58n/>). My overall interpretation of these results is that there is a tendency for African American oriented sources to focus on information that legitimizes the protest. A number of analyses where the focus is Michael Brown show that African American oriented sources are more likely than general public sources to focus on those details. In contrast, the general public sources tend to focus on the *consequences* of michael brown's death, including the protests and the police response.

I have a harder time understanding what a coherent liberal/conservative source coverage conclusion would be. In general, the models indicate that more conservative sources tend to have more of all dimensions that we measured, though in most cases, the relationship is not strong enough to reject a flat association. I think part of this is driven by the fact that there are so few truly conservative sources. Accordingly, our analysis might almost be more about the differences between relatively liberal sources and more moderate sources. Ultimately, one much needed step (in my view) is a close reading of some of the titles and captions to figure out whether some of these patterns might be driven by some kind of source-specific idiosyncracies, since the consistency of the general pattern across all measurements makes me a little suspicious. As Kaytee pointed out to me, our measurement technique is really straightforward, so in some sense, we know what they're writing about, but I still think a little more context would be helpful.

1 Descriptives

All of the data we are working with are drawn from press coverage of the shooting Michael Brown and subsequent protests. We targeted the top 50 news organizations and the top 18 African American news organizations, as indicated by Pew Research. For each of these sources, our final data includes any article in the 10 days after the shooting that mentions Michael Brown, along with all pictures published within that article. For this work, we are focusing on the titles of these articles, and the captions for the *featured* images

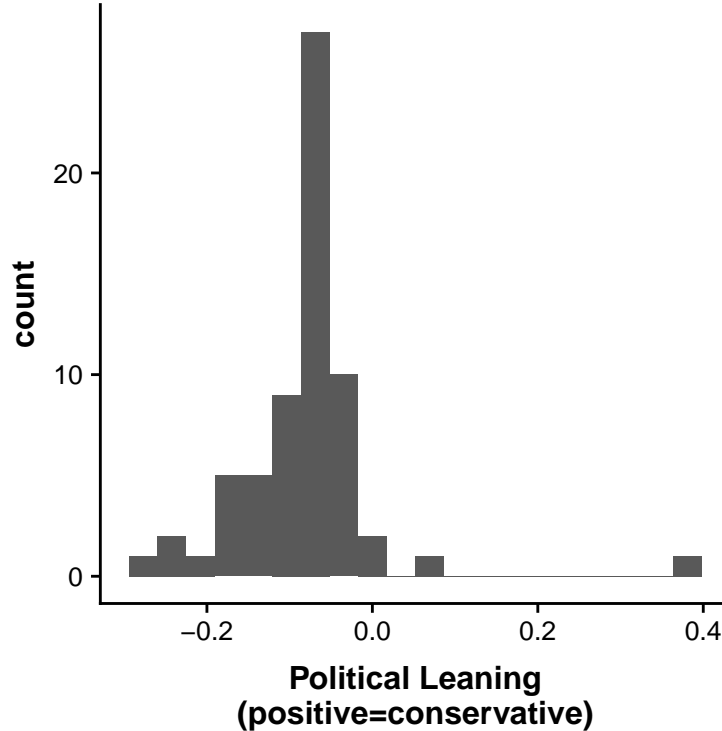


Figure 1: Source-level distribution of political orientation ratings

within the articles. Featured images are those that appear in the text of the version of the article published online (as opposed to images that are published as part of a gallery that is linked to within an article).

In total, this work covers 3278 articles and 5502 images, though 1282 images do not have a caption.

As part of this work, we are also using the political leaning of these news sources. We use the same political orientation estimates as in previous work. The distribution of political orientation is displayed below (Note that some sources are missing here, though I can't recall what the reason was... We have 64 source ratings.)

This distribution (figure 1 is a little difficult. Effectively we only have three sources that have conservative ratings (TheBlaze, The Daily Mail, and Fox News), with the vast majority of sources having a moderately liberal bent. This makes assessing the effect of political leaning difficult, but also seems like it's an accurate reflection of the media landscape (especially at the time of the shooting).

2 Police/Protest analyses

2.1 Captions & titles

2.1.1 Frequency

Figure 2 shows the proportion of texts (the union of captions and titles) that contain references to either police or protest. One can see that the proportions vary across sources, and level varies between police and protest references. Indeed, the proportion of all texts that refer to police is about 0.46, while the proportion of texts that refer to protest is about 0.36.

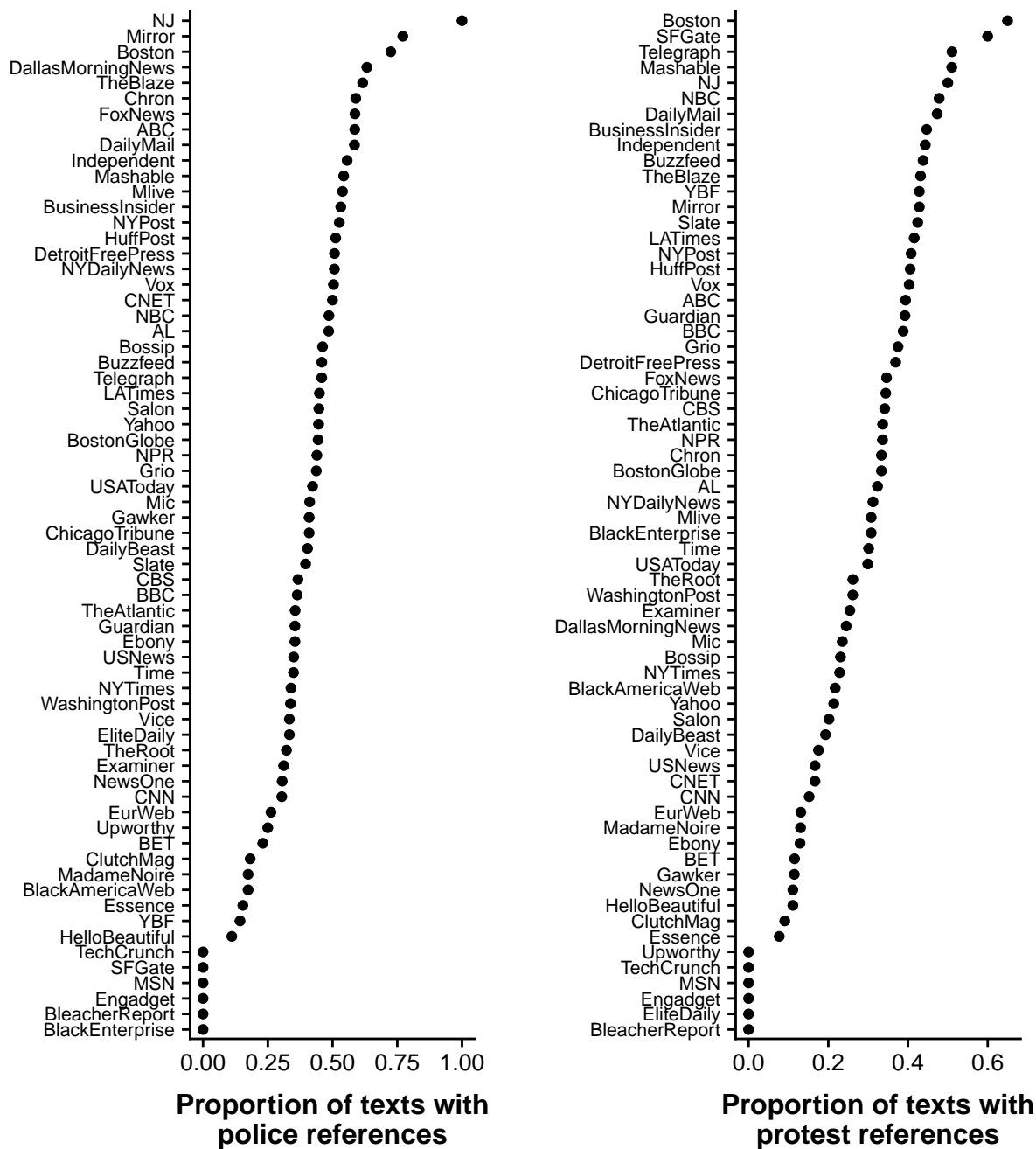


Figure 2: Proportion of captions and titles in each source that make reference to Police or Protest

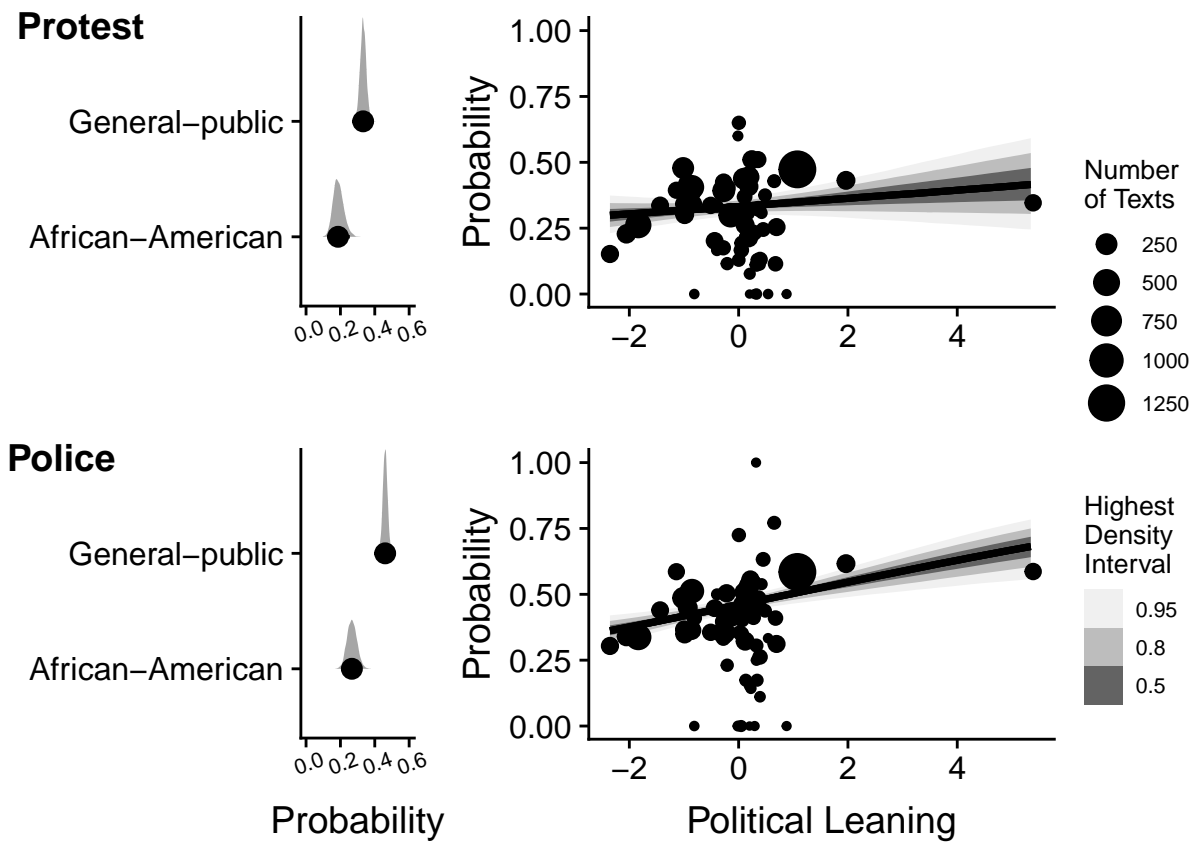


Figure 3: Modeled probability of making a reference to Police or Protest as a function of political orientation and audience

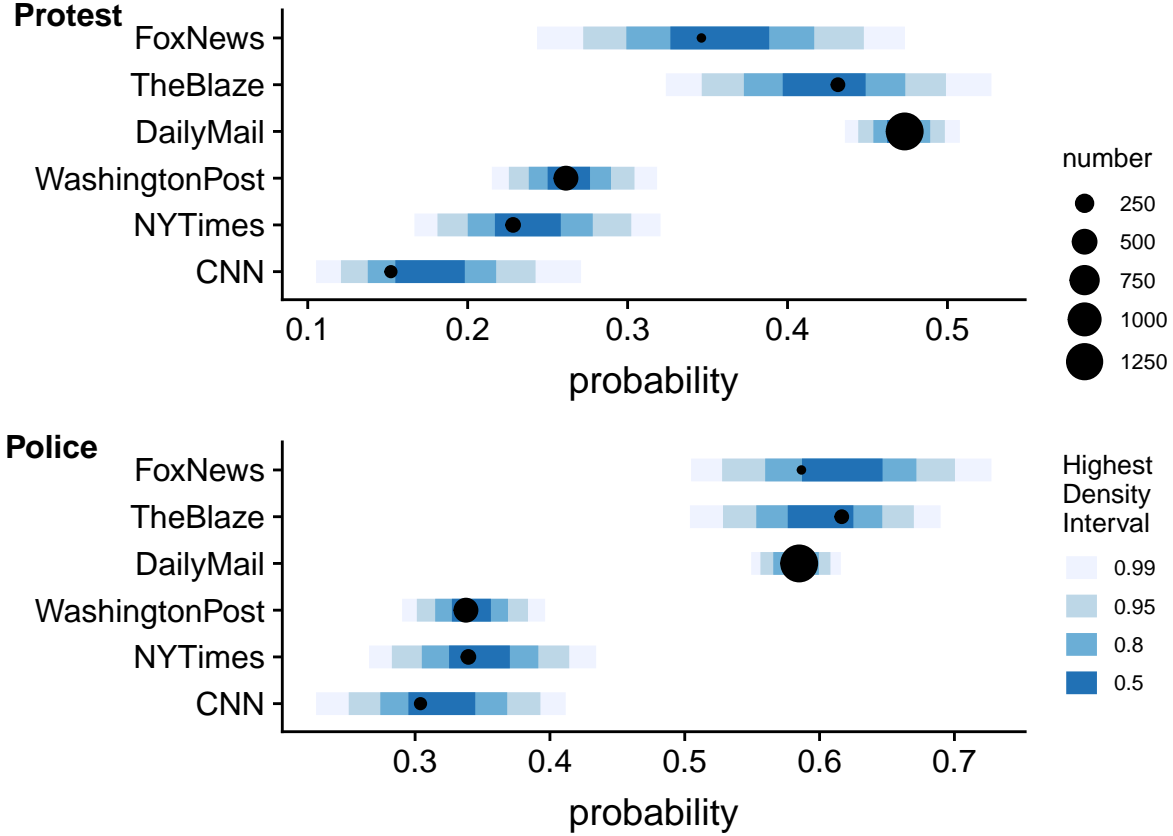


Figure 4: Spotlight analysis - the probability of referring to Police or Protest in captions and titles for the three most conservative and three most liberal sources. Blue bands indicate range of model predicted values, and black dot indicates observed data.

