Slanted images: Measuring nonverbal media bias during the 2016 election

Levi Boxell, *Stanford University*[*]

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Abstract

Using nearly one million images from the front page of news websites during the 2016 election period, I show how computer vision techniques can identify the faces of politicians across the images and measure the nonverbal emotional content expressed on each face. I find strong evidence for nonverbal media bias in both the choice of which politicians to cover and the emotional content of the images used. Liberal websites devoted 40 (14) percent of their visual political coverage to Donald Trump (Hillary Clinton) compared to 30 (25) percent among conservative outlets. Websites whose consumers are politically aligned with a candidate also portray the candidate with more positive emotions and less negative emotions than non-aligned websites. Moreover, I find evidence for important dynamics across the election cycle, with the partisan gap in who to cover increasing significantly after the primaries.

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1 Introduction

Nonverbal information can be more memorable and more persuasive than verbal information (Sullivan and Masters 1988; Graber 1990; Graber 1996). Much of the media consumed today is also nonverbal—political coverage is watched on television, images of politicians are posted alongside newspaper stories whether online or in print, and social media is littered with attention grabbing photos on shared posts. Despite this, large-scale studies of media bias have focused almost exclusively on textual or citation-based measures of media bias (e.g., Groseclose and Milyo 2005; Gentzkow and Shapiro 2010; Martin and Yurukoglu 2017).

To better understand the degree to which nonverbal bias is present across online media firms, I construct a novel dataset of nearly one million image files used during the 2016 election cycle. I then use facial recognition tools to extract nearly 80,000 faces of 61 politicians from 92 websites. For each face, the Microsoft Emotion API characterizes the face on eight different emotional categories: happiness, anger, fear, surprise, disgust, contempt, sadness, and neutral.

The displayed facial expressions of a politician are a useful indicator of nonverbal media slant. Facial expressions are readily altered by choosing different images, and visual portrayals of politicians have been show to influence opinions (Rosenberg and McCafferty 1987; Sullivan and Masters 1988; Rosenberg et al. 1991; Barrett and Barrington 2005b; Stewart et al. 2009). The computer-coded emotions also explain half of the variation in mean perceived favorability of an image as rated by human coders on MTurk.

Using the detected faces of politicians and the associated facial expressions, I find strong evidence of partisan nonverbal media bias in both the choice of who to cover and the emotional content of the images used. Liberal websites devoted 40 percent of their visual political coverage to Donald Trump compared to 30 percent among conservative outlets. On the other hand, conservative websites devoted 25 percent of their visual political coverage to Hillary Clinton compared to 14 percent among liberal outlets.

When choosing to cover Hillary Clinton, conservative websites were less likely to display her with positive emotions (happiness) and more likely to display her with negative emotions than liberal websites. Similarly, liberal websites portrayed Trump with less positive emotions and more negative emotions than conservative websites.

The method used and size of the dataset are also useful for examining whether nonverbal media bias varies across the election cycle. News coverage choices shifted significantly in response to each candidate becoming the presumptive party nominee—with outlets increasing the share of coverage devoted to the opposing candidate. There is less evidence for significant shifts across the election cycle in the partisan nature of the emotions used to portray each candidate.

Overall, these results shows that partisan outlets expressed bias during the 2016 election by shifting coverage towards the opposing candidate, by using relatively more negative emotions, and by recalibrating these choices in response to the dynamics of the election cycle.

This paper is most related to the literature on media bias. Previous reviews of the empirical literature have noted both (a) the primary focus on text-based measures of media bias and (b) the limited number of automated studies examining bias in tone or emotion (Groeling 2013; Puglisi and Snyder 2015). With regards to nonverbal slant, previous work has suggested the presence of nonverbal biases in the media and has found corroborating evidence in small-scale manual codings (Kepplinger 1982; Waldman and Devitt 1998; Barrett and Barrington 2005a; Coleman and Banning 2006; Grabe and Bucy 2009). This paper implements one of the first automated examinations of nonverbal slant that is scalable and applicable across domains.[1] Furthermore, the focus on facial expressions lends itself naturally to understanding bias in the tone or emotion of news coverage.

In the aftermath of the 2016 election, scholars began examining various aspects of the media ecosystem including fake news (e.g., Allcott and Gentzkow 2017), the internet and social media (e.g., Persily 2017; Boxell et al. 2018), and the coverage and tone choices of media outlets (e.g., Patterson 2016a,b; Searles and Banda 2019). This article contributes to the literature on media and the 2016 election by measuring nonverbal media bias in both who to cover and how to cover them, examining how this bias varies with the ideological-leanings of a website's users, and documenting the dynamics of nonverbal media bias across the election cycle.[2]

This paper also relates to a literature on facial codings of emotions and their applications in the social sciences. One of the most prominent frameworks for coding facial movements is the Facial Action Coding System or FACS (Ekman 1993). While broader in scope, the FACS framework is often used to map combinations of "action units" or muscle movements into seven basic or universal emotional categories: happiness, sadness, surprise, fear, anger, disgust, and contempt (Ekman and Cordaro 2011). The FACS framework and other emotion recognition frameworks are often applied manually in political science (e.g., Stewart et al. 2009; Stewart and Dowe 2013). With recent advances in machine learning tools, automated methods to detect

[1] Peng (2018) is a contemporaneous examination of automated measurement of nonverbal slant, but uses a limited number of websites and, due to the manner in which Peng's data was collected, is limited in its ability to examine bias in the choice of which politician to cover.

[2] See also Peng (2018).

facial emotions in images have been developed (e.g., Bartlett et al. 2005; Zeng et al. 2009; Ding et al. 2016). The Microsoft Emotion API used in this article is one implementation of such efforts.

Lastly, the data pipeline and method gives media researchers a platform to better understand visual media bias and communication patterns that can readily extend beyond political parties to any identifiable demographic groups, and highlights the new opportunities for using images as data to complement previous work on text as data. See Joo and Steinert-Threlkeld (2018) for a review of using images as data in political science research.[3]

2 Data and method

2.1 Website partisanship

The measure of a website's user partisanship comes from Faris et al. (2017). They use 2016 media link and social media sharing data to construct a measure of the partisan composition of 115 websites, subsequently denoted as the "partisanship score."[4] The partisanship score measures the relative frequency of Twitter shares made by Trump or Clinton supporters for each website on scale from -1 to 1. Positive partisanship scores indicate a higher frequency of shares by Trump supporters relative to Clinton supporters.

The Berkman-Klein partisanship scores are highly correlated with previous measures of audience segregation using both browser data (Gentzkow and Shapiro 2011; Flaxman et al. 2016) and survey responses (Pew Research Center 2014). The correlation between the Berkman-Klein scores and the Gentzkow and Shapiro (2011), Flaxman et al. (2016), and Pew Research Center (2014) measures are .788, .600, and .917 respectively among websites that overlap with the Berkman-Klein study.

2.2 Website images

To build the dataset of politician images, I attempt to scrape the archived version of the front page of each website from the Internet Archive's Wayback Machine and download the detected

[3]Other work in the social sciences using computer vision methods include Joo et al. (2014), Won et al. (2017), Peng (2018), Joo et al. (2019), and Xi et al. (2019).

[4]Of these websites, Mediaite.com is dropped.

images from this page.[5] The Wayback Machine's choice of whether or not to archive a version of a website is not random, but is a function of the popularity of the website along with their overall archiving capabilities at a given point in time. Websites can also explicitly restrict archiving. Furthermore, idiosyncratic issues with the scraping or the original archiving may have prevented some images from being downloaded and the extent of these issues may vary across websites.[6] Website fixed effects are included throughout to control for these issues.

The number of websites, duration of coverage, and quantity of images distinguish this dataset. The data used in this paper includes images published between September 2015 and April 2017, and contains nearly one million scraped files larger than 1 KB from 99 websites.

In contrast, among studies related to the nonverbal portrayal of politicians in the media, Waldman and Devitt (1998) examine 625 candidate images across 5 newspapers during the 1996 election; Barrett and Barrington (2005a) examine 435 candidate images across 7 newspapers during the 1998 and 2002 election seasons; Coleman and Banning (2006) examine 1,315 television "shots" of candidates across 3 broadcast news networks during the 2000 election; Grabe and Bucy (2007) examine 62 hours of broadcast news across the 1992–2004 election cycles; and Peng (2018) examines 13,026 candidate images from 15 websites around the 2016 election.

2.3 Identifying politicians

A key challenge given the number of images is determining which images contain politicians. The scraped images are not cleanly labeled and may contain multiple faces. To detect politician faces, a two-step procedure is used.

First, Matlab's eye detector is used to filter images that are likely to contain a face.[7] After this initial filtering, there are still more than 350,000 images remaining that contain a machine-recognizable face.

[5] I attempt to scrape the noon archive of each website, but accept the default re-direct from the Wayback Machine to alternative archives on the same day.

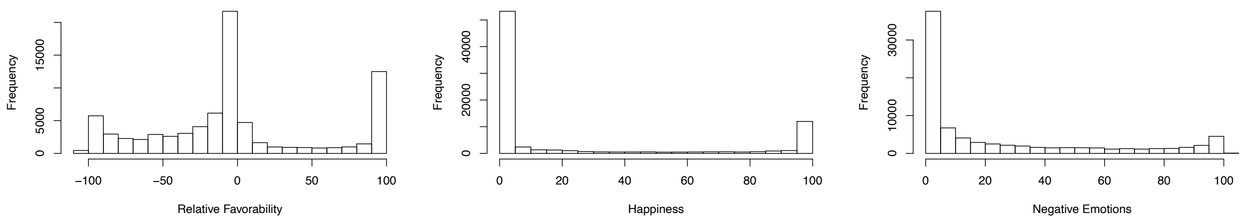
[6] To detect images, I search for "img" html tags and keep images with a recognized "src" value. This procedure does not capture all images from all websites equally, but will likely vary based on the underlying site architecture (e.g., using alternative html tags or html tag structure). Variations in file or location naming may also affect the scraping and downloading of images if they are not cleaned properly in the script. I attempt to exclude images associated with the Wayback Machine. Network connection and related issues may also influence whether an image is successfully downloaded. See code for details.

[7] I also restrict to images that loaded into Matlab and that were at least 1 KB in size, which is an API size restriction later. The Online Appendix compares Matlab's eye detector to a manual evaluation of whether an image contains a face. The results suggest Matlab is a useful tool in selecting images that will likely have a machine-recognizable face, i.e., images with many pixels and a human-observable face.

Second, Microsoft's Face API (a facial recognition machine learning tool) is used along with a manually labeled set of politician images to detect politician faces within each unlabelled, scraped image.[8] The algorithm first searches for faces in the image and then, for each face, assigns a match confidence score between zero and one for a given politician. Whether or not the API detects a face (or matches a face to a politician) depends on several aspects of the photo, such as the resolution, the size of the face, the angle of the face, and whether there are any obstructions to the face (e.g., a hand). The baseline results restrict the faces to those with a confidence score of at least 0.5, and the Online Appendix shows robustness to more conservative thresholds.

After these steps, the baseline sample contains 79,761 faces representing 61 politicians and 92 websites. There are 28,658 images of Donald Trump; 14,348 images of Hillary Clinton; and 8,336 images of Barack Obama. Throughout, I will use the term "image" and "face" interchangeably to refer to a face-image pair.

Figure 1: Histogram of Emotion Scores



Notes: Each plot presents a histogram of the emotion scores for images with at least 0.5 match confidence.

2.4 Measuring emotions

For each face, Microsoft's Emotion API is used to measure the emotional content on eight different dimensions: happiness, anger, fear, surprise, disgust, contempt, sadness, and neutral. The level of emotion across categories roughly sums to 100.

