SLANTED IMAGES

Measuring nonverbal media bias in the US 2016 elections

PRESENTED BY:

Giulia Valentini, 3225807
Lavinia Benetollo, 3265865
Alessandro Ferraiolo, 3238219
Francesco Arconte, 3243511

INTRODUCTION

NONVERBAL CUES

Images can be **more persuasive and memorable** than text.

RESEARCH GAP

Most media bias studies analyze **only textual content.**

CASE STUDY

The 2016 U.S. election: **high polarization** and **intense online media coverage.**

CORE IDEA

News outlets might **bias perceptions through image selection,** both on coverage and shown expressions.

RESEARCH QUESTION & CONTRIBUTION

Do news websites show partisan bias in who they feature?
How they visually portray political candidates?

What we'll cover:

DATASET ~1M front-page news images (2015–2017) from 92 U.S. sites

AI METHODS Face recognition + emotion detection for ~80k politician faces

FINDINGS Systematic link between outlet ideology and emotional portrayal

INNOVATION First economic study quantifying nonverbal media bias via machine learning in 2016 US elections

DATA COLLECTION & PREPROCESSING

SAMPLE

92 major **U.S. news sites** (2015–2017)

Partisan lean scored from the **Berkman-Klein dataset**

TIME FRAME

Sept 2015 to **Apr 2017**

(primaries → election → post-election)

DATA SOURCE

Internet Archive front-page snapshots (Wayback Machine)

SCALE

>1M
images downloaded

~350k
with human faces (MATLAB eye-detection filter)

FOCUS

61
key politicians

(Trump, Clinton, Biden, Sanders, Pence, etc.)

IDENTIFYING POLITICIANS IN IMAGES (FACE RECOGNITION)

MAIN CHALLENGE **Scraped images** are **unlabeled** and **may include multiple faces.**

STEP 1 **MATLAB eye detector** filters images likely to contain faces
~350,000 remain.

STEP 2 **Microsoft Face API + manually labeled politician set** identify specific politicians.
→ API assigns a **match confidence score (0–1)** for each detected face.

INCLUSION RULE **Accept ≥50%** confidence.

FINAL DATASET

79,761 faces, 61 politicians, 92 websites

TRUMP

appears
28.658 times

CLINTON

appears
14.348 times

OBAMA

appears
8.336 times

MEASURING EMOTIONS IN FACES (NONVERBAL SENTIMENT)

TOOL

Microsoft Emotion API

→

Measures 8 emotions

happiness, anger, fear, surprise, disgust, contempt, sadness, neutral (sum ≈ 100).

USEFULNESS

Effective for identifying positive, neutral, or negative portrayals.

FAVORABILITY INDEX

Happiness – (anger + fear + surprise + disgust + contempt + sadness).

High = positive portrayal; low/negative = negative; ≈0 = neutral/mixed.

This measure is uniform, allows scalable evaluation over ~80k faces; supports comparisons and time trends.

VALIDATION AND ROBUSTNESS

FACE IDENTIFICATION

Manual-labeled training + confidence threshold

Results robust to tighter thresholds.

EMOTION SCORING

Alternatives exist *(Face++, Sighthound, Google Vision)* but **Microsoft Emotion API aligns better with human judgments** (happiness ~0.85 and neutral ~0.67 correlations; single negative emotions are less reliable individually)