2.1.2 Models of audience & political orientation associations

Results are reported using the median and 95% highest density intervals from the posterior distribution. Figure 3 shows how the modeled probabilities vary as a function of political leaning (right column) and source audience (left column). These models indicate that sources that are oriented to the general public have higher rates of reference to both protest-related words ($p_{generalpublic} = 0.33$, $[0.3, 0.37]$; $p_{africanamerican} = 0.19$, $[0.13, 0.25]$, $prob_{gp>aa} > .99$) and for police-related words ($p_{generalpublic} = 0.46$, $[0.43, 0.49]$; $p_{africanamerican} = 0.27$, $[0.21, 0.32]$, $prob_{gp>aa} > .99$).

The associaton between political leaning and references to these concepts is not as directionally consistent. There is a slight tendency for more conservative sources to make reference to protest ($\beta = 0.07$, $[-0.06, 0.21]$), though we are unable to rule out zero as a probable value for this association. In contrast, it is apparent that more conservative sources are far more likely to make reference to police ($\beta = 0.17$, $[0.08, 0.27]$).

Of course, the data in figure 3 makes clear that Fox News has a high degree of leverage over the fitted model. Accordingly, we refit the models excluding data from this source and found that the results are similar. Indeed, the effect of source political orientation on the probability of making reference to police is actually stronger when Fox News is excluded from the data ($\beta = 0.24$, $[0.11, 0.36]$). We are still unable to rule out zero as a probable value when examining the effect of political orientation on references to protest ($\beta = 0.12$, $[-0.06, 0.32]$).

2.1.3 Spotlight

The our spotlight analysis focuses on the three most conservative and three most liberal sources. These are (from most conservative to most liberal) Fox News (standardized lean score = 5.39), The Blaze (1.96), The Daily Mail (1.07), The Washington Post (-1.84), The New York Times (-2.05), and CNN (-2.35). Figure 4 shows the observed proportion of texts that contain references to protest or police, along with the range of probabilities predicted to be credible by the model. One can see that the predicted probabilities generally correspond to the observed data, though it appears the predicted probabilities for police references are slightly over estimated for Fox News and protest references are slightly overestimated for CNN.

Table 1 (end of document) shows a random sample of three texts for each of these six sources, along with what type of text it is (photo caption or article title), and two indicator columns showing whether they were coded as containing police or protest references..

** Probably some commentary here about the titles & captions above **

2.2 Focusing on negative protest words

2.2.1 Frequency

Figure 5 shows the proportion of texts that contain references to either negative protest words (i.e. riot* or loot*). As expected proportions of this reduced category are diminished in comparison with the full set of protest words, with the overall mean of the source-level proportions about 0.09

2.2.2 Models of audience & political orientation associations

The pattern of results when modeling this category of word is largely similar to those seen for the more general protest and police categories. Figure 6 shows how the modeled probabilities vary as a function of political leaning (right column) and source audience (left column). The model indicates that sources that are oriented to the general public have higher rates of reference to both negative protest-related words ($p_{generalpublic} = 0.06$, [0.04, 0.07]; $p_{africanamerican} = 0.03$, [0.01, 0.05], $prob_{gp>aa} = 0.99$).

Again, there is a slight tendency for more conservative sources to use negative protest words ($\beta = 0.12$, [-0.07, 0.34]), though we are unable to rule out zero as a probable value for this association.

Once again, Fox News acts as a point with high leverage. Excluding Fox News and refitting the model leads to substantively similar conclusions, though the slope of the association between political leaning and probability of negative protest words becomes steeper, we are still unable to exclude zero as a probable value ($\beta = 0.26$, [-0.03, 0.54]).

2.3 Presence of protest and police images

2.3.1 Models of audience & political orientation associations

We repeated the same analysis, but examining the probability that featured images included police or protestors. Figure 7 shows how the modeled probabilities vary as a function of political leaning (right column) and source audience (left column). These models indicate that sources that are oriented to the general public have higher rates of both protest-related images ($p_{generalpublic} = 0.46$, [0.43, 0.5]; $p_{africanamerican} = 0.32$, [0.26, 0.4], $prob_{gp>aa} > .99$) and police-related words ($p_{generalpublic} = 0.36$, [0.33, 0.39]; $p_{africanamerican} = 0.16$, [0.12, 0.21], $prob_{gp>aa} > .99$).

These models also indicate that the association between political orientation and having featured images of protest is close to flat ($\beta = -0.04$, [-0.17, 0.12]). The association between political orientation and having featured images of police is estimated to be positive, though a flat association is roughly the lower bound of

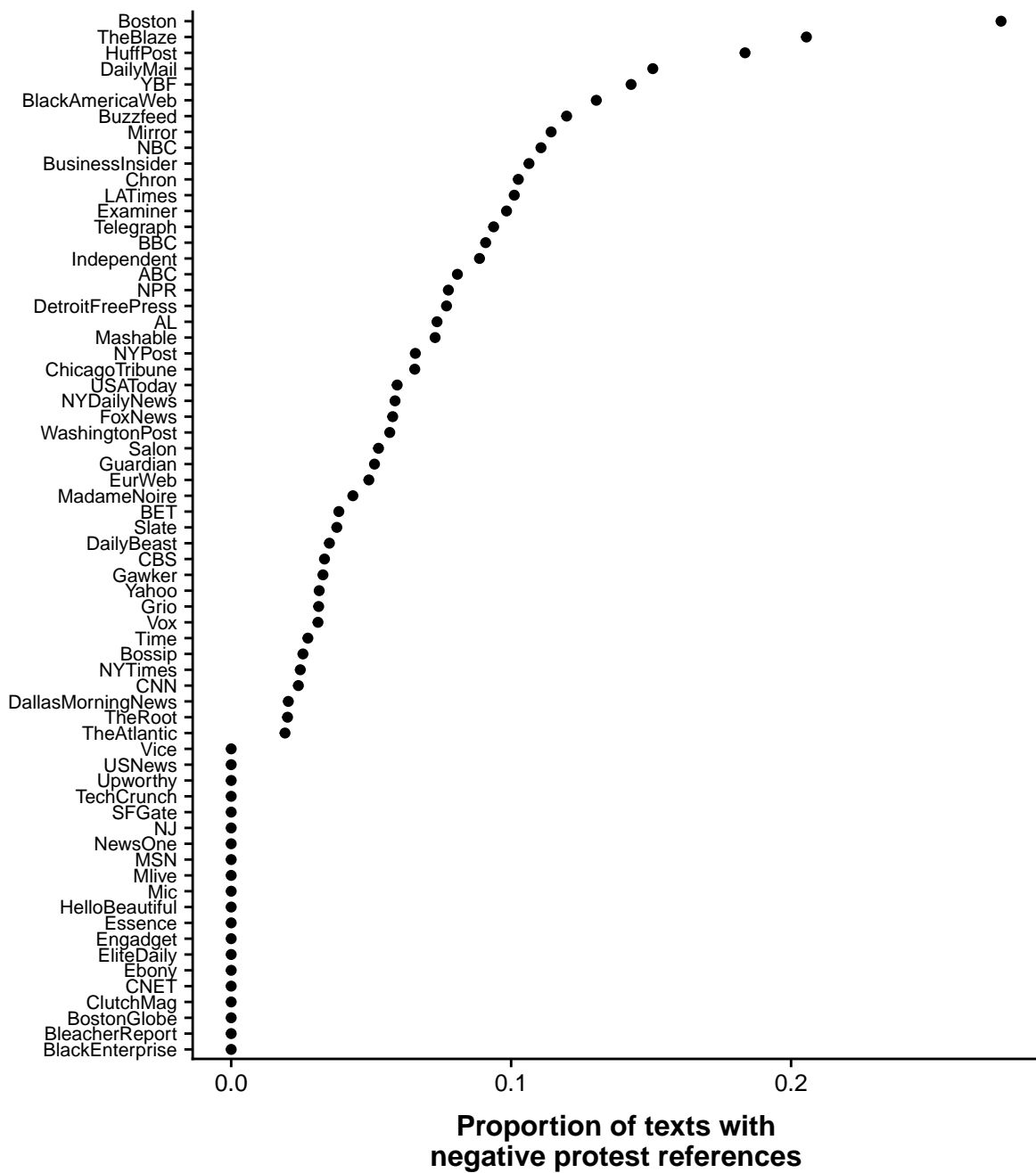


Figure 5: Proportion of captions and titles in each source that make reference to negative protest words

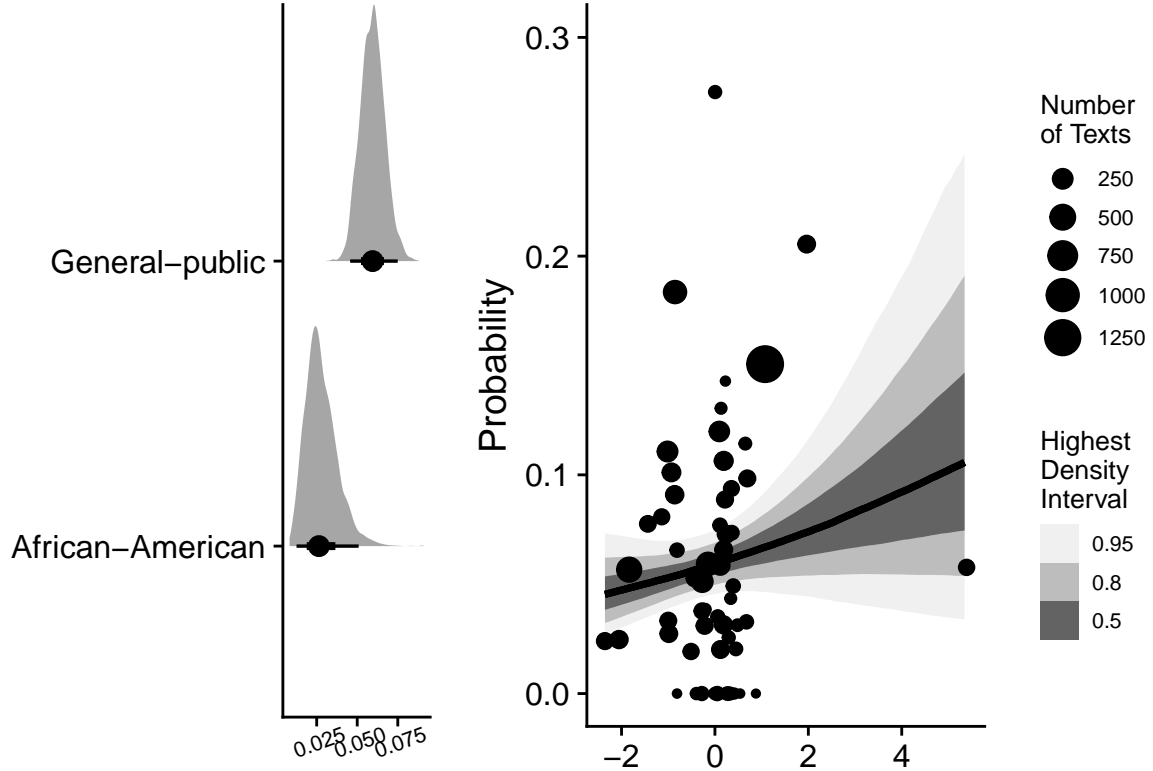


Figure 6: Modeled probability of making a reference to negative protest words

what is probable ($\beta = 0.11$, $[-0.01, 0.23]$). None of these findings are substantially changed when removing Fox News from the data.

3 Black/unarmed/teen/MB/killed references

Besides references to police and protest, we are also interested in the frequency and themes behind references to the precipitating event - the shooting of Michael Brown. We will refer to this category as legitimizing the protest as a shorthand, since it focuses on the tragic elements of the event (killing an unarmed teenager), along with details of Michael Brown as a person (his name, the fact that he is black).

3.1 Captions, Titles, & photos

3.1.1 Frequency

In total, there are 7496 article titles and captions to featured images, of which 4219 are captions. We count any of these items as having legitimized the protest if the text of these items has an element from our keyword list, *or* if the article they are associated with contains a picture of Michael Brown.

Figure 8 shows the proportion of items (the union of captions, titles, and images) that legitimizing the protest. The proportion varies widely across sources, but the overall level of references is fairly high. Indeed, average source-level proportion is 0.44.

As before, we now evaluate the degree to which our source-level information is associated with this variability.