Other APIs for emotion detection in faces include Face++ (https://www.faceplusplus.com/), Sighthound (https://www.sighthound.com/), and Google Vision (https://cloud.google.com/vision/).

[8]The set of politicians are selected by identifying, for each year in 2008, 2012, and 2016, the main Republican and Democratic presidential candidates, the vice presidents selected by each nominee, and the main congressional leaders for each party. A small dataset of labeled images is then constructed for each politician. See Online Appendix for details.

However, Peng (2018) finds higher correlation between human-perceived emotions and API labelling for Microsoft than these alternative APIs (see Online Appendix Table A6).[9] Peng (2018) finds that the Microsoft API's classification of happiness and neutral emotions aligns well with human coders (correlations of .85 and .67 respectively). However, the API's classification is less correlated with human coders for 'negative' emotions (anger, fear, surprise, disgust, contempt, and sadness) when evaluated individually.[10] For these reasons, the API is probably not appropriate for scholars interested in better understanding when each of these negative emotions are used in political communication. However, as discussed below, the API is an effective tool for distinguishing which images portray a candidate in a positive, neutral, or negative fashion, and thereby mapping high-dimensional image data into a single scalar measure of favorability or bias.

To construct a single measure of the emotional slant towards an individual in a given image, I define *relative favorability* to be the difference between positive emotions (happiness) and the sum of the negative emotions (anger, sadness, contempt, disgust, surprise, and fear). In a manual validation exercise of 300 randomly selected images for which the Microsoft API only detected a single face and had a match confidence of greater than 0.8, the facial emotion measure of relative favorability explains an estimated 42 percent of the observed variation in the population mean perceived favorability by human coders on MTurk, and the vector of emotion scores is estimated to explain 50 percent (see Online Appendix).

Figure 1 shows the distribution of emotion scores. The relative favorability scores cluster at -100, 0, and 100—indicating negative, neutral, and positive emotions respectively.

3 Documenting nonverbal media bias

Nonverbal media bias can present itself in both the choice of *who* to cover and the choice of *how* to cover them.

To examine partisan bias in the choice of *who* to cover, Panel A Figure 2 reports the share of images that depict a given politician or group of politicians separately for conservative websites and liberal websites. Across both types of websites, Trump was covered more than any other political figure. Previous work has likewise found that Trump received a disproportionate

[9] See https://azure.microsoft.com/en-us/services/cognitive-services/face/ for additional documentation and pricing information for the Microsoft API.

[10] The API's performance in distinguishing between positive, neutral, and the set of negative emotions may be greater than its performance in distinguishing across the set of negative emotions.

amount of the news coverage during the 2016 election (e.g., Patterson 2016a,b). However, this disparity in coverage is greatest among liberal websites where Trump received 39.8 percent of the visual coverage. In contrast, Clinton received 13.7 percent of the visual coverage among liberal websites. While Trump received a greater share of coverage among liberal websites than conservatives websites, Clinton received a greater share of coverage among conservative websites.

Panel A of Figure 3 plots the share of images of Trump minus the share of images of Clinton against the Berkman Klein partisanship score. Going from equal partisanship to completely Republican partisanship is associated with 16 percentage point increase in the share of images devoted to Clinton relative to Trump. Overall, partisan websites are relatively more likely to cover the opposing party than their own.

To examine partisan nonverbal media bias in the *how* politicians are portrayed, Panel B of Figure 3 reports the average happiness and negative emotion scores for various groups of politicians across conservative and liberal websites separately. Conservative websites were less likely to display Clinton with positive emotions (happiness) and more likely to display her with negative emotions than liberal websites. Similarly, liberal websites portrayed Trump with less positive emotions and more negative emotions than conservative websites. Similar conclusions are reached when examining the other sets of politicians. See the Online Appendix for the breakdown of the remaining emotions across website and politician groupings.

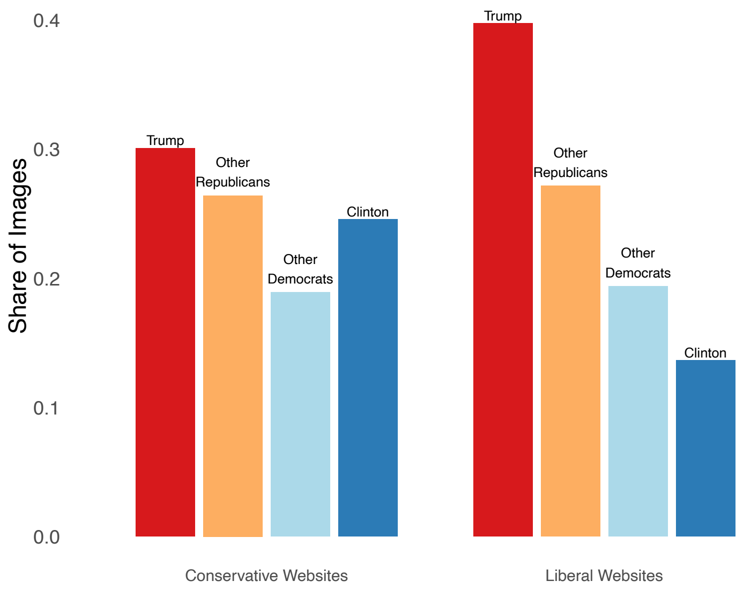
It is important to note that certain politicians may be more likely to display certain emotions irregardless of media slant. For example, consistent with previous work suggesting a connection between populism and anger (e.g., Salmela and von Scheve 2017), Donald Trump displays anger more frequently than many other politicians.[11] And, consistent with work examining gender emotional stereotypes in politics (e.g., Koo 2019), Hillary Clinton displays happiness more frequently than many other politicians.[12] Media bias in how to cover candidates exists when there is a *difference* in how conservative and liberal media outlets portray the *same* candidate.

[11] Bernie Sanders also portrays anger more frequently than many other politicians (see Online Appendix). Despite the association of anger with populism, liberal outlets are still more likely to portray Donald Trump with anger than conservative outlets (see Online Appendix).

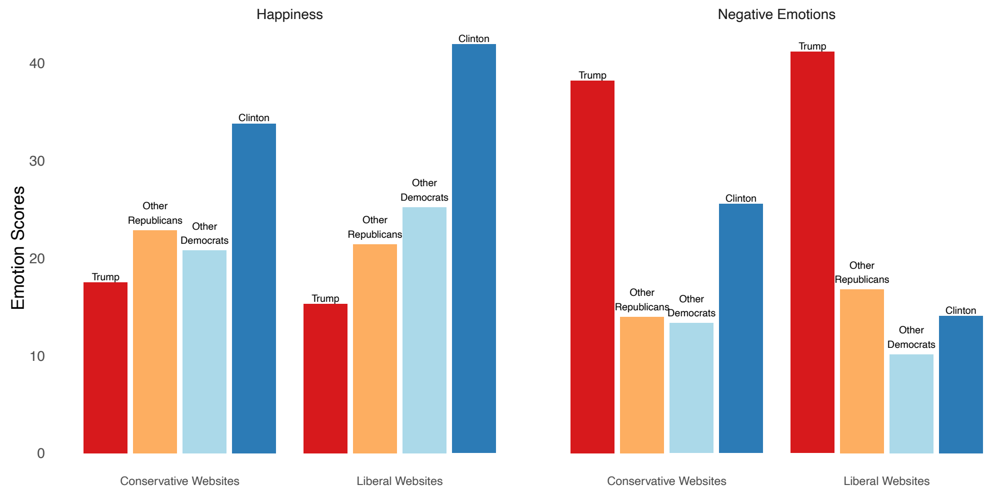
[12] Carly Fiorina and Sarah Palin also portray happiness more frequently than many other politicians, whereas Nancy Pelosi's use of happiness is closer to the average (see Online Appendix).

Figure 2: Nonverbal Media Bias During the 2016 Election

Panel A: Bias in Who to Cover



Panel B: Bias in How to Cover



Notes: Panel A plots the share of images that depict a given politician or group of politicians across conservative and liberal websites separately. The share is defined relative to the set of images in which a politician's face is detected. Panel B plots the average score for each emotion category for a given politician or group of politicians across conservative and liberal websites separately. Website types are defined by whether the Berkman-Klein partisanship score is positive or negative respectively.

To more formally examine these partisan differences in emotional slant, the following equation is estimated via OLS:

$$y_{ijt} = \alpha_i + \delta_j + \gamma c_j \mathbf{1}_{(i \in R)} + e_{ijt},$$

Table 1: Partisanship of Users and Politician Emotions

	Dependent Variable: Emotion Score x 100									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Neutral	Happ.	Anger	Sadness	Contempt	Disgust	Surprise	Fear	Neg.	Fav.
	Panel A: Trump and Clinton Images									
Partisanship x	1.50	9.77***	-3.40***	-0.07	-0.11	-0.26**	-5.90***	-1.54***	-11.28***	21.05***
Republican	(2.23)	(2.34)	(0.72)	(0.84)	(0.24)	(0.12)	(0.79)	(0.44)	(1.19)	(2.96)
Clusters	90	90	90	90	90	90	90	90	90	90
Observations	43006	43006	43006	43006	43006	43006	43006	43006	43006	43006
Mean	43.2	23.2	10.0	11.8	1.4	1.0	8.4	1.0	33.5	-10.3
Std. Dev.	38.4	38.2	22.0	22.8	5.6	4.4	20.4	5.3	35.5	63.0
	Panel B: Other Politician Images									
Partisanship x	2.04*	4.48**	-0.38	-4.71***	-0.56*	-0.07	-0.69	-0.11***	-6.52***	11.00***
Republican	(1.17)	(1.97)	(0.35)	(1.64)	(0.32)	(0.08)	(0.53)	(0.04)	(1.77)	(3.56)
Clusters	90	90	90	90	90	90	90	90	90	90
Observations	36755	36755	36755	36755	36755	36755	36755	36755	36755	36755
Mean	63.5	22.6	2.4	6.4	1.1	0.3	3.5	0.2	13.9	8.7
Std. Dev.	38.9	37.9	10.1	18.0	4.9	2.2	12.6	1.8	24.4	50.5
Website F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Politician F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Table shows the results from OLS regressions where the emotion score for a politician's face is the dependent variable and with politician and website fixed effects. Panel A restricts attention to faces of Donald Trump or Hillary Clinton. Panel B restricts attention to faces of all other politicians, excluding Donald Trump and Hillary Clinton. 'Partisanship x Republican' is the interaction between the Berkman Klein partisanship score with an indicator for whether the politician is a Republican. The emotion that is used as the dependent variable for each regression is noted in the column header. 'Neg.' denotes the sum of the anger, sadness, contempt, disgust, surprise, and fear scores. 'Fav.' denotes the happiness score minus the negative score. The mean and standard deviation of the dependent variable taken across all observations in each respective panel are included. Standard errors clustered by website are in parentheses. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels.

where y_{ijt} is the emotion score for instance t of politician i on website j, α_i are politician fixed effects, δ_j are website fixed effects, c_j is the partisanship score for website j, $\mathbf{1}_{(i \in R)}$ is an indicator for whether politician i is in the Republican party, and e_{ijt} is the error term.

The main parameter of interest γ captures the extent to which conservative leaning websites (those with higher partisanship scores c_j) portray Republican politicians (those with indicator $\mathbf{1}_{(i \in R)}$) more favorably than Democratic politicians. The fixed effects α_i, δ_j account for the fact that some politicians have higher propensities for certain emotions across all websites and that some websites have higher favorability scores across all politicians.

Table 1 reports the main results from this regression for each of the eight emotion categories. Panel A restricts attention to images of Donald Trump and Hillary Clinton. Panel B examines all other politicians identified. Standard errors are clustered by website throughout.