↓

avoid over-interpreting negatives

EMPIRICAL STRATEGY: MEASURING BIAS

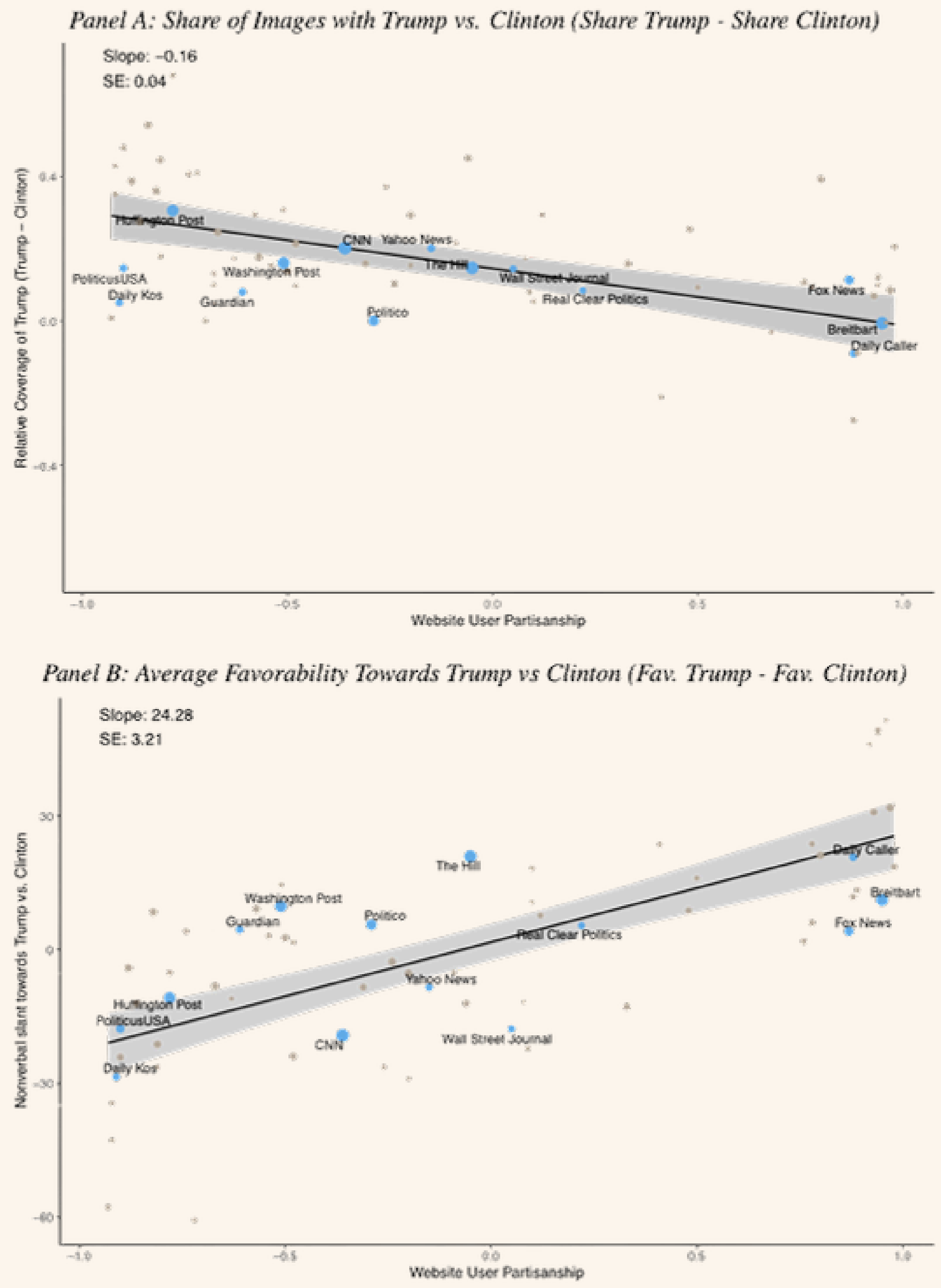


Figure 3: Nonverbal Bias is Correlated with Website User Partisanship

TWO DIMENSIONS OF BIAS

Who to Cover

Frequency of a politician's images across outlets

How to Cover

Emotional tone of each image (positive vs. negative).

KEY VARIABLE

Website partisanship score

(–1 = liberal to +1 = conservative), based on users' Twitter sharing patterns.

REGRESSION SETUP

$$y_{ij} = \alpha_i + \delta_j + \gamma\ (Partisanship_j \times Republican_i) + \varepsilon_{ij}$$

- ***y_ij:*** *emotion or favorability score of politician i on site j*
- ***Fixed effects (α_i,δ_j)*** *control for politician- and site-specific styles.*
- ***γ > 0:*** *aligned outlets show aligned-party politicians more favorably.*