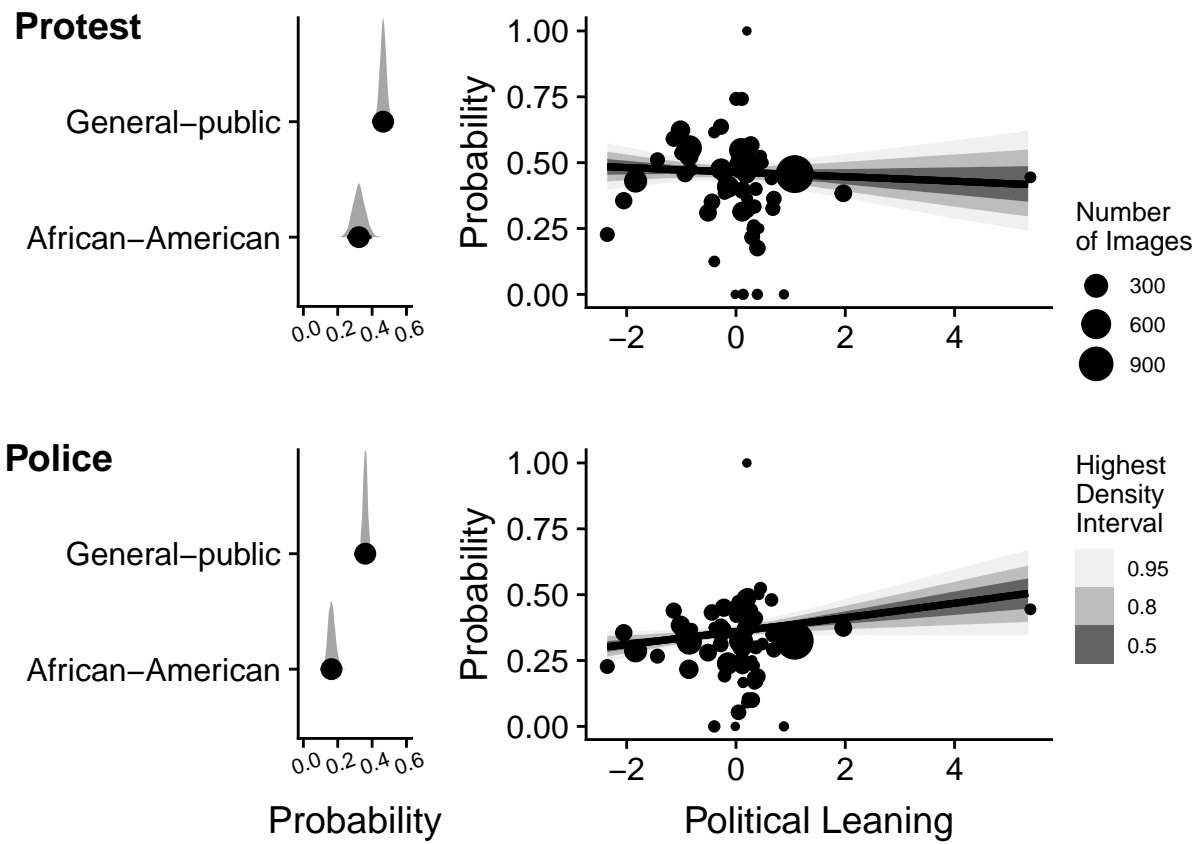


Figure 7: Modeled probability of featuring protest or police images

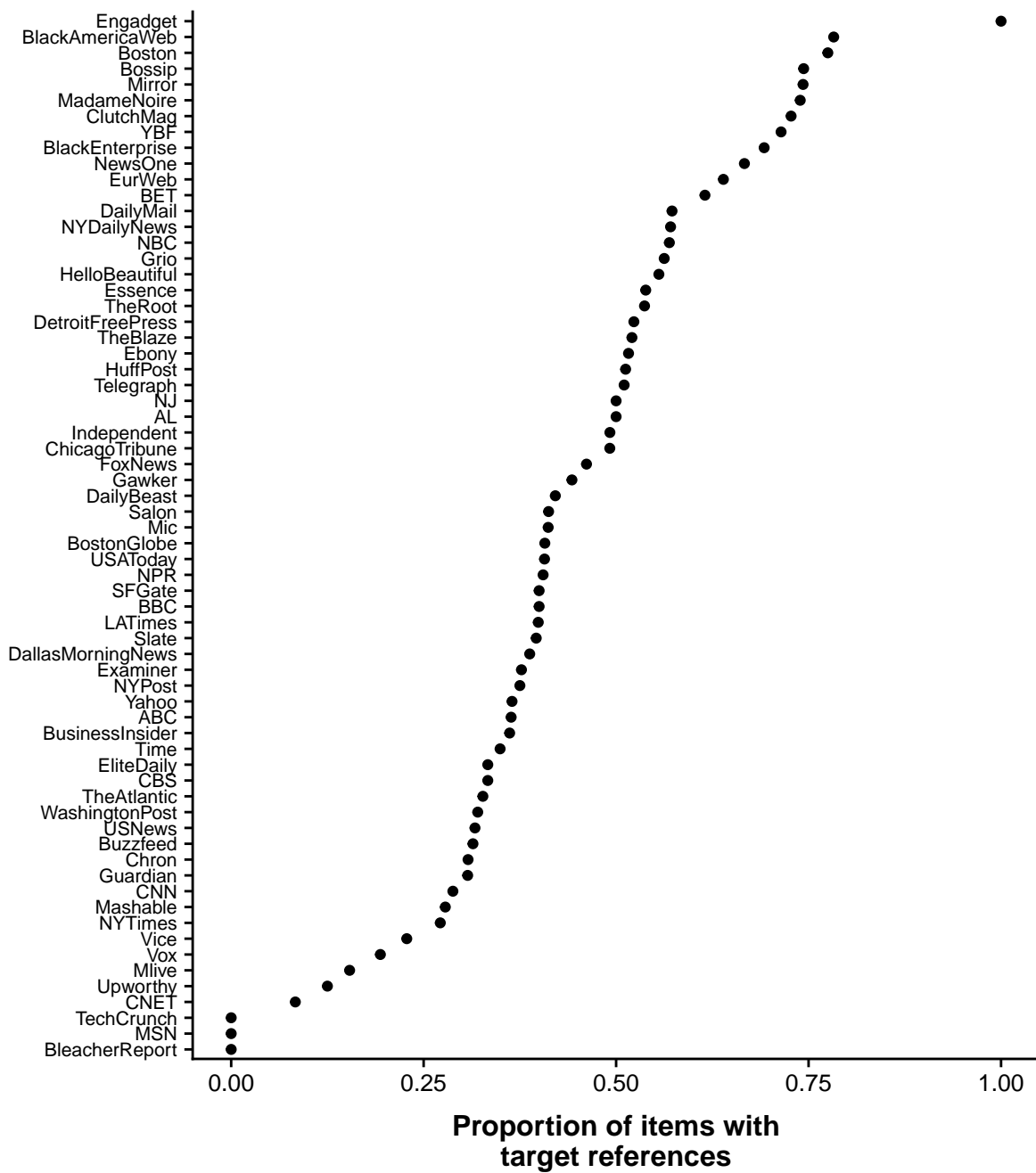


Figure 8: Proportion of captions and titles in each source that make reference to legitimizing the protest

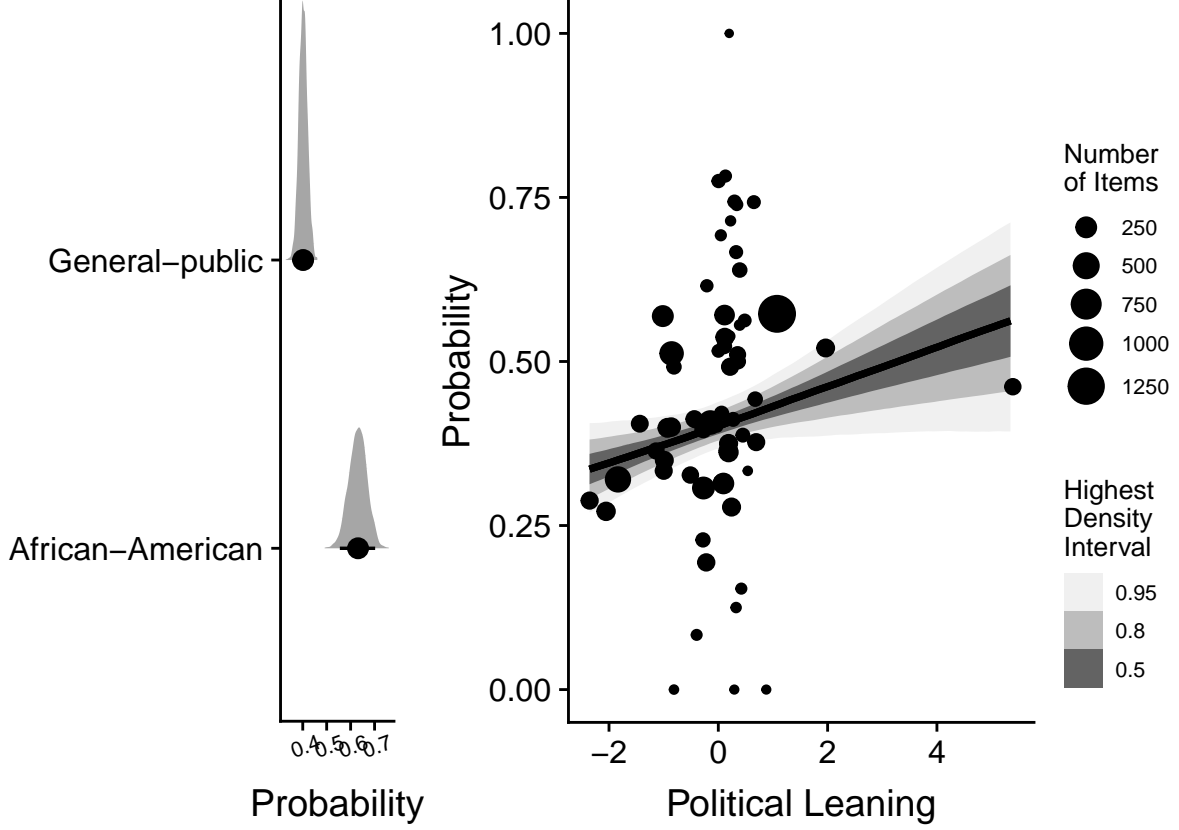


Figure 9: Modeled probability of legitimizing the protest, union of captions, titles & photos

3.1.2 Models of audience & political orientation associations

For the first time, we see that this macro category shows a pattern of results whereby african american oriented sources are much more likely to make reference to the concepts than are the general public sources ($p_{generalpublic} = 0.4, [0.37, 0.44]$; $p_{africanamerican} = 0.63, [0.56, 0.7]$, $prob_{gp>aa} < .01$. This pattern of results is shown in figure 9

Once again, more conservative sources to are more likely to make reference to this macro category ($\beta = 0.12, [0, 0.24]$). The outlier of Fox News is below the model fit, suggesting that excluding this observation would only increase the degree of this association, though this model was not actually fit.

3.2 Captions & titles only

3.2.1 Models of audience & political orientation associations

These basic patterns are replicated when examining just the text portion of these data, with african american oriented sources are more likely to make reference to the concepts than are the general public sources ($p_{generalpublic} = 0.4, [0.37, 0.43]$; $p_{africanamerican} = 0.62, [0.55, 0.7]$, $prob_{gp>aa} < .01$. This pattern of results is shown in figure 10

Once again, more conservative sources to are more likely to make reference to this macro category ($\beta = 0.12, [0.01, 0.24]$). ## Photos only

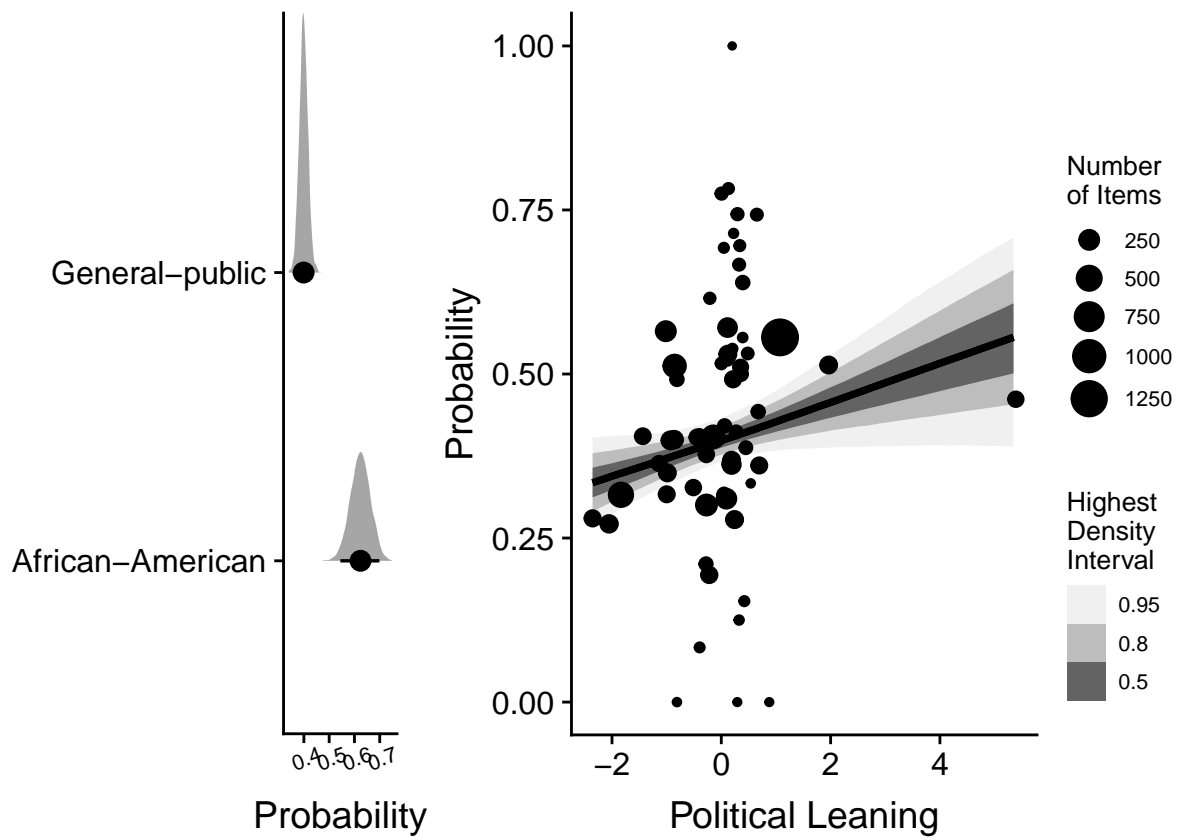


Figure 10: Modeled probability of legitimizing the protest, captions & title only