Focusing on Panel A, $\hat{\gamma}$ is positive and statistically significant at conventional levels for the happiness emotion (column 2). For the neutral emotion, $\hat{\gamma}$ is statistically indistinguishable from zero (column 1). For the negative emotions, $\hat{\gamma}$ is negative throughout and often statistically significant (columns 3–8). These results provide further corroboration for the use of the measure of relative favorability.

Using relative favorability as an outcome, column (10) shows that going from equal partisanship to a completely Republican partisanship score increases the relative favorability of Donald Trump compared to Hillary Clinton by 21.1 points. The 21.1 point increase is equivalent to a 0.33 standard deviation increase in relative favorability. The Online Appendix shows that these results are robust to restricting the data to higher levels of match confidence, using alternative specifications, and restricting the data to certain websites.

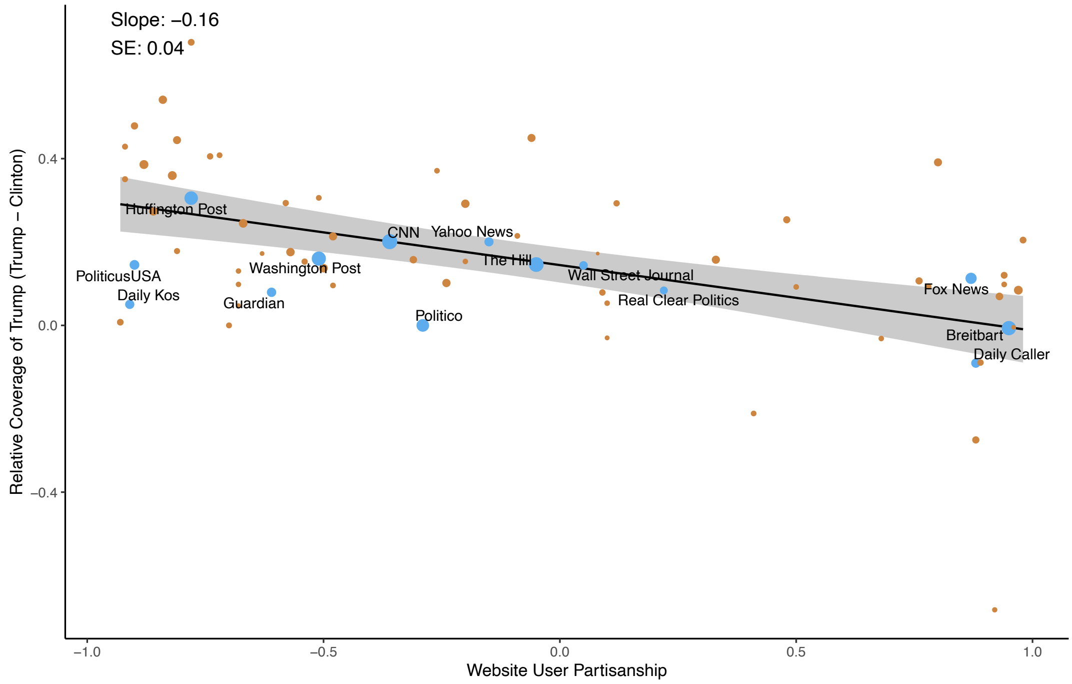
Panel B of Table 1 shows that the degree of slant is smaller in magnitude, but still statistically significant, for happiness, the sum of negative emotions, and relative favorability (columns 2, 9, and 10) when using images containing other politicians—suggesting the extent of nonverbal slant is not limited to the presidential nominees.

Panel B of Figure 3 plots the average nonverbal slant against the Berkman Klein partisanship score for each website. These website-aggregated results are consistent with the findings in Table 1. There is a strong, positive correlation between the partisanship scores and Republican-leaning slant that is consistent in magnitude to the results in Table 1.

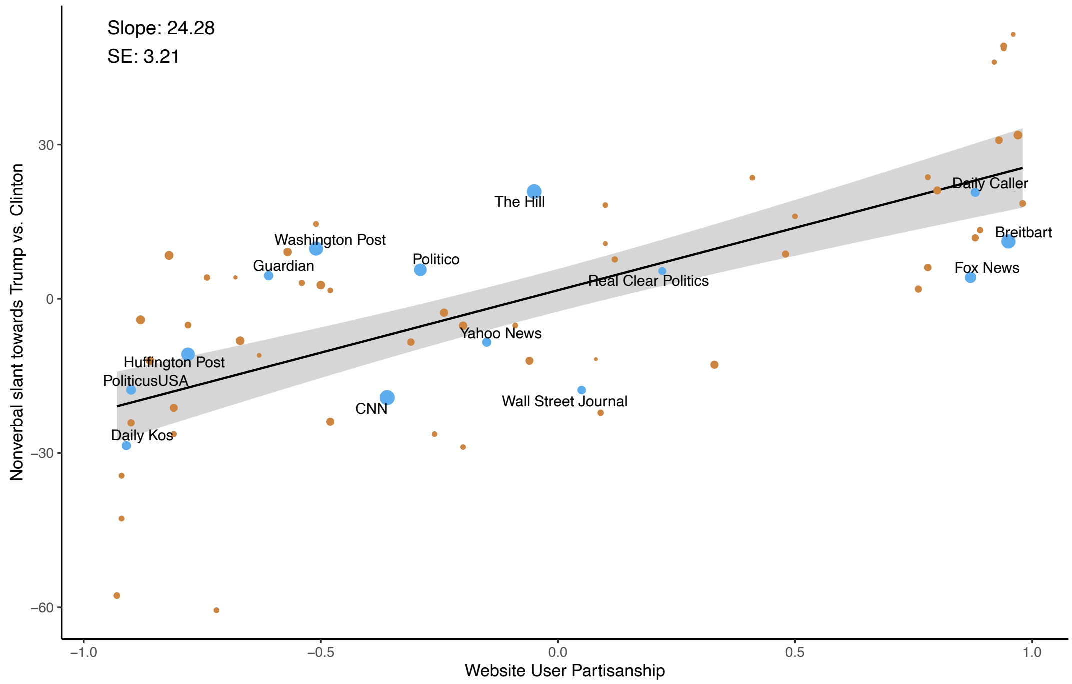
Overall, these results shows that partisan outlets expressed bias during the 2016 election by portraying the opposing candidate relatively more frequently and with less favorable emotions. These results are consistent with previous findings using crowd-sourced content analysis of text from 15 news outlets and blogs that partisan sources tend to express bias by criticizing the opposing party (Budak et al. 2016).

Figure 3: Nonverbal Bias is Correlated with Website User Partisanship

Panel A: Share of Images with Trump vs. Clinton (Share Trump - Share Clinton)



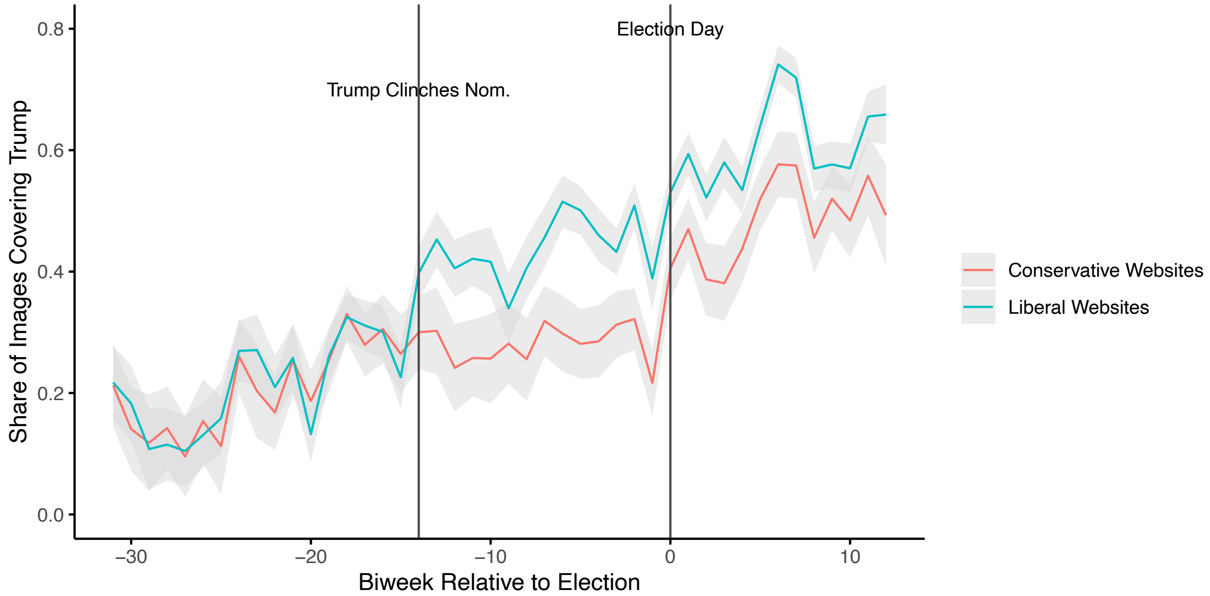
Panel B: Average Favorability Towards Trump vs Clinton (Fav. Trump - Fav. Clinton)



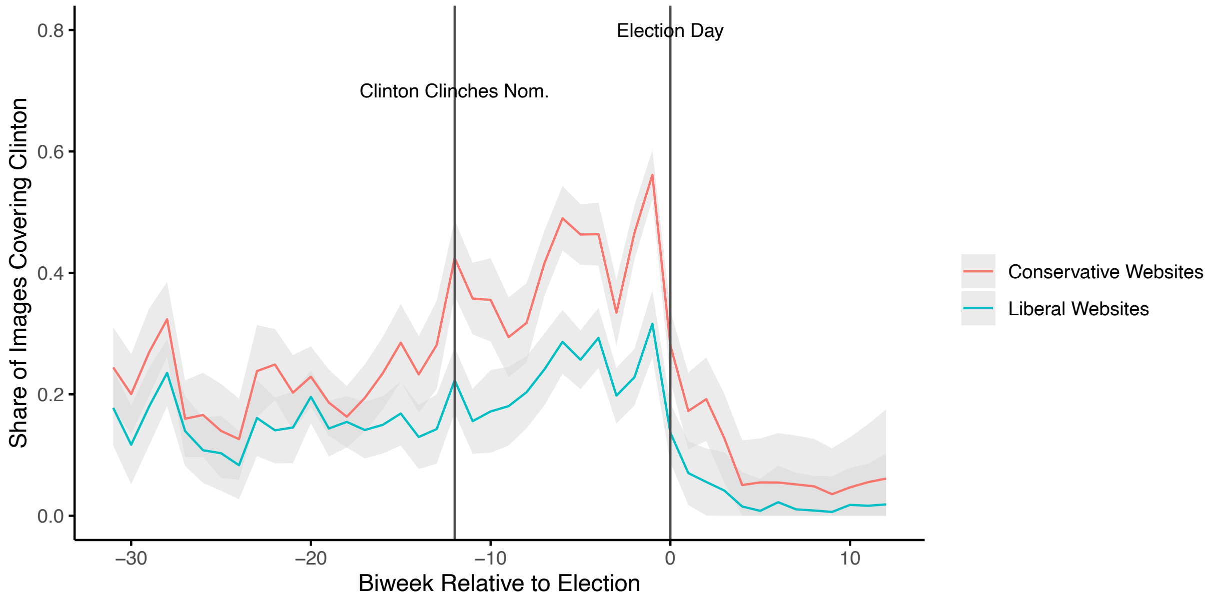
Notes: Panel A plots, out of the set of images with a recognized politician, the share of images with Donald Trump minus the share of images with Hillary Clinton against the Berkman Klein partisanship score for each website. Data is restricted to websites with more than 100 images containing a politician. Panel B plots the average relative favorability towards Donald Trump (demeaned across included websites) minus the average relative favorability towards Hillary Clinton (demeaned across included websites) against the Berkman Klein partisanship score for each website. Data is restricted to websites with more than 25 images of Trump and Clinton each. In both panels, the black solid line is the linear best fit with slope and heteroskedastic robust standard errors reported in the upper left. The labelled blue dots indicate websites with more than 10,000 Twitter shares or 2,000 media inlinks in the Berkman Klein data.