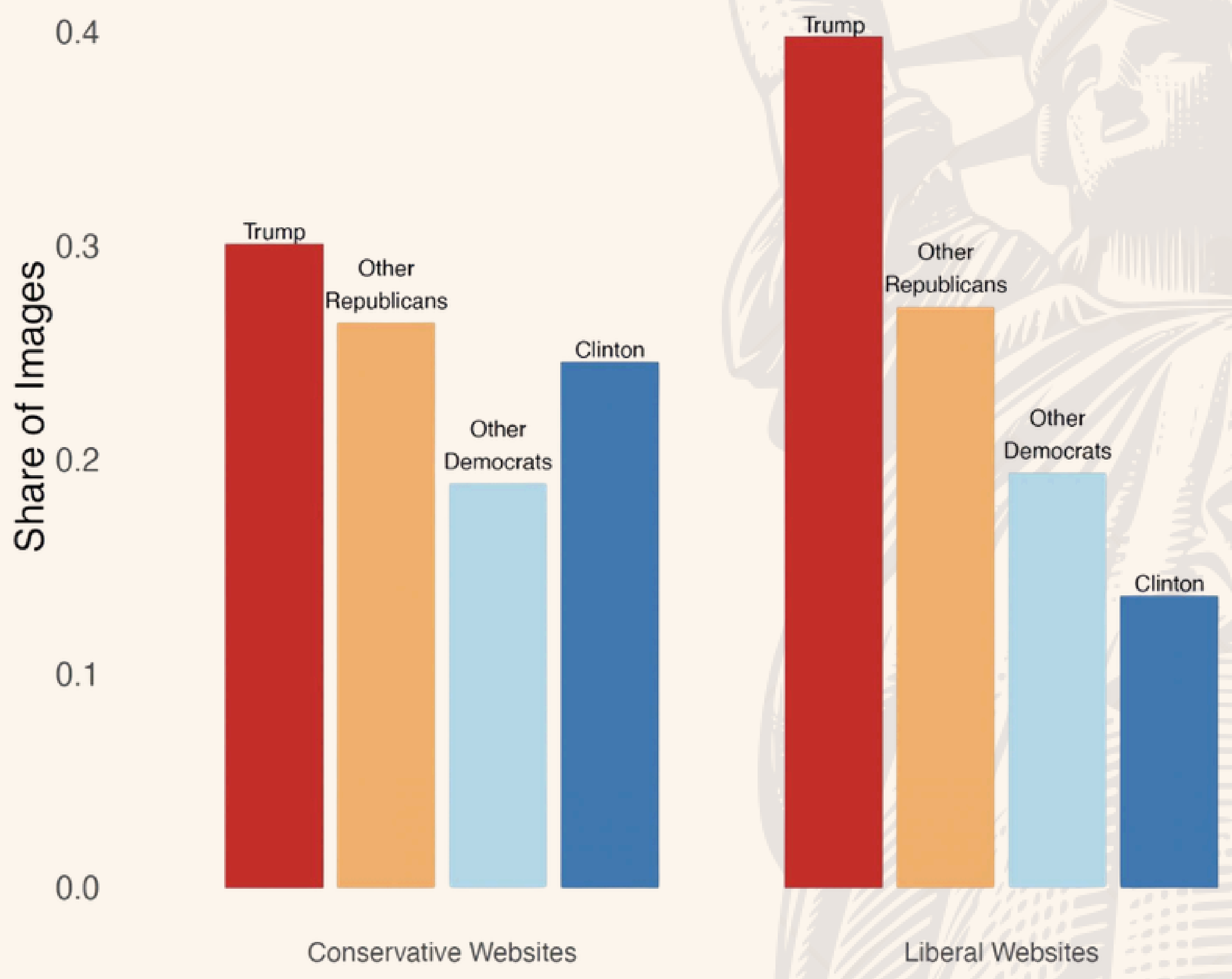
MAIN FINDINGS: BIAS IN WHO IS COVERED

OPPONENTS DOMINATE COVERAGE (IMAGE RATIOS IN WEBSITES)

Each side tends to visually highlight the opponent more:

Liberal sites
~40% Trump
~14% Clinton

Conservative sites
~30% Trump
~25% Clinton



OTHER POLITICIANS

Similar pattern → liberal outlets feature more Republicans; conservative outlets more Democrats.

OVER TIME

After nominations → coverage of the opposing candidate rises sharply (partisan focus intensifies).

MAIN FINDINGS: BIAS IN HOW CANDIDATES ARE PORTRAYED

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

EMOTIONAL SLANT

Aligned outlets

use more positive images for their own candidates.

Opposing outlets

use more negative or unflattering images of the rival candidates

QUANTIFYING THE GAP

From neutral to strongly conservative outlet

Republican image favorability **increases by ≈ 0.21** (percentage points)

Effect ≈ one-third of a standard deviation (0.33) → **LARGE** for emotion-based measures.

ROBUSTNESS OF RESULTS

Results stable across alternative specifications and thresholds.

BIAS DYNAMICS IN THE ELECTION CYCLE

TRUMP

EARLY 2016

Some **Republican-leaning websites** portrayed Trump with **relatively negative expressions,** showing possible support for other primary candidates and skepticism.

MAY 2016

Trump won primaries and:

- **Republican outlets** shifted to **much more positive coverage** of Trump's images
- **Democratic outlets spiked in negative portrayals** of Trump

CLINTON

Democratic-leaning websites' favorable portrayal of Clinton **was relatively steady throughout the entire year**, from the Democratic primaries to the elections.

Conservative sites' negative portrayal of Clinton was also fairly consistent, though they gave her more coverage later in the race as noted.

WEAKNESSES AND LIMITATIONS

THE TWO MAIN ISSUES RELATED TO RELIANCE ON ALGORITHMS

ACCURACY

The algorithm might **misclassify some expressions** or **perform differently across subpopulations** (e.g. subtle expressions or poor lighting could confuse the model).

OMITTED CONTEXT

The method might sometimes flag a "negative emotion" and interpret it as bias. However, it's **not always true that showing a negative image is a deliberate choice,** sometimes it's just a reflection of the reality.

GENERALIZABILITY

It is important to note that **this study covers online news websites' front pages only**, and that it may not capture bias in other media.

CORRELATION VERSUS CAUSATION

Finding that partisan sites show biased images **does not automatically mean those images change voters' minds or behavior.**
The study is **descriptive about bias, not about its effects**. That's left as an open question for future research.

OPEN QUESTIONS AND FUTURE RESEARCH

IMPACT ON AUDIENCE

Understanding the **causal effect of nonverbal bias on the public** is a crucial next step.

OTHER CONTEXTS

Would **similar patterns appear in other elections or countries** (like in Europe or the 2020/2024 US elections)**?**

OTHER FORMATS

Video frames on TV news or online video could also be analyzed with computer vision. **How would visual bias interact with traditional textual bias?**

IMPROVING ML TOOLS

Future research might use more advanced emotion recognition or even **detect things like crowd reactions, body language, or setting**

THANK YOU