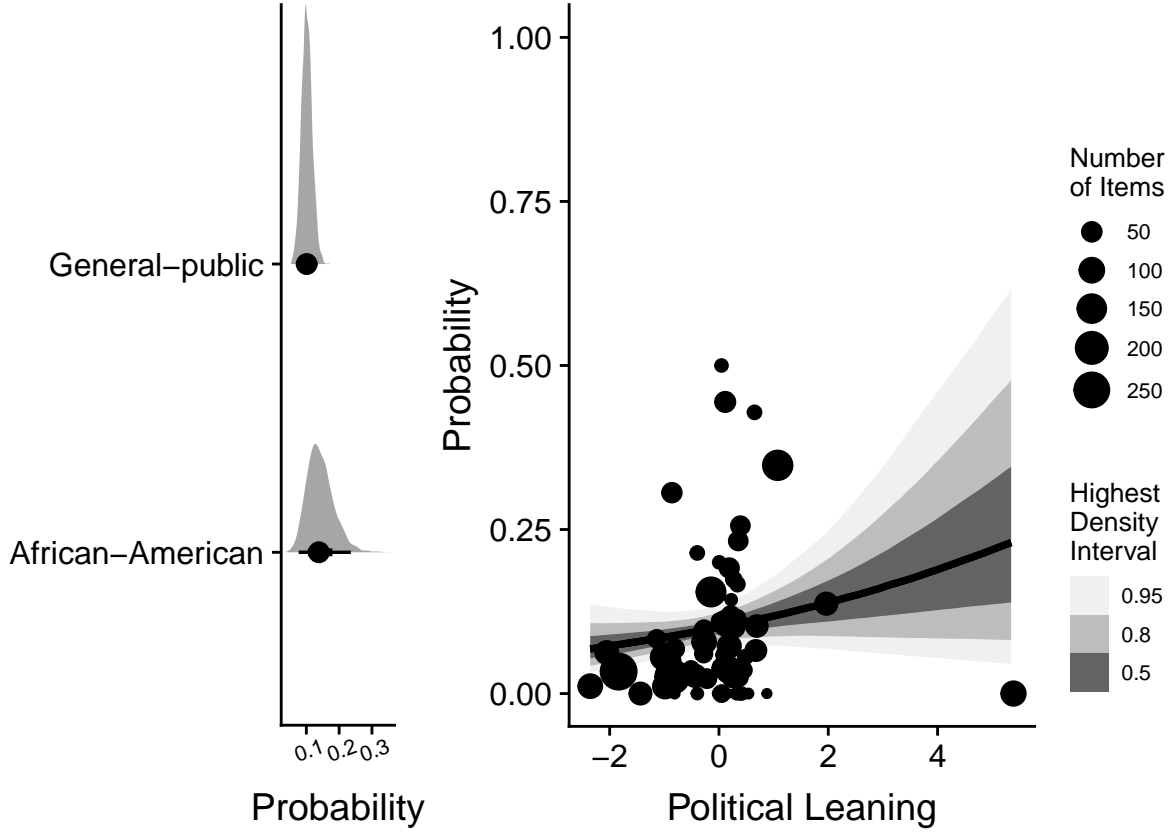


Figure 11: Modeled probability of legitimizing the protest, photos only

3.2.2 Models of audience & political orientation associations

When examining solely the image portion of these relationships as in figure 11, we see that the patterns are attenuated. In particular, there is no appreciable differences in the rate of depictions of Michael Brown between african american oriented sources and general public oriented sources ($p_{generalpublic} = 0.1, [0.07, 0.13]$; $p_{africanamerican} = 0.14, [0.07, 0.22]$, $prob_{gp>aa} < 0.16$

There is also no appreciable relationship between the political orientation of a source and the rate of depictions of Michael Brown ($\beta = 0.18, [-0.13, 0.49]$).

3.3 Active Kill Words

3.3.1 Frequency

There is substantial variability in the frequency with which active kill words are used (figure 12). Though there are a handful of small sources with with zero texts having active kill references, most of the distribution is between .05 and .3. The mean of these source-level proportions is 0.12.

3.3.2 Models of audience & political orientation associations

The analysis displayed in figure 13 suggests that African American sources are far more likely to use active kill words ($p_{generalpublic} = 0.09, [0.08, 0.11]$; $p_{africanamerican} = 0.14, [0.09, 0.19]$, $prob_{gp>aa} < 0.02$

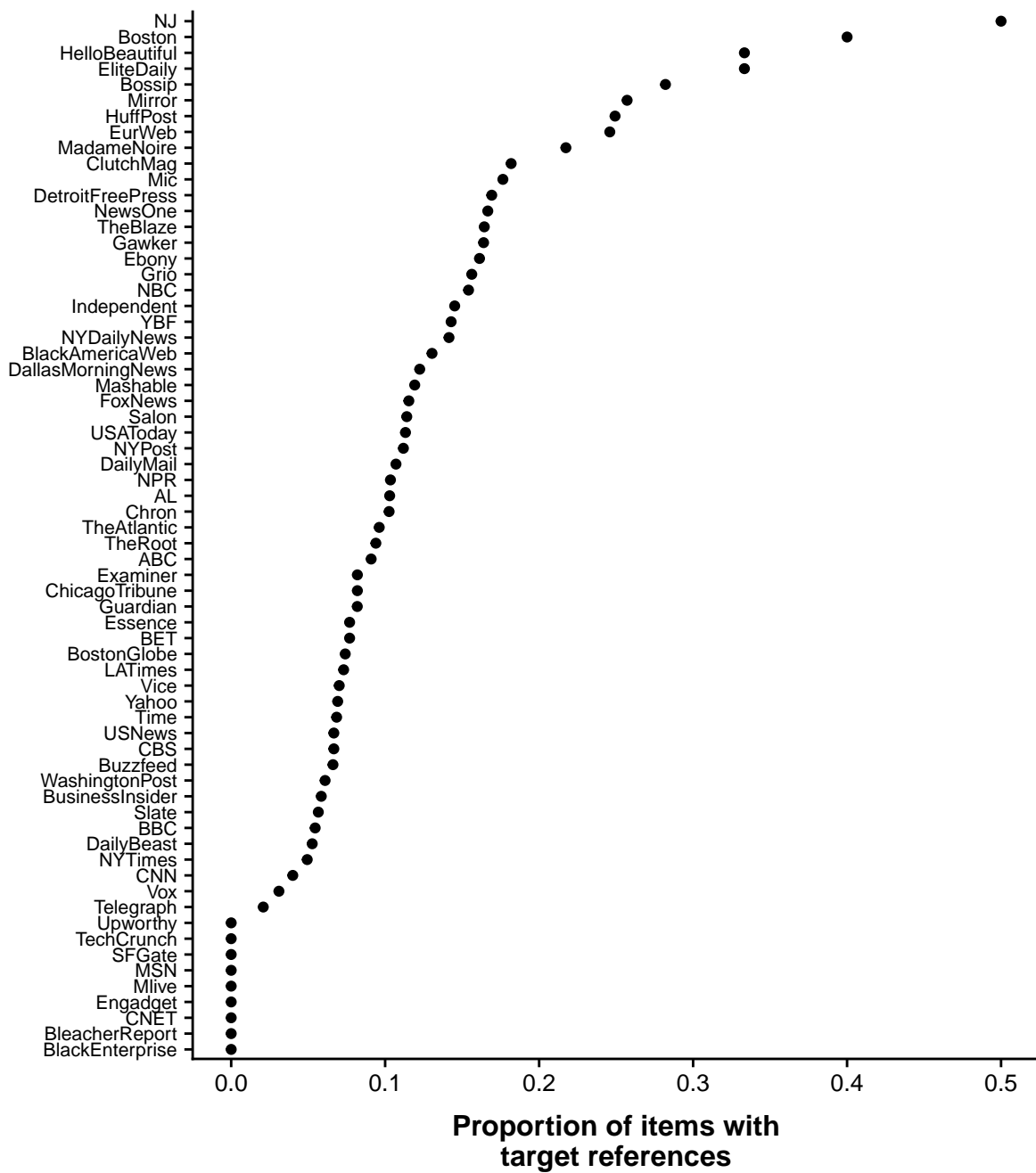


Figure 12: Proportion of captions and titles in each source that make reference to active kill words

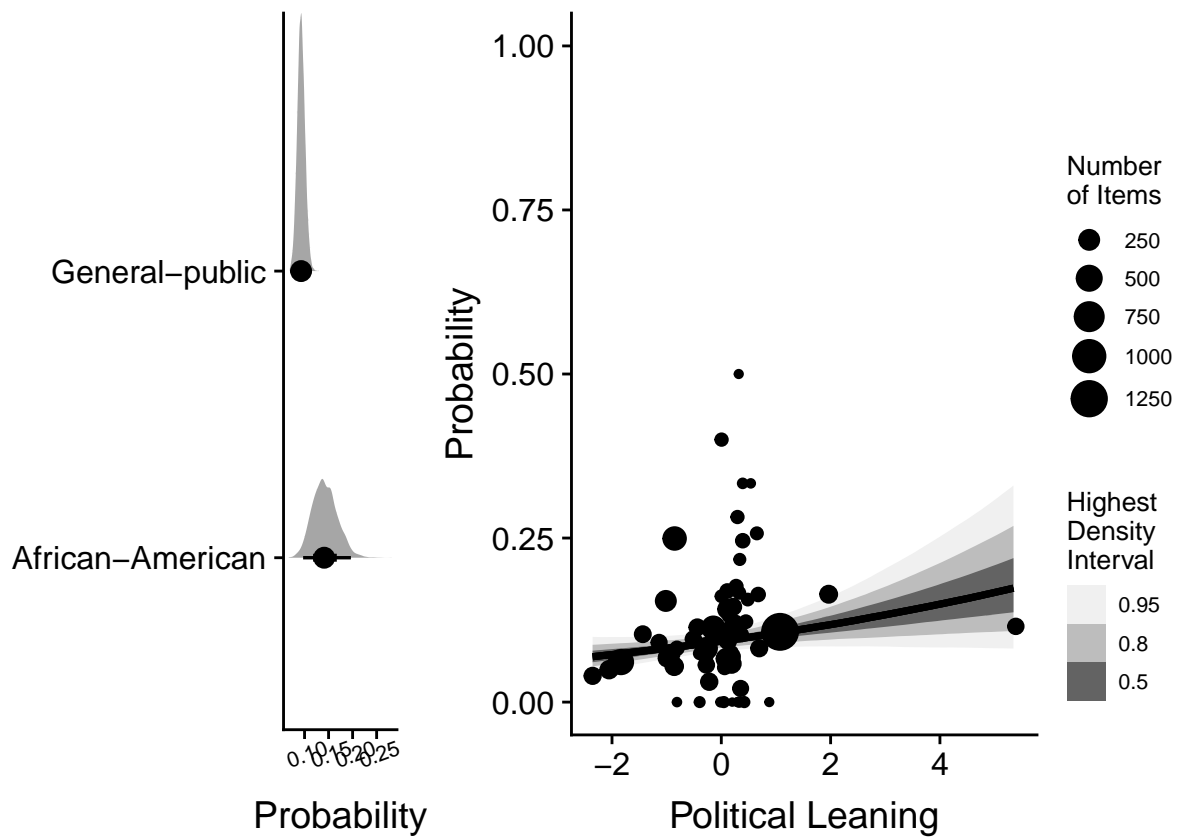


Figure 13: Modeled probability of making a reference to an active kill word

In contrast, the association between political orientation and likelihood of using active kill words is generally positive, with more conservative sources being more likely to use these charged terms, though zero cannot be ruled out as a probable value ($\beta = 0.14$, [-0.02, 0.28]).

3.4 Passive Kill Words

3.4.1 Frequency

There is also a good degree of variability in the frequency with which passive kill words are used (figure 14). There are a handful of small sources with with zero scored texts and one source with all texts having passive kill references. However, most of the distribution is between .15 and .5. The mean of these source-level proportions is 0.28.

3.4.2 Models of audience & political orientation associations

The analysis displayed in figure 15 suggests that there is no apparent relationship between African American and general public sources in how likely they are to use passive kill words ($p_{generalpublic} = 0.28$, [0.25, 0.32]; $p_{africanamerican} = 0.24$, [0.18, 0.32], $prob_{gp>aa} < 0.83$

In contrast, we see a strong association between political orientation and likelihood of using passive kill words, with more conservative sources being more likely to use these terms ($\beta = 0.16$, [0.02, 0.3]).

3.5 Factor Analysis

In our next stage, we examined the overall relationships between many of the concepts we have explored above. In particular, each article was scored as having a reference/image in one of the following categories:

- [Black | African American | white | Caucasian | race | ethnicity] • [unarmed | weaponless | innocent]
- [teen* | youth | young | adolescent | child | graduat* | high school]
- [Michael Brown | Michael | Mike | Brown]
- [kill* | gun* down | mow* down | murder* | slaughter* | butcher* | execut/ *massacr*]
- [dead | death | died | perish* | shot | shoot* | fatal*]
- Michael Brown featured images
- protest featured images
- police featured images

We then computed the proportion of articles within each source that had references/images for each of these categories.

3.5.1 Variable Correlations & factor loadings

Figure 16 displays the correlations of these proportions. Computing the eigenvalues of the correlation matrix indicates that there are three main factors underlying these variables. Table ?? below shows the variable loadings for each factor (with those below .3 suppressed for legibility).

```
##
## Loadings:
##           GLS1    GLS2    GLS3
## prot_img_prop           0.547
## pol_img_prop           0.848
## mb_img_prop      0.564
## race_ref_prop           -0.335    0.637
## inn_ref_prop      0.542
```

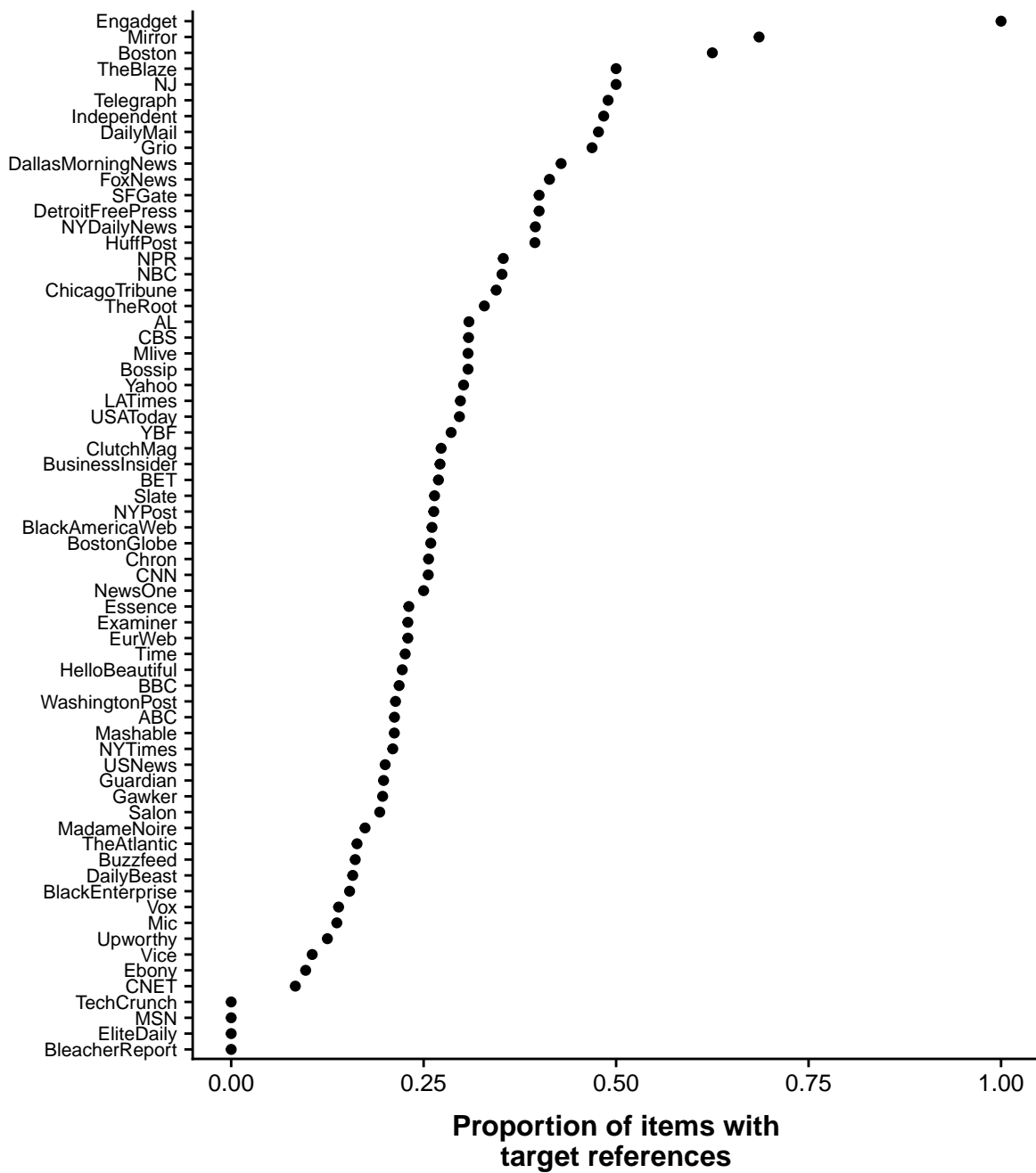



Figure 14: Proportion of captions and titles in each source that make reference to passive kill words