Figure 4: Trends in Coverage Bias Across the 2016 Election

Panel A: Share of Images Covering Donald Trump



Panel B: Share of Images Covering Hillary Clinton



Notes: Figure plots the share of images that depict a given politician or group of politicians across the set of conservative and liberal websites separately for each biweek relative to election day. The share is defined relative to the set of images in which a politician's face is detected. Website types are defined by whether the Berkman-Klein partisanship score is positive or negative respectively. The date each candidate clinched the nomination is defined to be May 3, 2016 for Donald Trump (when Ted Cruz suspended his campaign) and June 6, 2016 for Hillary Clinton. The shaded grey ribbons report 95 percent confidence intervals.

4 Trends in nonverbal media bias across the 2016 election

Another important question is the extent to which media bias varies over the election cycle.[13] That is, when did certain outlets start exhibiting differential coverage of the candidates during the 2016 election?

Figure 4 reports trends in the coverage choices of conservative and liberal outlets across the 2016 election period. Panel A shows that the share of visual political coverage devoted to Donald Trump was similar across conservative and liberal outlets prior to Trump becoming the presumptive Republican presidential nominee. However, once Trump clinched the nomination, the share of visual coverage devoted to Trump increased among liberal websites, but not conservative websites. This partisan gap in coverage of Trump persists throughout the campaign period.

Panel B of Figure 4 shows the share of visual coverage devoted to Hillary Clinton. Prior to Clinton becoming the presumptive Democratic presidential nominee, there was a slight (but growing) partisan gap in coverage—with conservative websites devoting a slightly larger share of coverage to Clinton. This gap persists throughout the campaign period, before receding again after the election. The Online Appendix contains regression estimates that provide further evidence for a difference in the partisan gap in the choice of who to cover between the primary and general election periods.

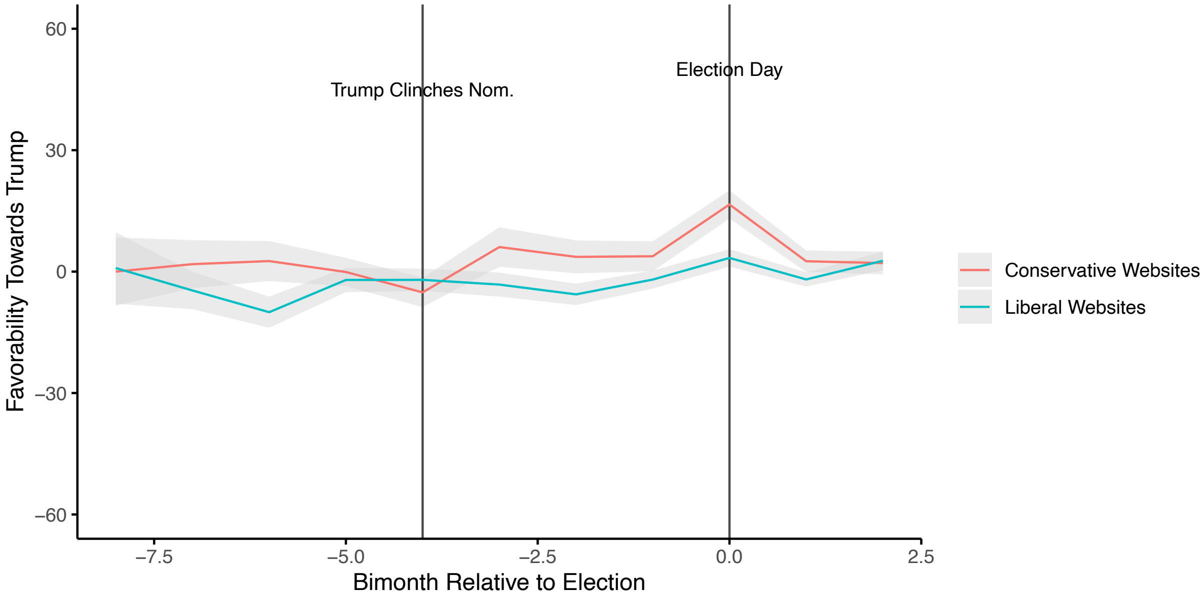
Figure 5 reports trends in the average favorability of nonverbal coverage of Trump and Clinton across conservative and liberal websites. Panel A shows that, when choosing to cover Trump, conservative websites consistently portrayed him with more positive emotions and less negative emotions than liberal websites did. The difference in average favorability between conservative and liberal websites is relatively consistent across the election period.

Panel B of Figure 5 shows that liberal websites consistently portrayed Clinton with more positive emotions and less negative emotions than conservative websites. Moreover, the gap in favorability between conservative and liberal websites is larger than the corresponding gap for Trump. While Panel B of Figure 5 indicates the gap in emotional slant between liberal and conservative websites increases for Clinton over the election, the Online Appendix finds no evidence for such an increase when restricting to a balanced panel of websites evaluated at the website level. See Online Appendix for trends in each emotion individually over the election cycle.

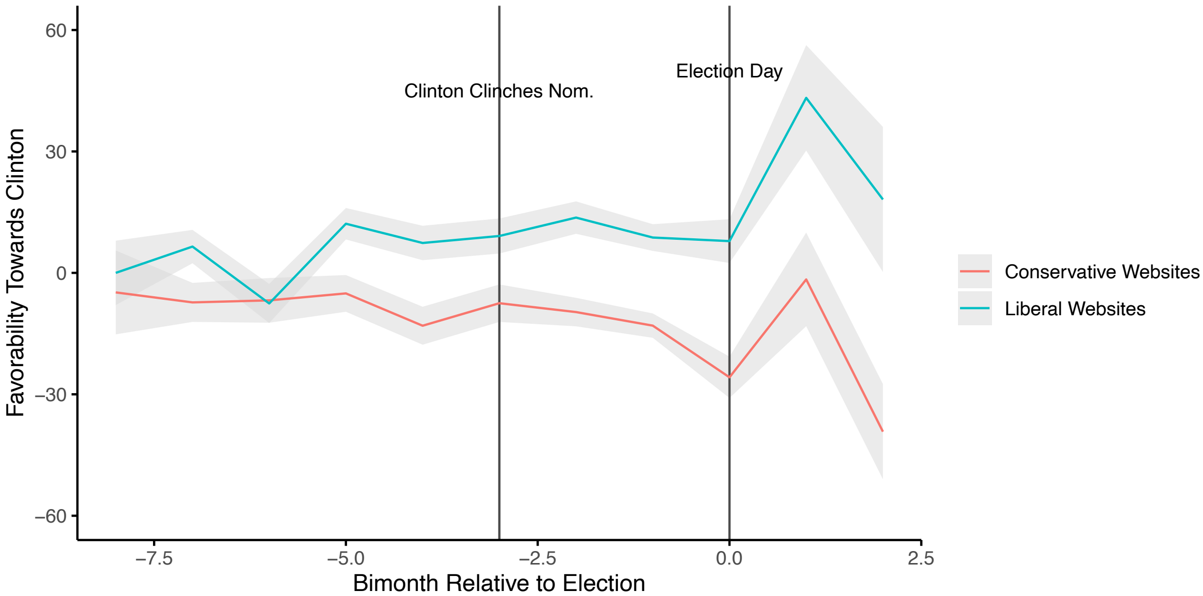
[13] Garz et al. (2020) examine trends in biased reporting of election polls across the election cycle.

Figure 5: Trends in Nonverbal Emotional Slant Across the 2016 Election

Panel A: Average Favorability Towards Donald Trump



Panel B: Average Favorability Towards Hillary Clinton



Notes: Figure plots the relative favorability towards a politician, as measured by facial emotions, across the set of conservative and liberal websites separately for each bimonth (60 day period) relative to election day. Measures of relative favorability are normalized to be 0 for Conservative (Liberal) websites for the first period in Panel A (Panel B). Website types are defined by whether the Berkman-Klein partisanship score is positive or negative respectively. The date each candidate clinched the nomination is defined to be May 3, 2016 for Donald Trump (when Ted Cruz suspended his campaign) and June 6, 2016 for Hillary Clinton. The shaded grey ribbons report 95 percent confidence intervals.

Overall, these results suggest that media bias responds to the dynamics of the election cycle—with biases in the choice of who to cover increasing in response to a candidate becoming the presumptive nominee. On the other hand, there is less evidence that the emotional slant of the coverage of candidates shifts over the election cycle.

5 Conclusion

This paper uses a large dataset of online images and validates a novel method of measuring nonverbal media bias in an automated and scalable fashion. The data and method are used to document the existence of widespread, nonverbal media bias across a large set of online news outlets. Partisan outlets expressed bias during the 2016 election by shifting coverage towards the opposing candidate, by using relatively more negative emotions, and by recalibrating these choices in response to the dynamics of the election cycle.

One limitation of the approach to measuring emotional slant is the restriction to facial expressions. The body positioning of candidates along with the general context of the photo can also be selectively chosen to portray candidates more favorably. Moreover, emotions labelled as "negative" (e.g., anger) may not have negative connotations in certain contexts, such as when addressing perceived injustices, and gender stereotypes may affect the ideal emotional display for a given politician. Despite these limitations, the above results demonstrate how off-the-shelf computer vision tools can be used to measure the emotions in facial expressions that capture a significant component of nonverbal emotional slant as perceived by human coders and that this measure of nonverbal emotional slant is highly correlated with website user partisanship.

While verbal media coverage dominated the media diets of consumers a century ago, media consumption today is highly nonverbal. Given the results above, future work should continue examining the implications of the recent rise in nonverbal media communication on political polarization and other outcomes of interest.

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Online Appendix

Slanted images: Measuring nonverbal media bias during the 2016 election

Levi Boxell, *Stanford University**

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*E-mail: lboxell@stanford.edu. See main text for funding and acknowledgements.

List of Figures

List of Tables

1 Politician Sample

The main Republican and Democratic presidential candidates are defined as follows for each year. For 2008, the sample includes candidates that withdrew after the primaries started. For 2012, the sample includes candidates that appeared on at least three primary ballots for Republicans and candidates that captured at least one percent of the primary vote for Democrats. For 2016, the sample includes candidates that withdrew after the primaries started for Republicans and candidates that were on at least 6 state ballots and invited to a forum or debate for Democrats.

The main congressional leaders include the President of the Senate, the President pro tempore, the Speaker of the House, the majority and minority leader of the House and Senate, and the majority and minority whip of the House and Senate.