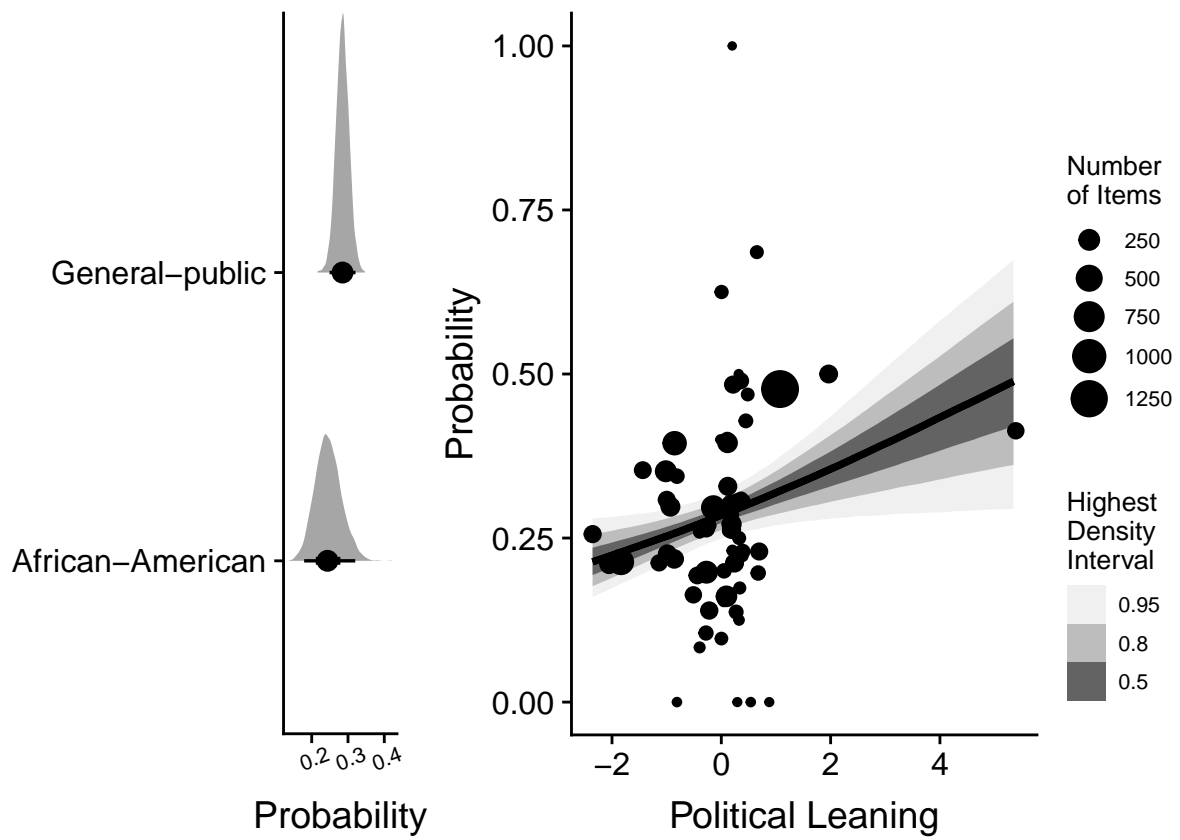


Figure 15: Modeled probability of making a reference to an passive kill word

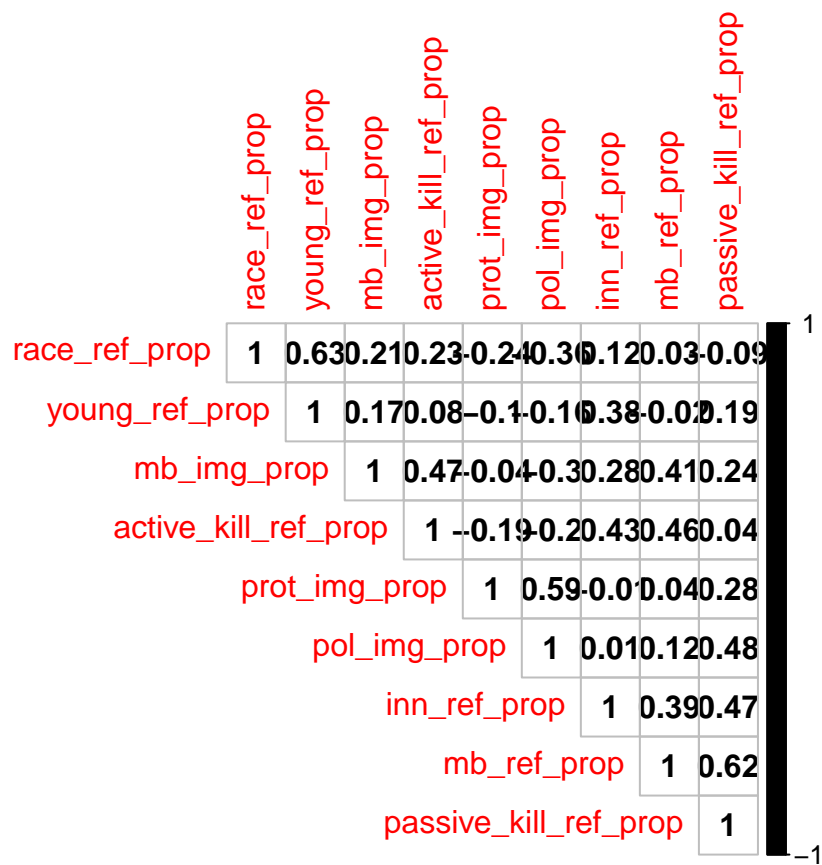


Figure 16: Correlation between underlying measurements

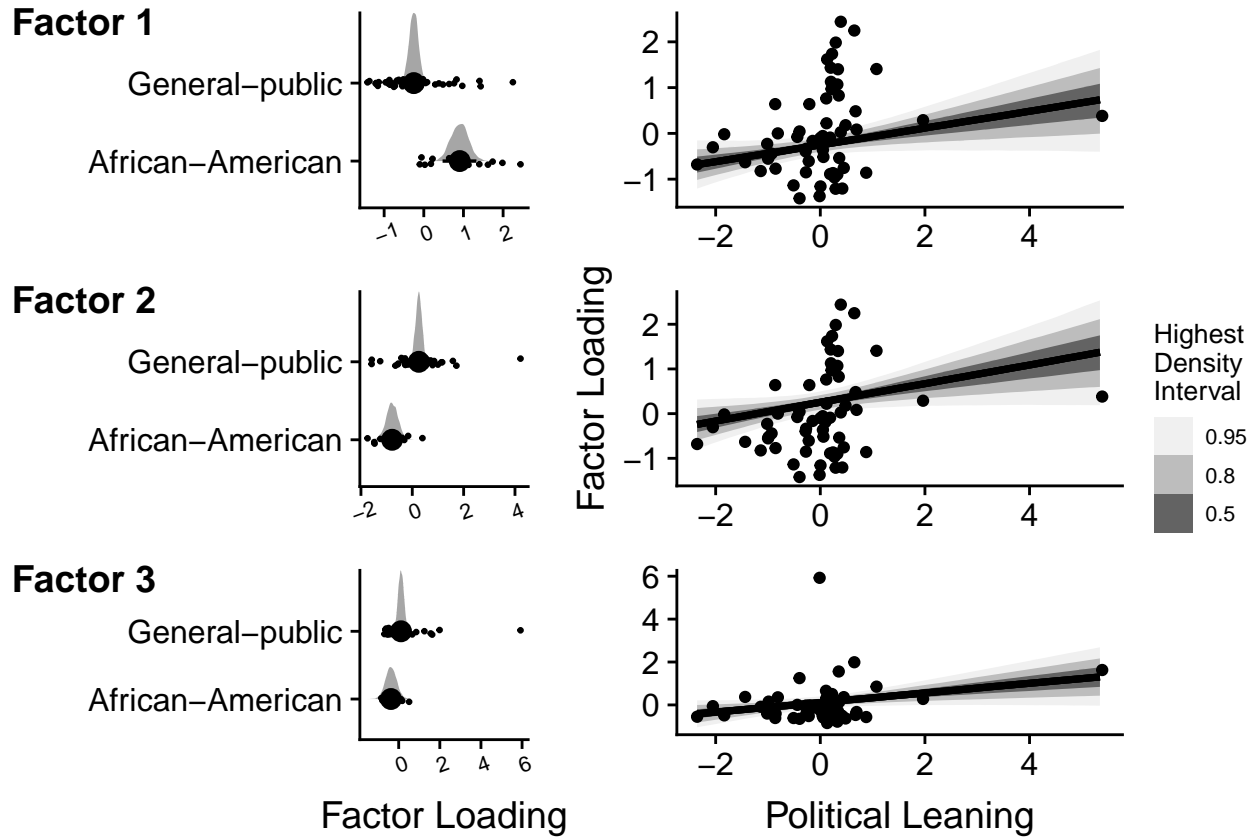


Figure 17: Modeled level of factor components

```
## young_ref_prop          0.950
## mb_ref_prop             0.832
## active_kill_ref_prop    0.634
## passive_kill_ref_prop   0.540 0.711
##
##           GLS1  GLS2  GLS3
## SS loadings  2.037 1.805 1.485
## Proportion Var 0.226 0.201 0.165
## Cumulative Var 0.226 0.427 0.592
```

The first factor is clearly about Michael Brown and his death. We see that references to Brown in text and presence of his images load highly onto this first factor, with references to active killing, passive killing, and his innocence also loading highly onto this factor. This factor appears to be a dimension on which Michael Brown is represented favorably.

The second factor is perhaps a bit more salacious. It focuses on passive killing, but both types of images also load highly onto this factor. We see that the emphasis on race is diminished for this factor.

The third factor does not emphasize Michael Brown or his death per se, but is more oriented toward the contextualizing details of the events. Namely the race and age dimensions.

3.5.2 Models of audience & political orientation associations

Figure 17 displays the models fit to these data. The patterns of representation by source audience show systematic differences along the first two factors. For the first factor, African American sources show much

more prominent emphasis than do general public sources (General Public = -0.25, [-0.48, -0.03]; African American = 0.91, [0.47, 1.33], $prob_{gp>aa} < .01$). In contrast, the general public news sources emphasize the second factor more (General Public = 0.26, [0, 0.49]; African American = -0.79, [-1.26, -0.32], $prob_{gp>aa} > .99$). The data do not suggest as strong of systematic variation by source audience for the third factor, though it is emphasized slightly more by the general public (General Public = 0.11, [-0.18, 0.39]; African American = -0.38, [-0.9, 0.15], $prob_{gp>aa} = 0.94$).

Though the effect of political orientation is generally positive across all three factors, no effect of political orientation is a plausible value for all three models ($factor1 = 0.18$, [-0.02, 0.38]; $factor2 = 0.21$, [-0.01, 0.42]; $factor3 = 0.22$, [-0.02, 0.47]).

3.6 Counting references per caption/title

We repeated many of the analyses described above, but instead of scoring each article in a binary fashion (presence or absence of any of the words), we summed the number of times a text had references to one of the target words. For these analyses, any target that was a bigram (e.g. ‘Michael Brown’) was counted as one hit, rather than two. Additionally, although we occasionally search for unigrams that are subsets of larger bigrams (as in searching for both ‘Brown’ and ‘Michael Brown’), hits in these cases are mutually exclusive (e.g. if the phrase ‘Michael Brown’ appears in the article, it would only match on ‘Michael Brown’ and would not match on ‘Brown’, thus yielding 1 hit from the target list).

3.6.1 Frequency

To begin with, we summed each text for the number of times we found phrases in our Black/unarmed/teen/MB/killed category. Figure 18 displays the average number of references per text across all sources, with most sources averaging around 1 hit per text. Examining the mean and variance across articles (ignoring source-level groupings), shows that the data are overdispersed, with the variance a bit more than twice the mean. Accordingly, we fit a negative binomial model to these data.

3.6.2 Models of audience & political orientation associations

As has been the case with many of these analyses, we observe systematic differences (figure 19) by audience type, with the general public sources making fewer references to this concept than African American sources ($M_{generalpublic} = 0.95$, [0.83, 1.05]; $M_{africanamerican} = 1.38$, [1.05, 1.75], $prob_{gp>aa} < .01$).

In contrast, though the association between number of references and political orientation is positive, negative values are also plausible ($\beta = 0.08$, [-0.01, 0.17]).