2 R^2 and Measurement Error

Let Y_i denote the population average[1] of the degree to which image i is perceived to portray a politician favorably. Let $\tilde{Y}_i = \frac{1}{|K(i)|}\sum_{k\in K(i)} Y_i^k$ denote the mean across a set of $K(i)$ viewers of i. In this case, $|K(i)| = 3$. Let $\bar{Y} = \frac{1}{n}\sum_i Y_i$, and assume

$$\mathbb{E}(Y_i|X_i) = \mathbb{E}(\tilde{Y}_i|X_i) = X_i\beta$$

where X_i is the vector of emotion scores for image i. If Y_i was observed, the R^2 for a given set of images would be

$$R^2 = \frac{\sum_i (X_i\hat{\beta} - \bar{Y})^2}{\sum_i (Y_i - \bar{Y})^2}.$$

However, only $\tilde{Y}_i$ is available. The R^2 for the OLS regression of $\tilde{Y}_i$ on X_i is

$$\tilde{R}^2 = \frac{\sum_i (X_i\hat{\beta} - \frac{1}{n}\sum_i \tilde{Y}_i)^2}{\sum_i (\tilde{Y}_i - \frac{1}{n}\sum_i \tilde{Y}_i)^2} = \frac{\sum_i (X_i\hat{\beta} - \frac{1}{n}\sum_i \tilde{Y}_i)^2}{\sum_i (Y_i - \frac{1}{n}\sum_i \tilde{Y}_i)^2 + \sum_i (\tilde{Y}_i - Y_i)^2}$$

which is biased downwards. Note that $\mathbb{E}\left[\sum_i (\tilde{Y}_i - Y_i)^2\right] = \sum_i V(\tilde{Y}_i)$ where $V(\tilde{Y}_i)$ is simply the variance of a sample mean which can be estimated given the multiple responses per image. Then

$$\hat{\tau} = \frac{\sum_i (\tilde{Y}_i - \frac{1}{n}\sum_i \tilde{Y}_i)^2}{\sum_i (\tilde{Y}_i - \frac{1}{n}\sum_i \tilde{Y}_i)^2 - \sum_i \hat{V}(\tilde{Y}_i)}$$

is an estimate of the ratio $R^2/\tilde{R}^2$.[2] In the MTurk sample, $\hat{\tau} = 1.5$. Scaling the reported R^2 values in Table A7 by 1.5 gives the estimated R^2 if the population average Y_i was observed.

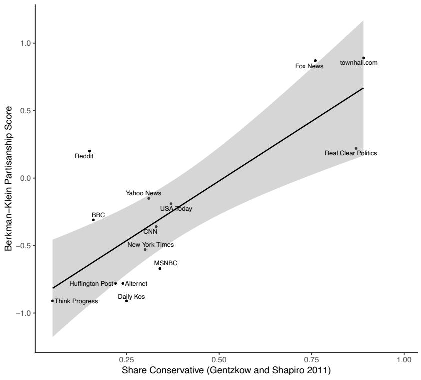
Table A7 shows this intuition empirically. Column (1) reports the R^2 from using each MTurk response individually as an observation while Column (3) uses the mean across MTurk responses for a given image. The R^2 in Column (3) is 65 percent larger because it reduces the measurement error in the dependent variable.

[1]The population in this case is the universe of viewers, not the universe of images.

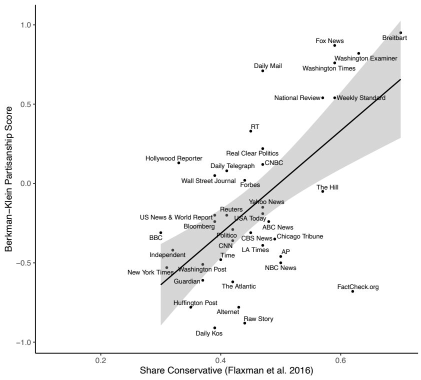
[2]$\hat{V}(\tilde{Y}_i) = \frac{1}{|K(i)||K(i)-1|}\sum_{k\in K(i)}(Y_i^k - \tilde{Y}_i)^2$ is the estimate of the variance of the sample mean.

Figure A1: Validation of Berkman-Klein Partisanship Scores

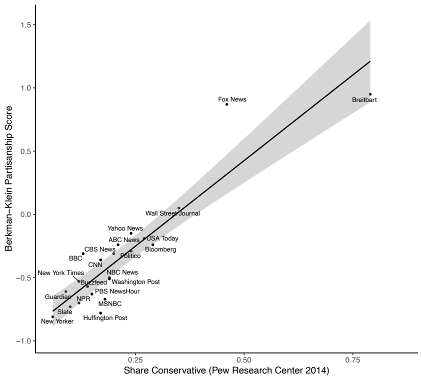
Panel A: Gentzkow and Shapiro (2011)



Panel B: Flaxman et al. (2016)

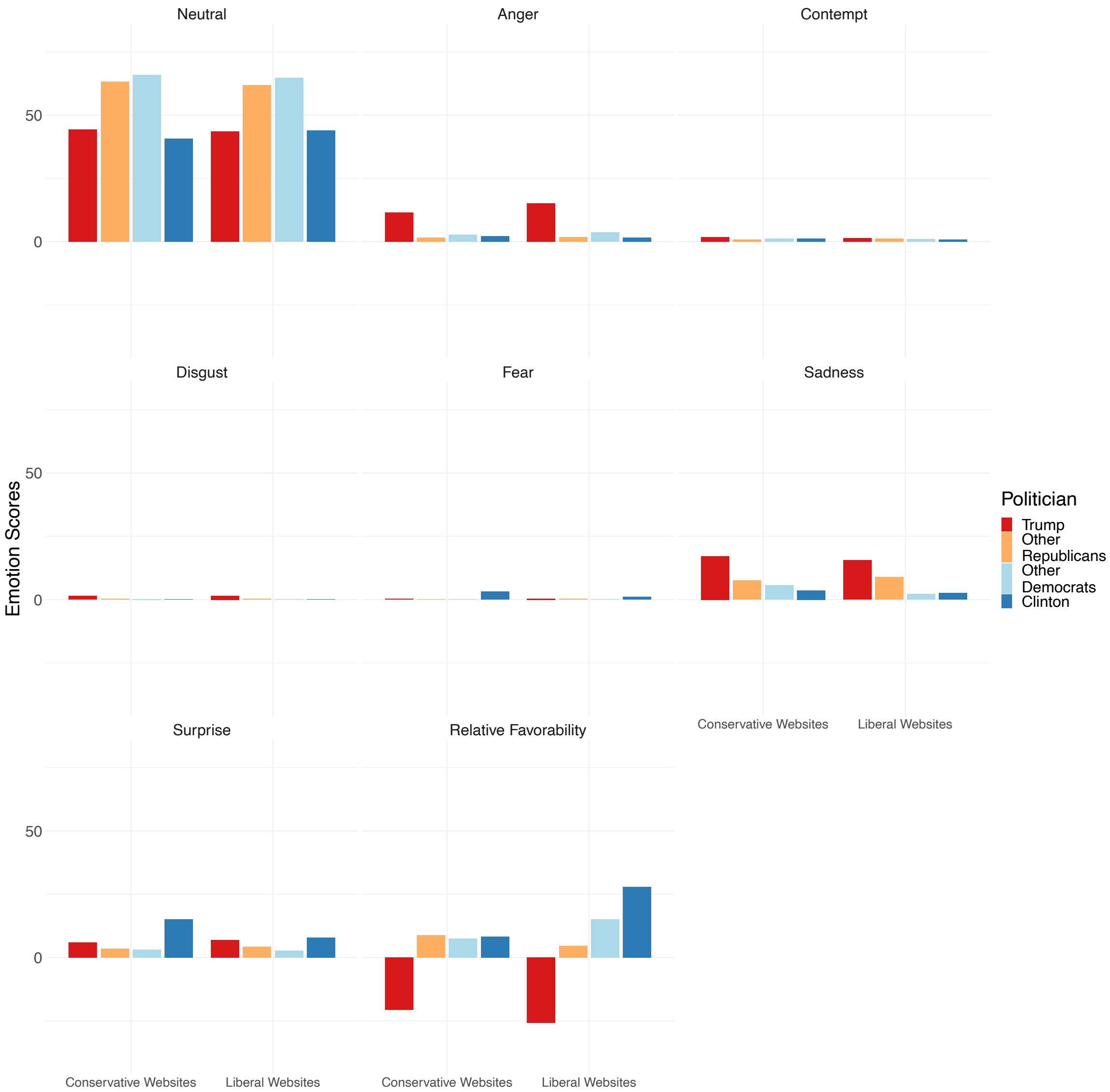


Panel C: Pew Research Center (2014)



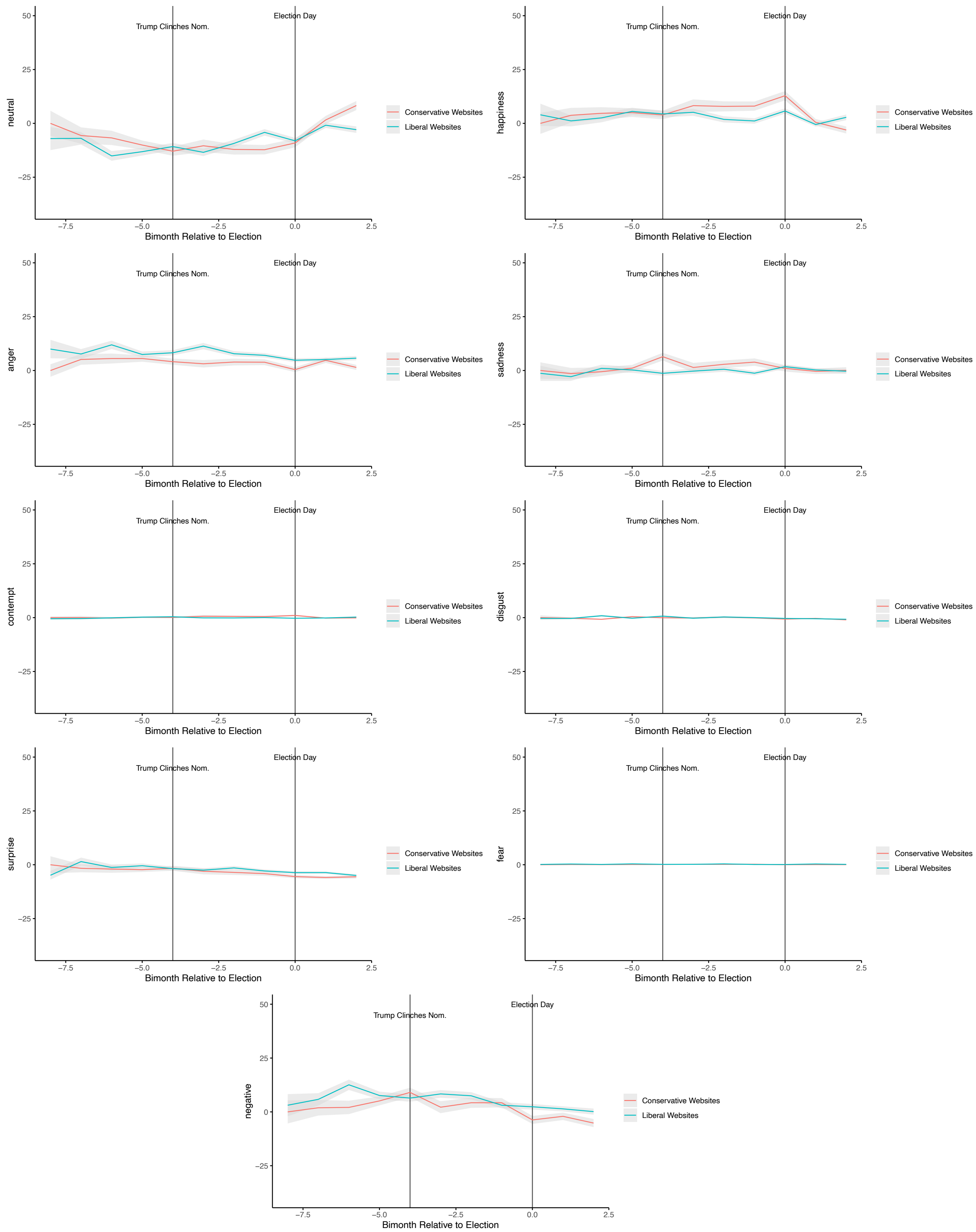
Notes: Each panel plots the relationship between the Berkman-Klein Partisanship scores (y-axis) and various other measures of user partisanship. Panel A uses the share conservative for websites in Table II of Gentzkow and Shapiro (2011). Panel B uses the share conservative for websites in Online Appendix Table 5 of Flaxman et al. (2016). Panel C uses the share of of ‘mostly conservative’ and ‘consistently conservative’ for each news source in Pew Research Center (2014), which is not necessarily restricted to the website version of each source.