3.7 Counting references per caption/title/photo

3.7.1 Frequency

Adding in instances of Michael Brown pictures (of which there are 357) as part of the summing procedure modestly increases the overall source-level averages, as illustrated in figure 20. These additions do not appreciably change the relationships described above.

3.7.2 Models of audience & political orientation associations

Repeating the analysis in which we focus on just the active kill words, but examine counts instead of presence/absence also gives a similar result to what we had previously observed. Figure 21 shows that African

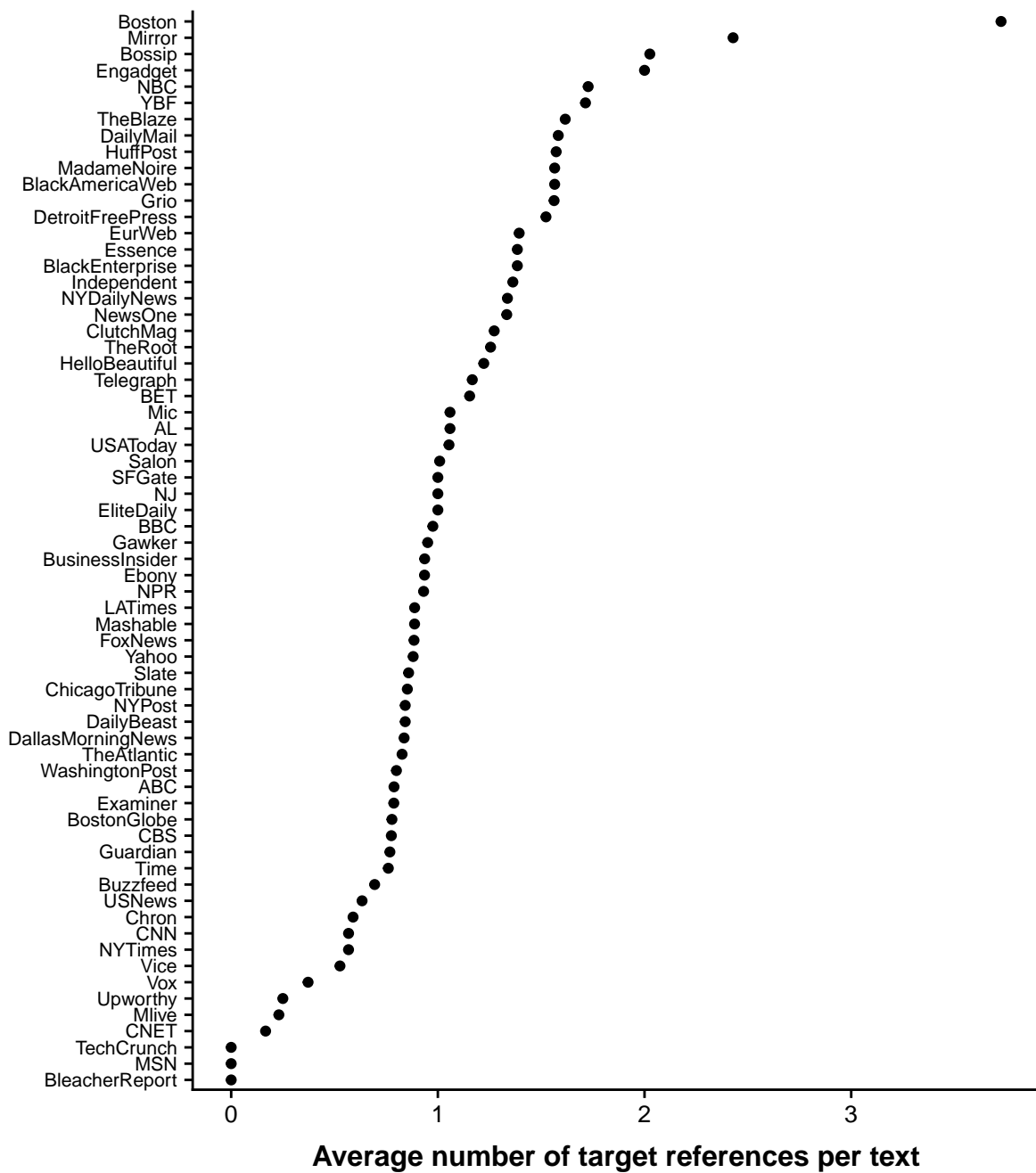


Figure 18: Average number of text instances of legitimizing the protest per source

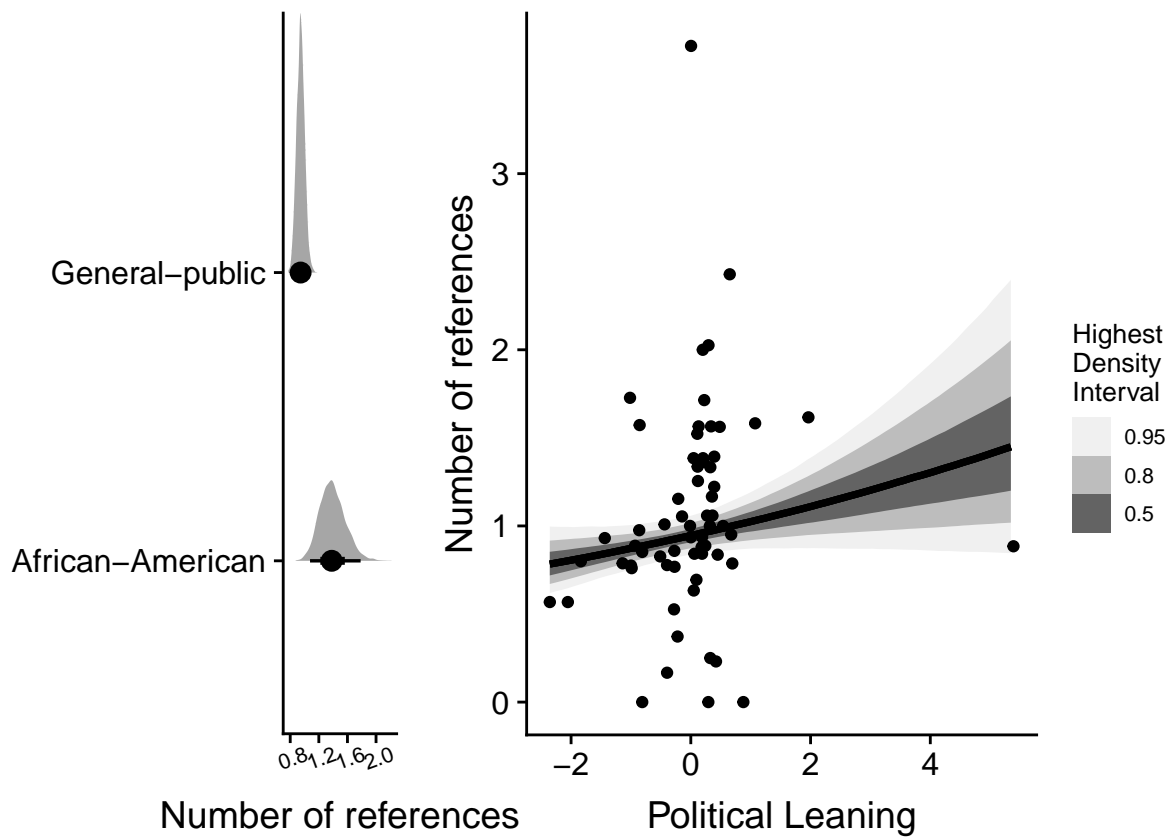


Figure 19: Modeled source-level counts of the number of references to legitimizing the protest

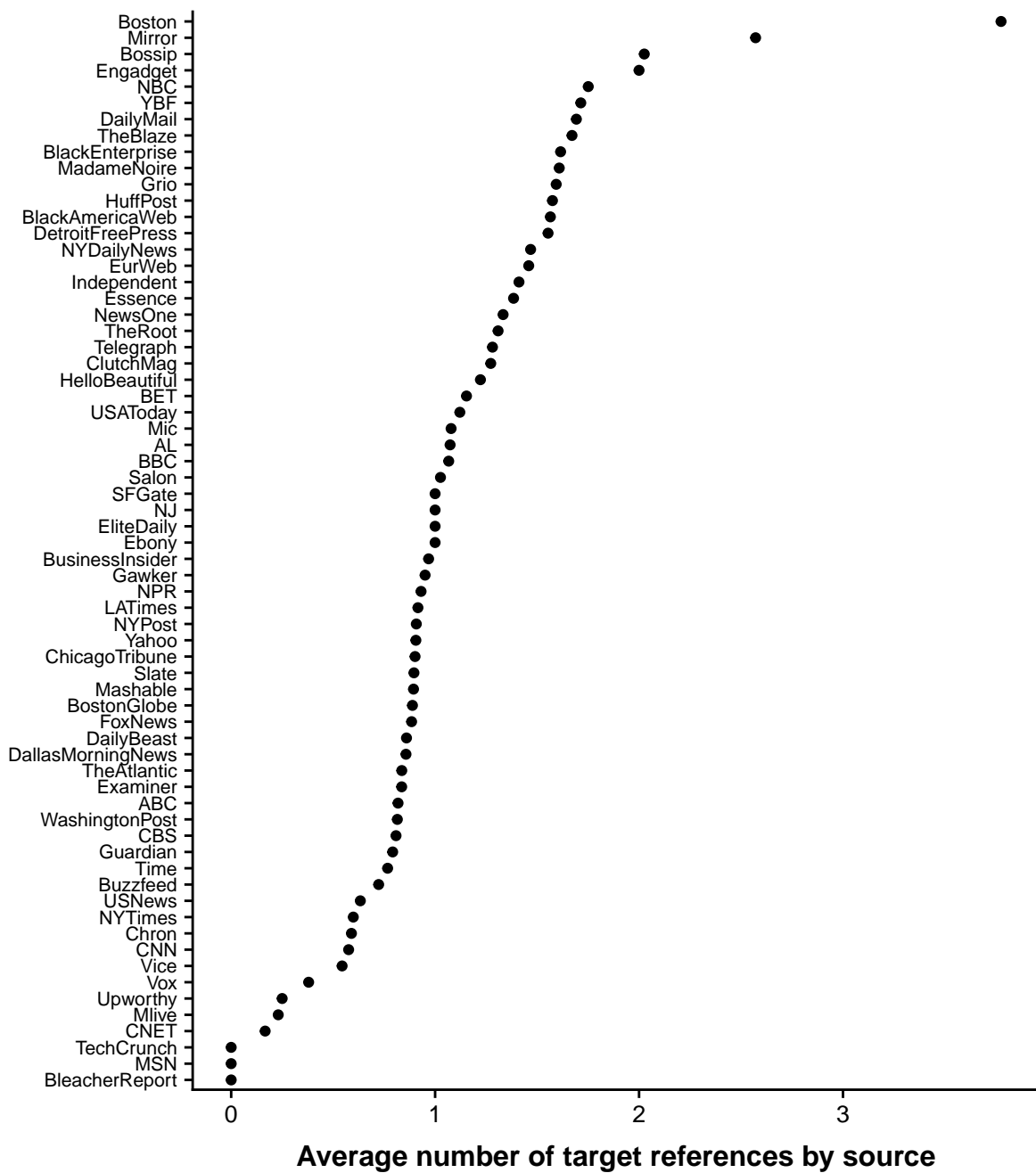


Figure 20: Average number of instances of legitimizing the protest per source, text and pictures combined

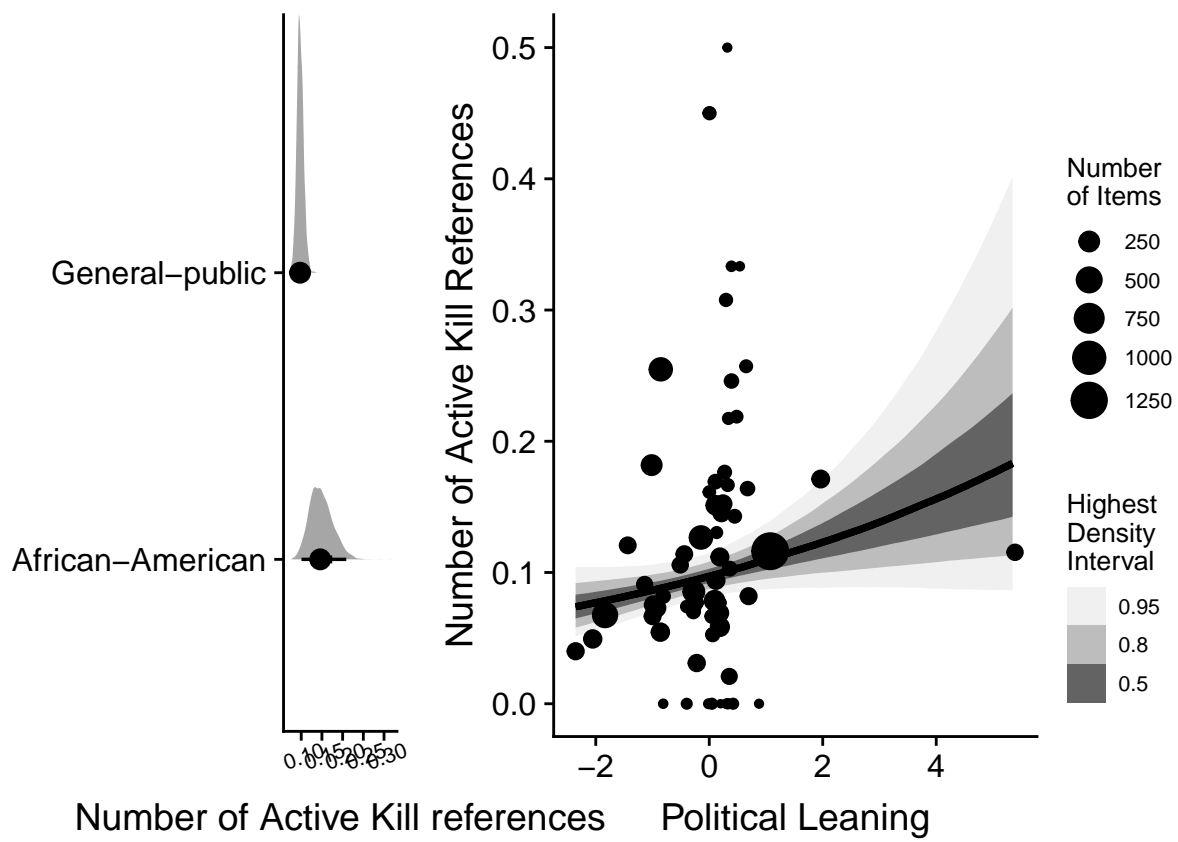


Figure 21: Modeled source-level counts of the number of references to active kill words, text and pictures combined