Figure A2: Bias in How to Cover by Politician and Website Type



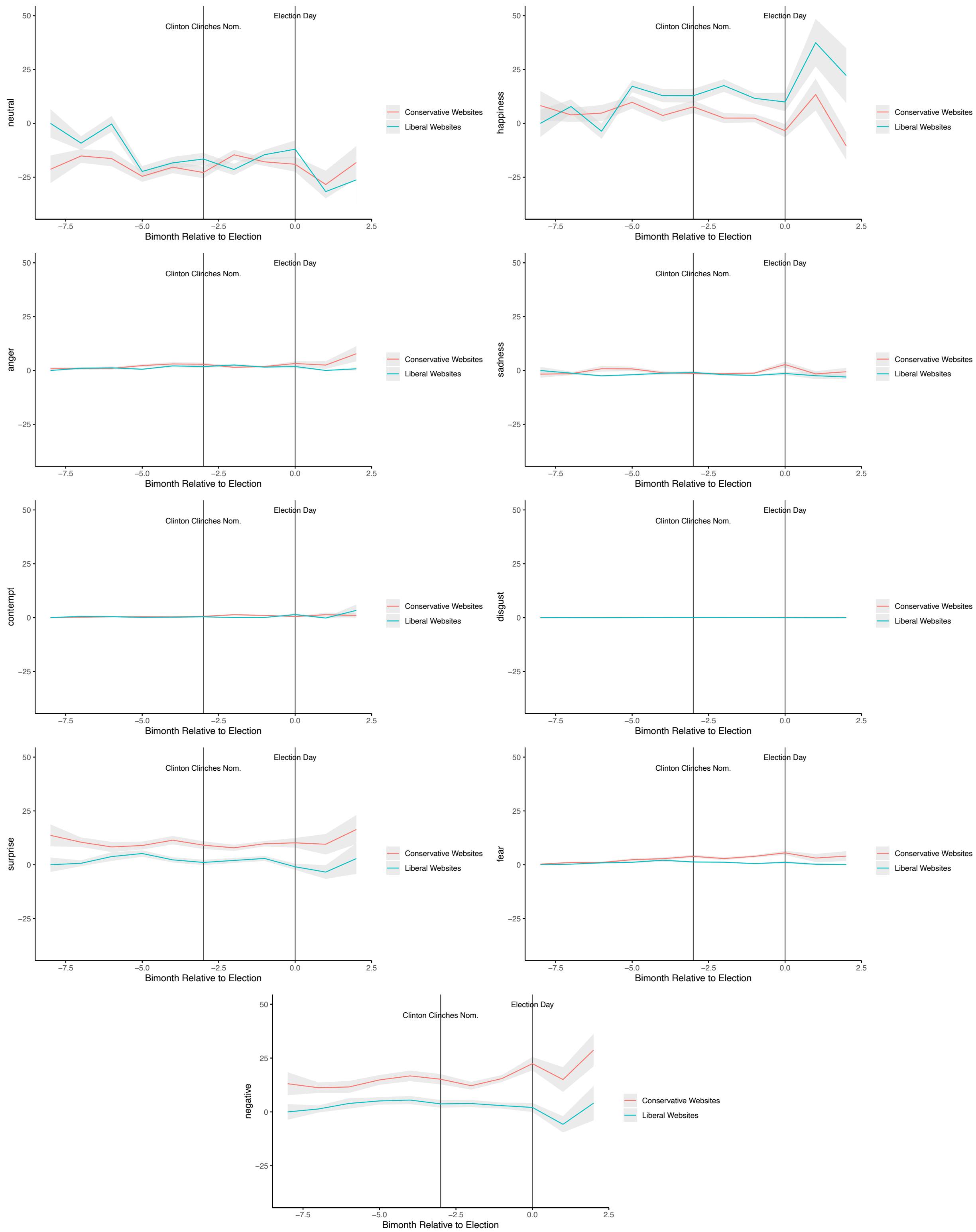
Notes: Figure plots the average score for each emotion category for a given politician or group of politicians across the set of images from conservative and liberal websites separately. Website types are defined by whether the Berkman-Klein partisanship score is positive or negative respectively.

Figure A3: Trends in Emotions Used Across the 2016 Election—Trump



Notes: Figure plots the emotions used to cover Donald Trump, as measured by facial emotions, across the set of images from conservative and liberal websites separately for each bimonth relative to election day. Measures of for each emotion are normalized to be 0 for Conservative websites for the first period. Website types are defined by whether the Berkman-Klein partisanship score is positive or negative respectively. The date Donald Trump clinched the nomination is defined to be May 3, 2016 (when Ted Cruz suspended his campaign). The shaded grey ribbons report 95 percent confidence intervals.

Figure A4: Trends in Emotions Used Across the 2016 Election—Clinton



Notes: Figure plots the emotions used to cover Hillary Clinton as measured by facial emotions, across the set of images from conservative and liberal websites separately for each bimonth relative to election day. Measures of for each emotion are normalized to be 0 for Liberal websites for the first period. Website types are defined by whether the Berkman-Klein partisanship score is positive or negative respectively. The date Clinched the nomination is defined to be June 6, 2016. The shaded grey ribbons report 95 percent confidence intervals.

Table A1: Number of Images by Politician

Politician	Total
Alan Keyes	242
Barack Obama	8336
Ben Carson	1471
Bernie Sanders	3557
Carly Fiorina	676
Chris Christie	803
Chris Dodd	252
Donald Trump	28658
Gary Johnson	290
Harry Reid	452
Hillary Clinton	14348
Jeb Bush	1054
Joe Biden	739
John Boehner	370
John Cornyn	207
John Kasich	622
John McCain	444
Kevin McCarthy	291
Marco Rubio	2063
Mike Huckabee	458
Mike Pence	1276
Mitch McConnell	1143
Mitt Romney	357
Nancy Pelosi	554
Newt Gingrich	769
Paul Ryan	2960
Rand Paul	482
Richard Durbin	129
Rick Santorum	160
Robert Byrd	145
Rudy Giuliani	360
Sarah Palin	314
Steny Hoyer	256
Ted Cruz	3596
Tim Kaine	538
Total	79761

Notes: Table shows the number of images in the baseline sample for each politician. Only politicians with at least 125 total images are included. The 'Total' row includes all politicians in the sample including those not mentioned explicitly in the table.

Table A2: Number of Images by Website

Website	Image Count	Website	Image Count
ABC News	413	Alternet	1608
Bipartisan Report	365	BizPacReview	259
Breitbart	3989	Business Insider	874
Buzzfeed	381	CBS News	184
CNBC	140	CNN	204
Conservative Tribune	1414	CSPAN	334
Daily Caller	4726	Daily Kos	416
Daily Newsbin	524	EndingtheFed	216
FactCheck.org	1274	FiveThirtyEight	476
Fox News	629	Free Beacon	1474
Gateway Pundit	663	Gawker	201
Guardian	365	Huffington Post	2155
IBTimes	680	InfoWars	4029
Inquisitr	150	Judicial Watch	192
Media Matters	3262	Mother Jones	318
MSNBC	1646	NBC News	5692
Newsweek	1318	Observer	710
Occupy Democrats	1271	opensecrets.org	354
PBS NewsHour	615	People	407
Political Insider	173	Politico	420
PoliticusUSA	4800	Raw Story	3151
Real Clear Politics	1442	RedState	2076
Reuters	257	Right Scoop	2733
RT	476	Salon	409
sanders.senate.gov	328	Talking Points Memo	2331
tedcruz.org	222	The Federalist	1419
The Hill	3233	The Intercept	190
The Nation	847	The Onion	1268
The Week	3285	Time	164
townhall.com	1346	US News & World Report	176
US Uncut	877	Vanity Fair	161
Vox	194	Wall Street Journal	431
Washington Post	524	Washington Times	1096
Yahoo News	459	Zero Hedge	332
		Total	79761

Notes: Table shows the number of images for each website after restricting to images with at least 50 percent match confidence. Only website with at least 125 images are shown. The total row is the sum across all websites.

Table A3: Average Emotion by Politician

Politician	Neutral	Happiness	Anger	Sadness	Contempt	Disgust	Surprise	Fear	Neg.	Rel. Fav.
Alan Keyes	0.826	0.160	0.003	0.004	0.004	0.001	0.002	0.000	0.014	0.146
Barack Obama	0.696	0.215	0.013	0.048	0.010	0.002	0.015	0.001	0.089	0.126
Ben Carson	0.642	0.273	0.002	0.045	0.025	0.001	0.008	0.003	0.084	0.189
Bernie Sanders	0.595	0.248	0.087	0.014	0.021	0.002	0.031	0.002	0.157	0.091
Carly Fiorina	0.490	0.438	0.025	0.005	0.006	0.002	0.033	0.001	0.072	0.366
Chris Christie	0.698	0.096	0.085	0.009	0.005	0.010	0.091	0.004	0.206	-0.110
Chris Dodd	0.719	0.198	0.058	0.012	0.010	0.000	0.002	0.000	0.083	0.115
Donald Trump	0.438	0.160	0.140	0.161	0.016	0.015	0.067	0.004	0.402	-0.241
Gary Johnson	0.578	0.240	0.045	0.005	0.014	0.002	0.112	0.003	0.182	0.058
Harry Reid	0.798	0.126	0.017	0.015	0.008	0.002	0.034	0.000	0.076	0.050
Hillary Clinton	0.422	0.375	0.020	0.031	0.010	0.001	0.119	0.022	0.203	0.172
Jeb Bush	0.688	0.201	0.014	0.010	0.005	0.001	0.080	0.002	0.111	0.089
Joe Biden	0.569	0.295	0.049	0.063	0.004	0.003	0.015	0.001	0.136	0.159
John Boehner	0.710	0.138	0.007	0.116	0.012	0.007	0.009	0.001	0.151	-0.013
John Cornyn	0.868	0.075	0.003	0.040	0.001	0.000	0.012	0.000	0.057	0.018
John Kasich	0.746	0.146	0.022	0.021	0.012	0.001	0.050	0.001	0.107	0.039
John McCain	0.754	0.122	0.026	0.048	0.009	0.003	0.035	0.002	0.123	-0.000
Kevin McCarthy	0.687	0.228	0.017	0.027	0.002	0.002	0.036	0.001	0.085	0.144
Marco Rubio	0.678	0.232	0.009	0.022	0.004	0.000	0.053	0.001	0.089	0.143
Mike Huckabee	0.633	0.199	0.075	0.009	0.007	0.004	0.071	0.002	0.168	0.031
Mike Pence	0.665	0.214	0.028	0.065	0.008	0.003	0.016	0.001	0.121	0.093
Mitch McConnell	0.636	0.157	0.003	0.111	0.002	0.001	0.084	0.006	0.206	-0.049
Mitt Romney	0.467	0.361	0.040	0.050	0.012	0.005	0.061	0.004	0.171	0.190
Nancy Pelosi	0.401	0.296	0.012	0.028	0.004	0.002	0.238	0.020	0.303	-0.007
Newt Gingrich	0.786	0.170	0.028	0.009	0.003	0.001	0.002	0.000	0.043	0.127
Paul Ryan	0.608	0.240	0.004	0.099	0.026	0.000	0.022	0.001	0.152	0.089
Rand Paul	0.813	0.081	0.007	0.008	0.004	0.001	0.085	0.000	0.106	-0.026
Richard Durbin	0.818	0.149	0.002	0.016	0.002	0.000	0.012	0.000	0.033	0.116
Rick Santorum	0.339	0.510	0.021	0.075	0.012	0.003	0.038	0.002	0.151	0.358
Robert Byrd	0.753	0.179	0.039	0.017	0.007	0.001	0.005	0.000	0.068	0.111
Rudy Giuliani	0.647	0.178	0.024	0.019	0.008	0.009	0.110	0.006	0.175	0.002
Sarah Palin	0.342	0.452	0.020	0.020	0.017	0.007	0.137	0.005	0.206	0.246
Steny Hoyer	0.754	0.174	0.018	0.020	0.012	0.001	0.020	0.000	0.072	0.102
Ted Cruz	0.469	0.216	0.006	0.276	0.008	0.011	0.010	0.004	0.315	-0.098
Tim Kaine	0.354	0.525	0.032	0.023	0.006	0.002	0.056	0.001	0.121	0.404
Total	0.646	0.235	0.027	0.032	0.008	0.003	0.047	0.003	0.119	0.115

Notes: Table shows the average emotion values for images in the baseline sample for each politician. Only politicians with at least 125 total images are included. The 'Total' row includes all politicians in the sample including those not mentioned explicitly in the table and is the average across politicians' averages.