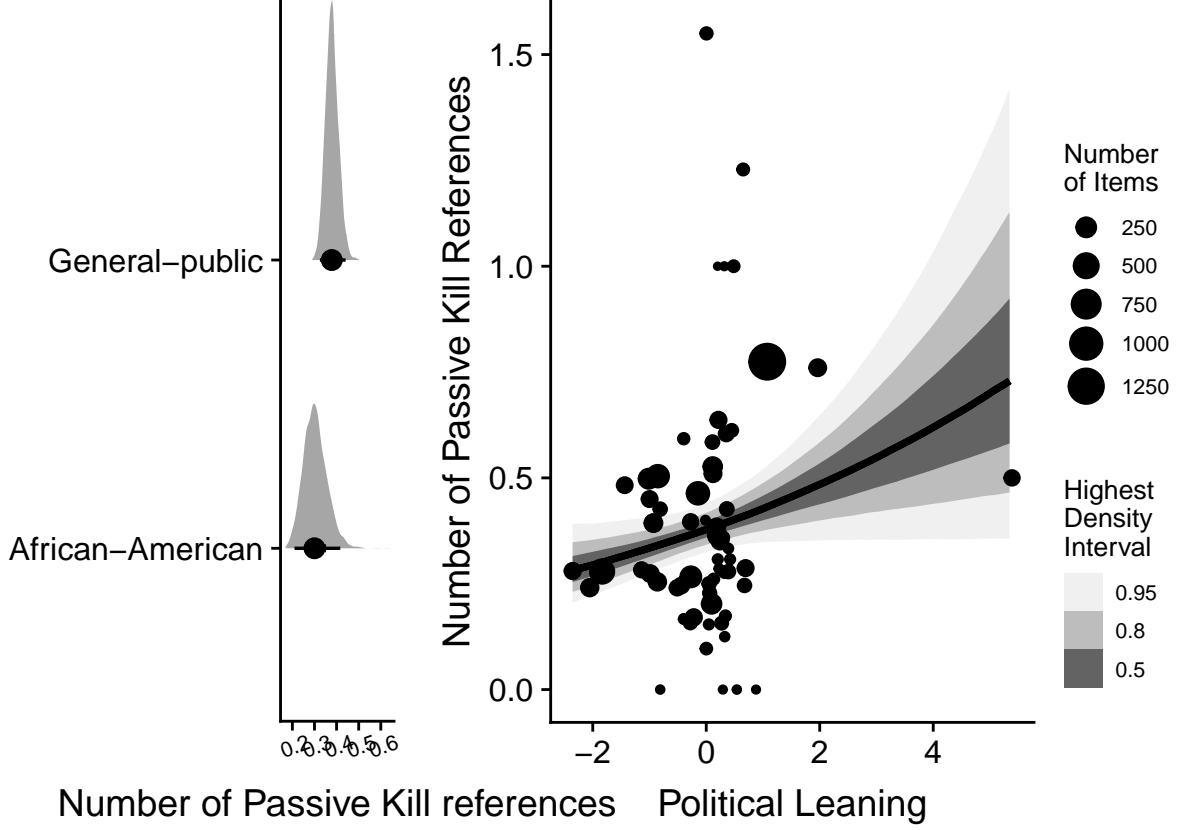


Figure 22: Modeled source-level counts of the number of references to passive kill words, text and pictures combined

American oriented sources are more likely to make active killing references in comparison to General public oriented sources ($M_{generalpublic} = 0.1$, [0.08, 0.11]; $M_{africanamerican} = 0.15$, [0.1, 0.2], $prob_{gp>aa} = 0.03$).

There relationship between political orientation and active kill references is also similar to what was seen when modeling probabilities. That is, there is a slightly positive association between political orientation and active kill references, such that more conservative sources are more likely to make these references, though we are unable to rule out zero as a probable value ($\beta = 0.12$, [-0.03, 0.25]).

Repeating the analysis in which we focus on just the passive kill words, but examine counts instead of presence/absence also gives a similar result to what we had previously observed. Figure 22 shows that while general public sources tend to have higher counts of passive kill words, the modeled relationship fails to rule out a flat association between source and counts of passive killing references ($M_{generalpublic} = 0.38$, [0.32, 0.44]; $M_{africanamerican} = 0.3$, [0.2, 0.4], $prob_{gp>aa} = 0.89$).

We also see that there is an association between political orientation and passive kill references, such that more conservative sources are more likely to make these references, though zero is barely included as a probable value here as well ($\beta = 0.12$, [-0.01, 0.24]).

4 Temporal Dynamics

The shooting has important temporal dynamics that have heretofore been overlooked. For instance, although the fact that a white officer killed a young black man was clear from the beginning, the officer's name was not released until August 15th, a full six days after the shooting. Additionally, protests waxed and waned

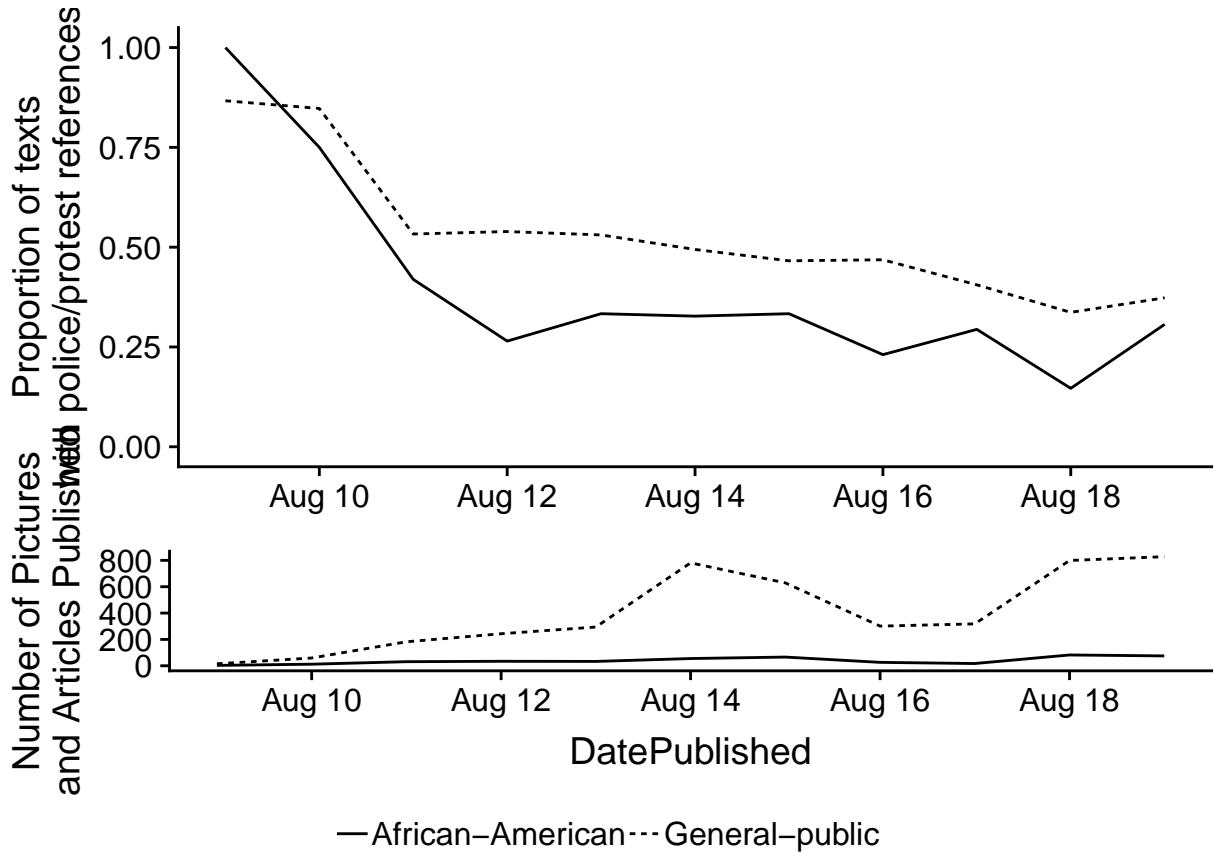


Figure 23: Proportion of texts with police or protest references by day and audience type (top), and total number of texts by day and audience type (bottom)

in the days following the shooting, with some days featuring relatively little activity, and others featuring widespread looting, heavily militarized police, and crackdowns on the press. We want to ensure that our analyses are not being driven by outlier coverage due to some of the more acute events that received heavy press coverage. Accordingly, we now investigate some simple summary plots of key variables from the analyses above, but examine these trends over time.

4.1 Audience type

4.1.1 Police & Protest words

4.1.2 Police & Protest images

4.1.3 Legitimizing the Protest: words and images

Figure ?? shows that the patterns observed above remain consistent throughout the timeline with similar longitudinal patterns of coverage over time, though the general public shows a bump in mentions on August 16th and 17th that does not appear for African American sources.

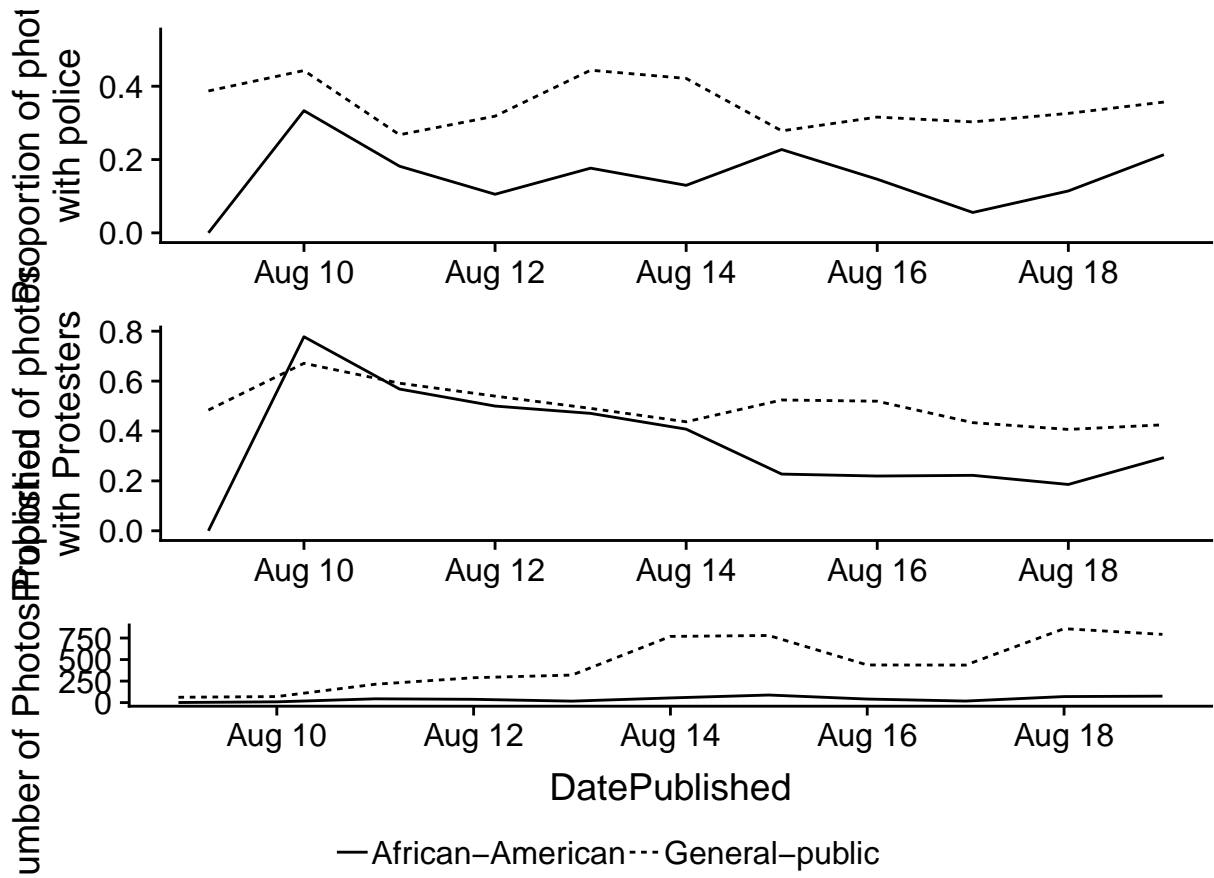


Figure 24: Proportion of articles with police (top) or protest images (middle) by day and audience type, and total number of images by day and audience type (bottom)

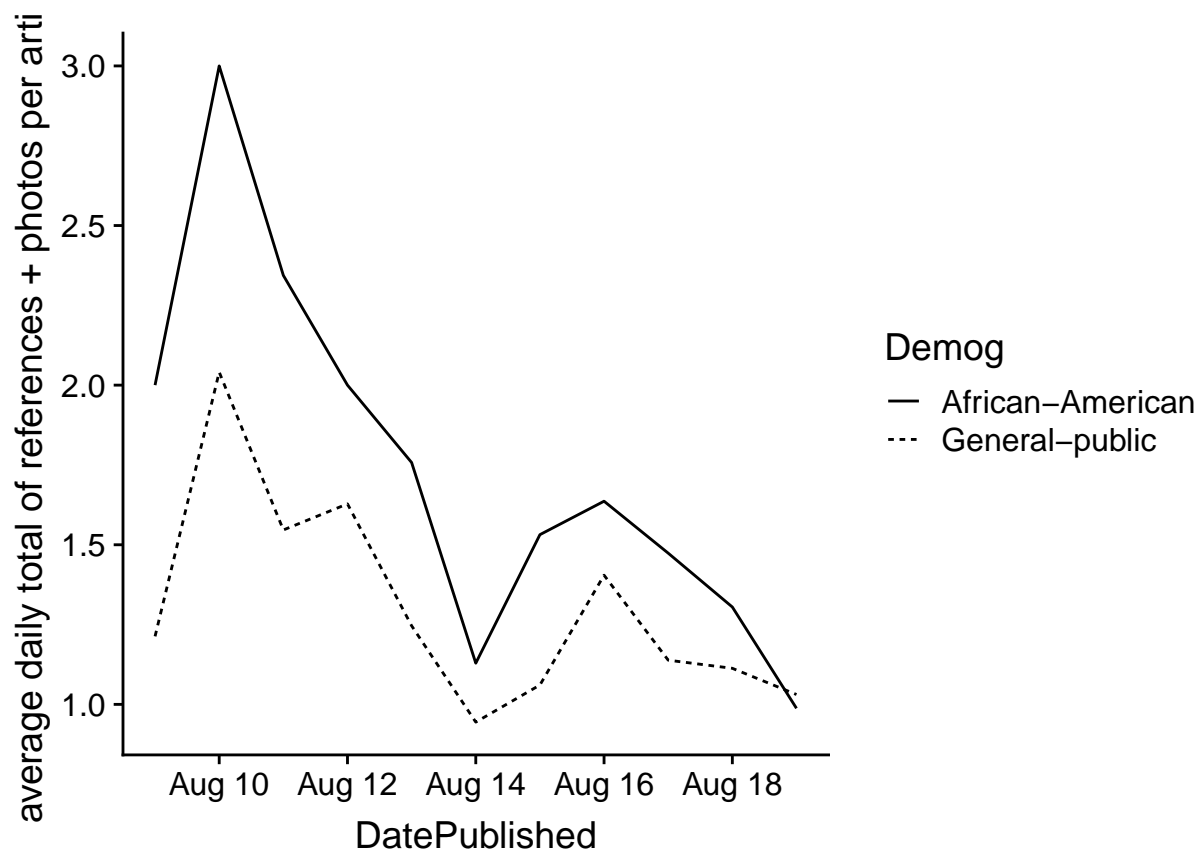


Figure 25: Total number of instances legitimizing the protest by day and audience type.