Table A4: Website Slant

Website	Overall Slant	SD	Website	Trump-Clinton Slant	SD
Daily Kos	-25.365	(8.078)	New York Times	-32.229	(27.024)
PoliticusUSA	-15.990	(2.144)	Daily Kos	-24.010	(14.510)
CNN	-15.510	(11.011)	Time	-19.364	(15.050)
RT	-13.212	(7.492)	Talking Points Memo	-16.664	(6.985)
Time	-11.174	(10.897)	CNN	-14.677	(15.288)
Business Insider	-11.092	(6.236)	Wall Street Journal	-13.206	(9.780)
New York Times	-10.341	(20.092)	PoliticusUSA	-13.168	(4.522)
Yahoo News	-10.064	(7.846)	RT	-8.272	(10.865)
Huffington Post	-9.280	(3.486)	Business Insider	-7.507	(9.594)
Wall Street Journal	-8.970	(7.683)	Mother Jones	-7.504	(19.160)
ABC News	-6.359	(7.815)	Huffington Post	-6.233	(5.333)
Reuters	-4.778	(11.186)	Yahoo News	-3.898	(10.757)
Raw Story	-4.125	(2.830)	MSNBC	-3.620	(5.917)
MSNBC	-1.476	(3.772)	Reuters	-0.691	(15.668)
Buzzfeed	-1.112	(9.050)	Raw Story	0.459	(4.641)
Talking Points Memo	-0.168	(4.369)	ABC News	1.846	(11.987)
Fox News	2.320	(6.628)	NBC News	7.216	(3.107)
Politico	2.814	(7.109)	Fox News	8.700	(9.241)
NBC News	3.126	(2.145)	Guardian	9.050	(14.076)
New York Post	3.519	(19.840)	Real Clear Politics	9.944	(6.689)
Guardian	5.660	(8.380)	Politico	10.191	(9.614)
Salon	6.112	(8.923)	New York Post	10.631	(25.876)
Breitbart	11.260	(2.647)	Salon	12.990	(12.771)
Washington Post	11.470	(7.053)	Buzzfeed	13.660	(13.949)
The Hill	12.873	(2.230)	Washington Post	14.317	(10.953)
InfoWars	15.592	(2.451)	Breitbart	15.716	(4.127)
Gateway Pundit	15.854	(6.365)	Daily Caller	25.253	(3.519)
Daily Caller	16.542	(2.361)	The Hill	25.402	(3.704)
Right Scoop	16.613	(4.329)	Right Scoop	25.624	(6.781)
Real Clear Politics	17.199	(3.720)	InfoWars	35.398	(3.096)
Mother Jones	20.079	(10.643)	Gateway Pundit	36.390	(8.020)

Notes: Table reports, on the left side, the average relative favorability towards Republicans (demeaned across all websites) minus the average relative favorability towards Democrats (demeaned across all websites). The right side of the table reports the same differential measure of favorability, but for Donald Trump and Hillary Clinton. The websites ranked have more than 5,000 Twitter shares or 2,000 media inlinks in the Berkman Klein data and more than 5 images of both Trump and Clinton. The standard deviation estimates are constructed by taking the standard deviation of the demeaned average relative favorability for each website-partisan group separately, dividing by the square root of the number of images in each website-partisan group, and summing across both partisan groups. The Republican-leaning estimate for Mother Jones is driven by a disproportionate number of positive Carly Fiorina images—dropping Carly Fiorina or restricting attention to Donald Trump and Hillary Clinton removes this discrepancy.

Table A5: Manual Evaluation of Matlab Filtering

	(1)	(2)	(3)	(4)
Image Size Restriction	0	100	200	300
Panel A: Observations labelled as containing a face per MTurkers				
Prop. of obs. with same classification by Matlab	0.36	0.51	0.68	0.82
	[663]	[428]	[181]	[74]
Panel B: Observations labelled as not containing a face per MTurkers				
Prop. of obs. with same classification by Matlab	0.94	0.88	0.81	0.61
	[550]	[249]	[91]	[33]
Intraclass correlation coefficient for MTurk	0.93	0.92	0.89	0.91

Notes: Table shows the results from manual evaluation of a random sample of images of at least 1 kb in size from the raw dataset . For each image, the image was classified by two or three MTurk users into whether it had 0, 1, 2, 3, 4, or 5+ faces. For each MTurk observation, an indicator was then constructed for whether a face was observed by the manual classification and whether a face was observed by Matlab's eye filter. The columns restrict observations to images where both the height and width are of at least 0, 100, 200, and 300 pixels in dimension. Panel A indicates the proportion of observations that were labelled by as containing a face by the MTurk user that also were labelled as containing a face by Matlab. Panel B indicates the proportion of observations that were labelled as not containing a face by the MTurk user that were also labelled as not containing a face by Matlab. The number of observations are in brackets below. The bottom row contains the intraclass correlation coefficient for the MTurk-constructed indicator for whether an image contains at least one face.

Table A6: Manual Evaluation of Emotion Classification from Peng (2018)

	(1) Microsoft	(2) Face++	(3) Sighthound	(4) Google Vision
Anger (.88)	.54***	.29***	.31***	.23***
Disgust (.81)	.36***	.25***	.09*	NA
Fear (.50)	.19***	.08*	.11**	NA
Happiness (.96)	.85***	.79***	.71***	.80***
Sadness (.64)	.28***	.04	.18***	.17***
Surprise (.77)	.39***	.24***	.23***	.36***
Neutral (.74)	.67***	.46***	.36***	NA
N	738	791	783	772

Table Title from Peng (2018; Table 1): *Correlations Between Human-Perceived and Computer Vision Services–Detected Facial Expressions*

Table Notes from Peng (2018; Table 1): *Analyses were performed on images containing only one face of the candidate (N = 791). The sample size varied, as some faces detected by Face++ were not detected by other services. NA = not available. The inter-rater reliability for each item is provided in brackets. *p < .05, **p < .01, ***p < .001.*

Table A7: Manual Evaluation of Image Favorability

	Dependent Variable: Perceived Favorability by MTurkers										
	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)
Relative Fav.	0.89***	0.91***	0.89***	Happiness	1.28***	1.27***	1.28***	Happiness	1.28***	1.27***	1.28***
	(0.09)	(0.08)	(0.09)		(0.13)	(0.13)	(0.13)		(0.13)	(0.13)	(0.13)
				Negative	-0.32**	-0.38**	-0.32**	Anger	-0.24	0.01	-0.24
					(0.15)	(0.17)	(0.15)		(0.24)	(0.34)	(0.24)
								Sadness	-0.32	-0.50*	-0.32
									(0.24)	(0.27)	(0.24)
								Contempt	-0.87**	-0.95**	-0.87**
									(0.42)	(0.42)	(0.43)
								Disgust	3.48***	1.63	3.48***
									(0.95)	(1.14)	(0.96)
								Surprise	-0.23	0.01	-0.23
									(0.22)	(0.26)	(0.22)
								Fear	-8.75	-17.17	-8.75
									(15.15)	(15.96)	(15.27)
Politician F.E.	N	Y	N		N	Y	N		N	Y	N
Clusters	300	300	300		300	300	300		300	300	300
Observations	900	900	300		900	900	300		900	900	300
R^2	0.17	0.24	0.28		0.19	0.25	0.32		0.20	0.26	0.33

Notes: Table shows the results from OLS regressions where the perceived favorability scored by MTurkers is the dependent variable. Each image is scored three times by a different MTurker. Images are restricted to those for which the Microsoft API only detected a single face and for which the match confidence on the face is greater than 0.8. The perceived favorability values are -2 (Very Negative), -1 (Negative), 0 (Neutral), 1 (Positive), and 2 (Very Positive). A sixth option was given to indicate that the individual matched by the Microsoft API was not contained within the image; this option was never selected indicating a high degree of match confidence. 'Negative' denotes the sum of the anger, sadness, contempt, disgust, surprise, and fear scores. 'Relative Fav.' denotes the happiness score minus the negative score. Columns (7)-(9) take the average of the three perceived favorability scores as the dependent variables. Standard errors clustered by image are in parentheses. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels. The intraclass correlation coefficient for the perceived favorability scores is .40.

Table A8: Bias in Who to Cover

	Dependent Variable: Indicator for Republican Politician							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logit	OLS	Logit	OLS	Logit	OLS	Logit
Partisanship Score	-0.14***	-0.65***	-0.15***	-0.70***	-0.11***	-0.51***	-0.12***	-0.58***
	(0.03)	(0.13)	(0.03)	(0.13)	(0.03)	(0.16)	(0.03)	(0.16)
log(Twitter Shares)			0.03	0.15			0.03	0.17
			(0.02)	(0.10)			(0.02)	(0.13)
log(Media Inlinks)			-0.05	-0.26			-0.06*	-0.32
			(0.03)	(0.16)			(0.03)	(0.19)
Clusters	90	90	90	90	88	88	88	88
Observations	43006	43006	43006	43006	22769	22769	22769	22769

Notes: Table shows the results from OLS and logit regressions where an indicator for whether the politician is a Republican in the image is the dependent variable. Sample is restricted to images of Donald Trump and Hillary Clinton. 'Partisanship Score' is the measure of partisanship for the website from the Berkman Klein data, 'log(Twitter Shares)' is the log of the number of twitter shares in the Berkman Klein data, and 'log(Media Inlinks)' is the log of the number of media inlinks reported by the Berkman Klein data. Columns (1)-(4) restrict to images with at least 0.5 match confidence. Columns (5)-(8) restrict to images with at least 0.7 match confidence. Standard errors clustered by website are in parentheses. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels.