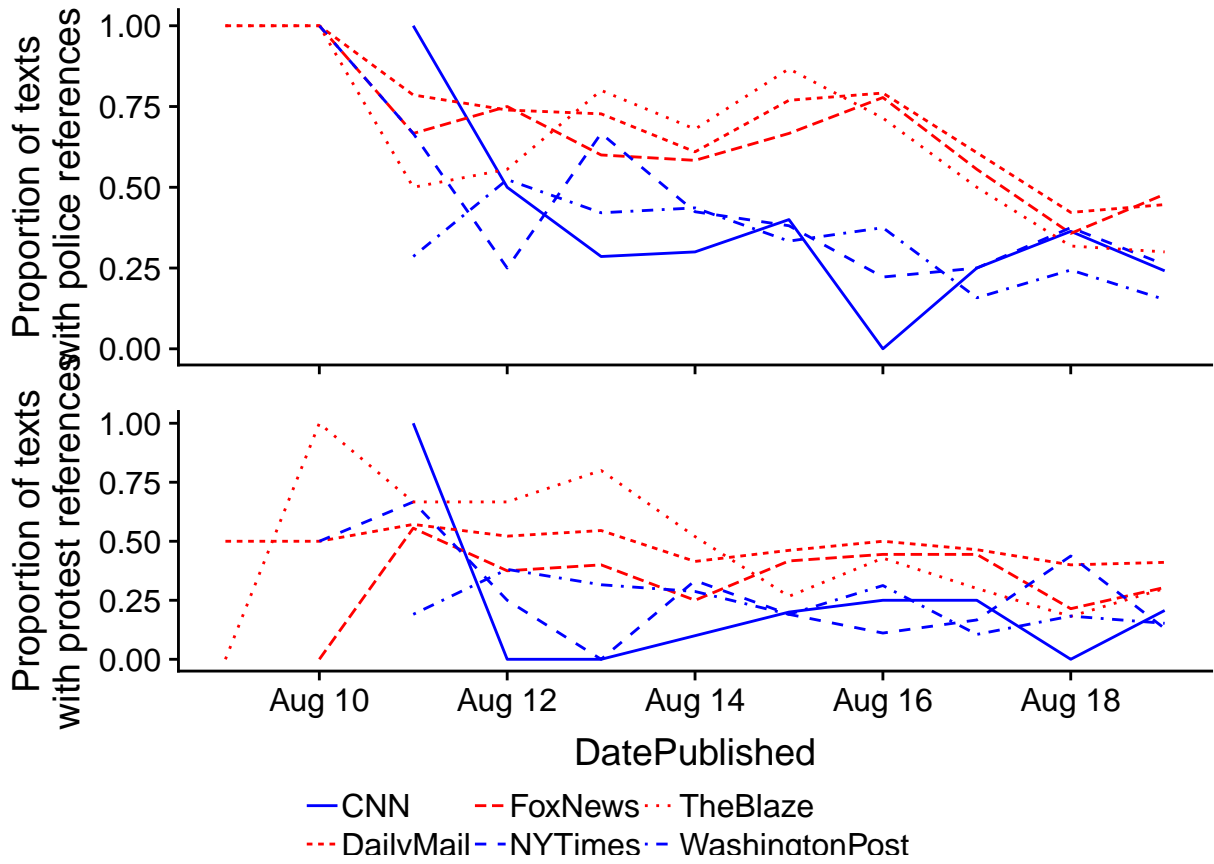


Figure 26: Proportion of texts with police (top) and protest (bottom) references by day and source.

4.2 Liberal and Conservative sources

4.2.1 Police and protest words

4.2.2 Police and protest images

4.2.3 Legitimizing the Protest: words and images

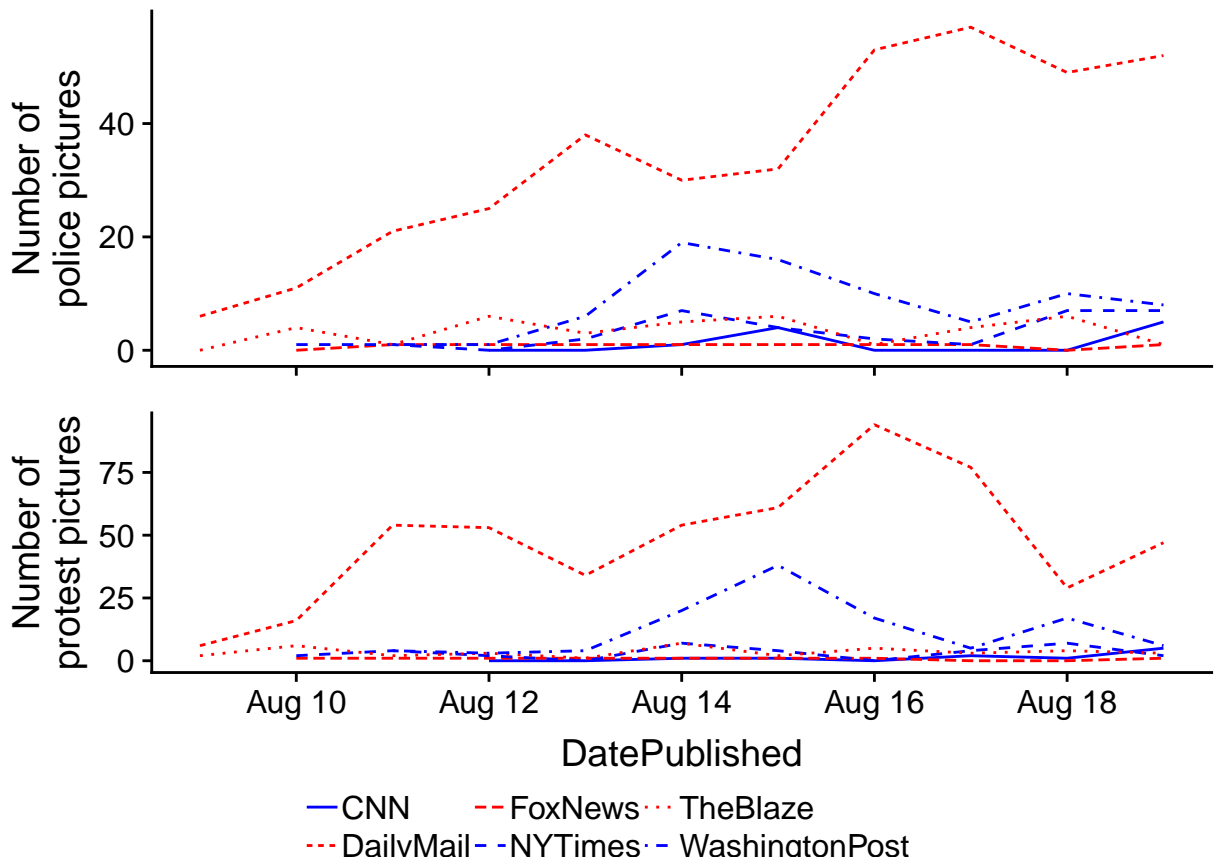


Figure 27: Number of images of police (top) and protest (bottom) references by day and source.

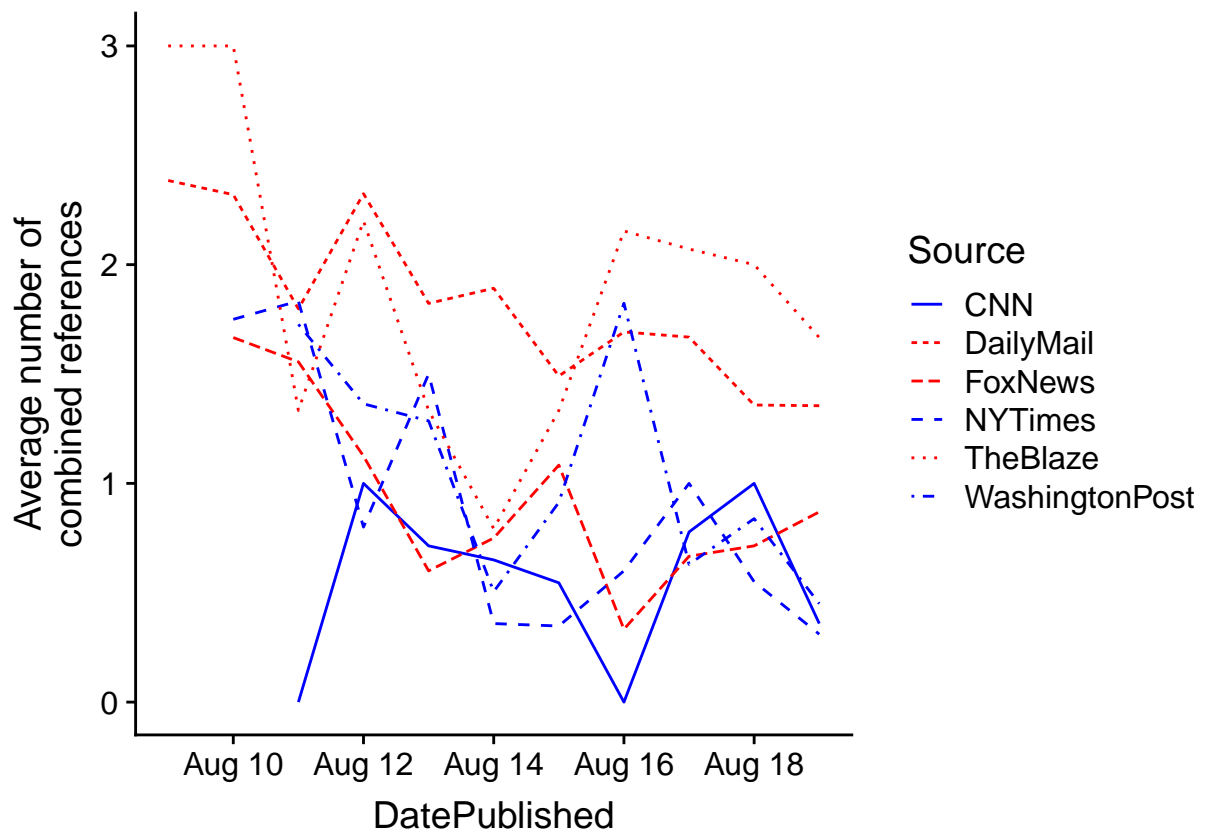


Figure 28: Total number of instances humanizing the tragedy by day and source.

Table 1: A random sample of texts from the three most conservative and three most liberal sources.

Source	text	type	police_ref	protest_ref
CNN	Demonstrators raise their arms in protest after a police shooting that killed an unarmed black teenager.	Caption	1	1
CNN	A town in turmoil – 5 things about Ferguson, Missouri	Title	0	0
CNN	New head of Ferguson security: 'How would I feel?'	Title	0	0
NYTimes	National Guard troops arrived in Ferguson on Monday. Gov. Jay Nixon said the Guard would have only a limited role, protecting the police command post.	Caption	1	0
NYTimes	Several newspapers led with the story about the clashes between residents and the police in Ferguson, Mo., on Thursday morning.	Caption	1	0
NYTimes	President Obama at a news conference Thursday on Martha's Vineyard, where he spoke about the situation in Iraq and in Ferguson, Mo.	Caption	0	0
WashingtonPost	Even before Michael Brown's slaying in Ferguson, racial questions hung over police	Title	1	0
WashingtonPost	In the battle for America's identity, Ferguson is Ground Zero	Title	0	0
WashingtonPost	Grand jury will hear case of Staten Island man who died after police chokehold	Title	1	0
DailyMail	Mission creep? Obama vows MORE airstrikes and increasing military aid to Iraqis after 'almost flawless' operation to end siege of thousands on mountain	Title	0	0
DailyMail	Shocked: Wesley Lowery took to Twitter to make his feelings about his treatment by police very clear	Caption	1	0
DailyMail	Guide to developments in Missouri police shooting	Title	1	0
TheBlaze	Surreal Video, Images Out of Ferguson as Unrest Resumes Following Shooting of Unarmed Teen: 'I Can't Believe This is Happening'	Title	0	1
TheBlaze	A makeshift memorial sits in the middle of the street where 18-year-old Michael Brown was shot and killed by police, Monday, Aug. 11, 2014, in Ferguson, Mo. The FBI has opened an investigation into the fatal shooting of an unarmed black teenager on Saturday whose death stirred unrest in a St. Louis suburb.	Caption	1	1
TheBlaze	The Eye-Opening Words of a Lifelong Ferguson Resident Who Bought a Shotgun and Handgun as Looting, Unrest Raged in His Town	Title	0	1
FoxNews	Friday Lightning Round: ObamaCare, Ferguson protest	Title	0	1
FoxNews	Lawyer: Family of Missouri teen killed by cop asking Justice Department to oversee 2nd autopsy	Title	1	0
FoxNews	Family's attorney: Ferguson police are trying to assassinate character of teen shooting victim	Title	1	0