Table A9: Bias in Who to Cover Over the Election Cycle

	Image-level (unbalanced)			Website-level (balanced)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Primaries	Post-Primaries	Post-Election	Primaries	Post-Primaries	Post-Election
Partisanship Score	-0.07	-0.20***	-0.09***	-0.04	-0.18***	-0.09***
	(0.04)	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)
Clusters	82	73	67	61	61	61
Observations	13409	13579	13504	61	61	61

Notes: Columns (1)–(3) show the results from OLS regressions where an indicator for whether the politician is a Republican in the image is the dependent variable. Columns (4)–(6) show the results from OLS regressions where, after restricting to images of Donald Trump and Hillary Clinton, the share of images of Donald Trump is the dependent variable. Columns (4)–(6) also restrict to a balanced panel of websites with a nonmissing share variable in all periods. Columns (1) and (4) restrict data to images before either Trump or Clinton clinched the nomination (May 3, 2016). Columns (2) and (5) restrict data to images after both nomination had been clinched (June 6, 2016), but before the election. Columns (3) and (6) restrict data to the post-election period, inclusive (November 8, 2016). Sample is restricted to images of Donald Trump and Hillary Clinton throughout. 'Partisanship Score' is the measure of partisanship for the website from the Berkman Klein data. Standard errors clustered by website are in parentheses. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels.

Table A10: Bias in Who to Cover Over the Election Cycle, Separately by Candidate

	Donald Trump			Hillary Clinton		
	(1)	(2)	(3)	(4)	(5)	(6)
	Primaries	Post-Primaries	Post-Election	Primaries	Post-Primaries	Post-Election
Partisanship Score	0.01	-0.08***	-0.04	0.05	0.15***	0.06***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Clusters	64	64	64	64	64	64
Observations	64	64	64	64	64	64

Notes: Columns (1)–(3) show the results from OLS regressions where the share of images of Donald Trump is the dependent variable (taken across all images with identified politicians). Columns (4)–(6) show the results from OLS regressions where the share of images of Hillary Clinton is the dependent variable (taken across all images with identified politicians). Separately for Columns (1)–(3) and Columns (4)–(6), the data is restricted to a balanced panel of websites with a nonmissing share variable in all periods. Columns (1) and (4) restrict data to images before either Trump or Clinton clinched the nomination (May 3, 2016). Columns (2) and (5) restrict data to images after both nomination had been clinched (June 6, 2016), but before the election. Columns (3) and (6) restrict data to the post-election period, inclusive (November 8, 2016). 'Partisanship Score' is the measure of partisanship for the website from the Berkman Klein data. Standard errors clustered by website are in parentheses. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels.

Table A11: Partisanship of Users and Emotional Slant, Robustness

	Dependent Variable: Relative Favorability										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Partisanship x Republican	20.75***	20.88***	19.84**	21.05***	21.05***	0.42***	40.88***	35.06***	12.10***	20.58***	21.05***
	(2.84)	(3.54)	(8.22)	(0.81)	(0.89)	(0.04)	(8.24)	(8.25)	(2.88)	(3.41)	(2.96)
Partisanship										-16.73***	
										(3.05)	
Republican											-42.25***
											(2.21)
Website F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y
Politician F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Clusters	90	88	74	2	—	90	54	36	39	90	90
Observations	37816	22769	2085	43006	43006	43006	25699	17307	17291	43006	43006

Notes: Table shows the results from OLS regressions where the emotion score for a politician's face is the dependent variable and with politician and website fixed effects unless otherwise specified. Sample is restricted to images of Donald Trump and Hillary Clinton. 'Partisanship x Republican' is the interaction between the Berkman Klein partisanship score with an indicator for whether the politician is a Republican. The emotion that is used as the dependent variable for each regression is noted in the column header. 'Negative' denotes the sum of the anger, sadness, contempt, disgust, surprise, and fear scores. 'Relative Fav.' denotes the happiness score minus the negative score. All emotion scores are scaled by 100. Columns (1)-(3) restrict to images with a match confidence of at least 0.6, 0.7, and 0.8 respectively. Columns (4) and (5) use standard errors clustered by politician and robust standard errors respectively. Column (6) uses the log of the relative favorability measure after shifting it to be positive. Columns (7)–(9) restrict observations to websites with negative partisanship scores, positive partisanship scores, and at least 1000 media inlinks respectively. Columns (10) and (11) replace the website and politician fixed effects with the Berkman Klein partisanship score ('Partisanship') and an indicator for Republican politicians ('Republican') respectively. Standard errors clustered by website are in parentheses unless otherwise specified. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels.

Table A12: Partisanship of Users and Emotional Slant, Separately by Candidate

	Donald Trump			Hillary Clinton		
	(1)	(2)	(3)	(4)	(5)	(6)
	Happiness	Negative	Rel. Favorability	Happiness	Negative	Rel. Favorability
Partisanship Score	2.55	-4.20*	6.75**	-12.31***	8.62***	-20.93***
	(1.70)	(2.30)	(3.33)	(3.15)	(1.65)	(4.28)
Clusters	87	87	87	84	84	84
Observations	87	87	87	84	84	84

Notes: Table shows the results from OLS regressions where the average emotion scores across images for each candidate-website pair is the dependent variable. Columns (1)–(3) restrict attention to Donald Trump. Columns (4)–(6) restrict attention to Hillary Clinton. 'Partisanship Score' is the measure of partisanship for the website from the Berkman Klein data. Standard errors clustered by website are in parentheses. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels.

Table A13: Emotional Slant Over the Election Cycle

	Primaries			Post-Primaries			Post-Election		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Happiness	Negative	Relative Fav.	Happiness	Negative	Relative Fav.	Happiness	Negative	Relative Fav.
Partisanship Score x Republican Politician	4.11	-12.10***	16.21***	14.02***	-8.75***	22.77***	10.45***	-17.23***	27.68***
	(2.51)	(1.60)	(3.17)	(3.70)	(1.16)	(4.10)	(3.34)	(3.69)	(5.52)
Website F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Politician F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clusters	82	82	82	73	73	73	67	67	67
Observations	13409	13409	13409	13579	13579	13579	13504	13504	13504

Notes: Table shows the results from OLS regressions where the emotion score for a politician's face is the dependent variable and with politician and website fixed effects. Sample is restricted to images of Donald Trump and Hillary Clinton. 'Partisanship Score x Republican Politician' is the interaction between the Berkman Klein partisanship score and an indicator for whether the politician is a Republican. The emotion that is used as the dependent variable for each regression is noted in the column header. 'Negative' denotes the sum of the anger, sadness, contempt, disgust, surprise, and fear scores. 'Relative Fav.' denotes the happiness score minus the negative score. All emotion scores are scaled by 100. Columns (1)–(3) restrict data to images before either Trump or Clinton clinched the nomination (May 3, 2016). Columns (4)–(6) restrict data to images after both nomination had been clinched (June 6, 2016), but before the election. Columns (7)–(9) restrict data to the post-election period, inclusive (November 8, 2016). Standard errors clustered by website are in parentheses. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels.

Table A14: Emotional Slant Over the Election Cycle, Balanced Panel of Websites

	Primaries			Post-Primaries			Post-Election		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Happiness	Negative	Relative Fav.	Happiness	Negative	Relative Fav.	Happiness	Negative	Relative Fav.
Partisanship Score x Republican Politician	15.21**	-16.51***	31.72***	17.53**	-9.12***	26.64***	5.49	-11.62**	17.11
	(6.76)	(5.90)	(10.63)	(6.95)	(2.97)	(8.43)	(7.58)	(4.78)	(10.93)
Website F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Politician F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clusters	54	54	54	54	54	54	54	54	54
Observations	108	108	108	108	108	108	108	108	108

Notes: Table is the same as Table A13 except that (a) the average emotion scores across images for each candidate-website pair is taken separately across each period, and (b) the sample is restricted to a balanced panel of websites with non-missing values for each candidate in each period. Table shows the results from OLS regressions where the average emotion score for a politician's face is the dependent variable and with politician and website fixed effects. Sample is restricted to images of Donald Trump and Hillary Clinton. 'Partisanship Score x Republican Politician' is the interaction between the Berkman Klein partisanship score and an indicator for whether the politician is a Republican. The emotion that is used as the dependent variable for each regression is noted in the column header. 'Negative' denotes the sum of the anger, sadness, contempt, disgust, surprise, and fear scores. 'Relative Fav.' denotes the happiness score minus the negative score. All emotion scores are scaled by 100. Columns (1)–(3) restrict data to images before either Trump or Clinton clinched the nomination (May 3, 2016). Columns (4)–(6) restrict data to images after both nomination had been clinched (June 6, 2016), but before the election. Columns (7)–(9) restrict data to the post-election period, inclusive (November 8, 2016). Standard errors clustered by website are in parentheses. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels.

Table A15: Emotional Slant Over the Election Cycle, Balanced Panel of Websites (Trump Only)

	Primaries			Post-Primaries			Post-Election		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Happiness	Negative	Relative Fav.	Happiness	Negative	Relative Fav.	Happiness	Negative	Relative Fav.
Partisanship Score	4.81**	-4.88**	9.69***	1.55	0.02	1.53	-0.53	-0.87	0.34
	(2.09)	(2.30)	(3.70)	(3.71)	(2.37)	(5.51)	(2.44)	(2.37)	(4.31)
Website F.E.	N	N	N	N	N	N	N	N	N
Politician F.E.	N	N	N	N	N	N	N	N	N
Clusters	60	60	60	60	60	60	60	60	60
Observations	60	60	60	60	60	60	60	60	60

Notes: Table is similar to Table A14, but the data is restricted to images of Donald Trump, the sample is restricted to a balanced panel of websites with non-missing emotion values for Donald Trump in each period, and all fixed effects are excluded since there is a single observation per website. Table shows the results from OLS regressions where the average emotion score for a politician's face is the dependent variable. 'Partisanship Score' is the Berkman Klein partisanship score. The emotion that is used as the dependent variable for each regression is noted in the column header. 'Negative' denotes the sum of the anger, sadness, contempt, disgust, surprise, and fear scores. 'Relative Fav.' denotes the happiness score minus the negative score. All emotion scores are scaled by 100. Columns (1)–(3) restrict data to images before either Trump or Clinton clinched the nomination (May 3, 2016). Columns (4)–(6) restrict data to images after both nomination had been clinched (June 6, 2016), but before the election. Columns (7)–(9) restrict data to the post-election period, inclusive (November 8, 2016). Standard errors clustered by website are in parentheses. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels.

Table A16: Emotional Slant Over the Election Cycle, Balanced Panel of Websites (Clinton Only)

	Primaries			Post-Primaries			Post-Election		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Happiness	Negative	Relative Fav.	Happiness	Negative	Relative Fav.	Happiness	Negative	Relative Fav.
Partisanship Score	-11.57***	11.26***	-22.83***	-13.79***	9.72***	-23.52***	-6.67	11.65***	-18.32***
	(3.44)	(3.15)	(5.37)	(3.53)	(2.53)	(5.24)	(5.05)	(2.65)	(6.87)
Website F.E.	N	N	N	N	N	N	N	N	N
Politician F.E.	N	N	N	N	N	N	N	N	N
Clusters	55	55	55	55	55	55	55	55	55
Observations	55	55	55	55	55	55	55	55	55

Notes: Table is similar to Table A14, but the data is restricted to images of Hillary Clinton, the sample is restricted to a balanced panel of websites with non-missing emotion values for Hillary Clinton in each period, and all fixed effects are excluded since there is a single observation per website. Table shows the results from OLS regressions where the average emotion score for a politician's face is the dependent variable. 'Partisanship Score' is the Berkman Klein partisanship score. The emotion that is used as the dependent variable for each regression is noted in the column header. 'Negative' denotes the sum of the anger, sadness, contempt, disgust, surprise, and fear scores. 'Relative Fav.' denotes the happiness score minus the negative score. All emotion scores are scaled by 100. Columns (1)–(3) restrict data to images before either Trump or Clinton clinched the nomination (May 3, 2016). Columns (4)–(6) restrict data to images after both nomination had been clinched (June 6, 2016), but before the election. Columns (7)–(9) restrict data to the post-election period, inclusive (November 8, 2016). Standard errors clustered by website are in parentheses. ***, ** , and * indicate significance at the 1, 5, and 10 percent levels.