The Media During the Rise of Trump: Identity Politics, Immigration,"Mexican" Demonization and Hate-Crime

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Abstract

In this study, we investigate the role of the US online media ecosystem in Donald Trump's rise and consolidation to power (2013-2019). We analyze over 54 million articles from online U.S. media and locate a media narrative shift related to three issues that Trump focused on during his 2016 presidential campaign: immigration, Latin people, and identity politics. Given this, we develop Natural Language Processing techniques based on word embeddings to quantify biased representations of minorities in the media across time. We locate an increase in biased speech that parallels Trump's rise to power, and a clear partisan pattern to this bias. Comparing articles related to Latinos/as, African Americans, Asian Americans, and Jewish Americans, we show that the most biased representations in terms of stereotypes and prejudice are found when the media uses the term "Mexicans," which Trump used as a blanket term for a diverse Latin and Hispanic population. We develop econometric models to understand the narrative shift and to associate media reporting with real-world dynamics. We find that the media's focus on the new narratives and the intensity of biased representations are statistically associated with hate-crime incidents at the state level. These results illustrate how media amenability to politicians' agenda-building can result in the discrimination of social groups, as well as how problematic media reporting is linked to real-world harms. Consequently, we reflect on the role of the media as gatekeepers of public discourse and discuss the conditions for a diverse and inclusive media ecosystem.

Introduction

The 2016 presidential elections embodied a social shift as the first African-American U.S. President was replaced by a conservative, anti-immigration candidate who came to power on the strength of his populistic rhetoric (Hall, Goldstein, and Ingram 2016). The rise of Donald Trump in the political scene closely paralleled the emergence of identity and migration related issues dominating the political agenda. The Republican candidate centered his 2016 political election campaign on countering the dangers of a stigmatizing social "other". His signature claim was to stop immigration coming from the south, broadly framing a diverse Latin population[1] under the signifier "Mexicans", from which the U.S. society needed to be guarded. As Trump gained prominence, he systematically violated emergent norms promoting social diversity (Conway, Repke, and Houck 2017), criticizing them as partisan values, while supporting elements of "white identity politics" (Sides, Tesler, and Vavreck 2016): Trump's rhetoric suggested a zero-sum game in which the empowerment of ethnic, social and gender minorities results in discrimination against white Americans. This position found surprising levels of electoral support, and Trump's 2016 election can be seen as part of a "cultural backlash" (Inglehart and Norris 2016). Some conservative Americans felt isolated and alienated from the rise of progressive values in American society and saw them as replacing familiar traditional norms. These voters were drawn to and united by Trump's "us-versus-them" rhetoric. (Bucy et al. 2020).

Problem Statement

Although the rise of immigration related issues and identity politics in US discourse with Trump's rise to power correlates in terms of time series, questions remain about the media's role in this process. It is unclear how media reported on these identity politics. Did the demonization of social minorities by candidate Trump lead to biased media reporting on minorities? Did reporting on Latin people broadly change, when Trump promoted "Mexicans" as a "new" social other? Furthermore, if the shift in political-agenda setting by Trump was associated with a media narrative shift, it is also worth interrogating whether a rise in anti-minorities speech has led to a corresponding rise in hate crime, which increased the same period (BBC 2018).

Answering the above questions not only advances understanding of the relation between Trump, the US online media ecosystem and minorities, but also on the consequences of tactics followed by multiple political actors across the globe. Politicians such as Marie Le Pen in France, Orban in Hungary, and Parties such as the AfD in Germany put on political performances similar to these of Trump, by promoting identity politics (Keane 2020) in order to attract news media

[1]Throughout the manuscript, we use interchangeably the terms *Latin population(s)* and *Latino(s)/a(s)*, instead of the gender neutral term *Latinx*, since these terms are prefered by the social group (see Noe-Bustamante et al.(2021))

attention, promote their political agenda and entice the electorate. This study can shed light on how amenable media ecosystems are in such tactics, as well as what the potential harms to the social groups being targeted might be.

Given this, we seek the answer to the following research questions:

RQ1: Did a media narrative shift take place during the rise and consolidation of Donald Trump in the political landscape (a) around immigrants, (b) the Latin community, and more broadly (c) around identity politics?

RQ2: How did language used to report on minorities in the US reflect existing prejudices and stereotypes during this period?

RQ3: Is there an association between news coverage that focuses on "othering" minority groups and hate crimes affecting those groups?

Original Contribution

- Analyzing over 54 million articles from U.S. media between 2013 and 2019, we measure the issue salience of immigration, identity politics and minority representation across time. By exploiting interrupted time-series analysis, and drawing from media agenda-setting and framing theories, we illustrate that media reporting followed Trump's agenda during his election campaigning.
- We train monthly word embedding datasets on the articles of each media category, resulting in 360 models taking 33.1 billion tokens as input. We measure bias against four social minorities (African American, Asian American, Jewish, Latin American) by quantifying prejudice and stereotypes in the trained word embeddings. We measure prejudice by adapting the Word Embeddings Association Test (WEAT). We also develop and apply a variance-based method to quantify the importance of stereotypes for each population. We locate a partisan bias when media report on minorities. We find that Latin populations described as "Mexican" are the most discriminated minority and draw connections between the findings and Trump's attitudes.
- We conduct a time-series analysis to investigate the interconnectedness of the issues that the media reports on, locating other real-world causes for the generation of articles on the issues, as well as detecting media associations of hate-crime on the state level. We locate that media reports on immigration and identity politics are statistically interconnected, and that there is an association between hate-crimes and media reports that focus on identity politics and others that discriminate minority groups.
- We discuss the results and emerging issues, and reflect on the conditions required to create a diverse and inclusive media ecosystem.

Background & Related Work

Identity Politics as Politicians' Agenda

Over the past decade, scholars have observed an increasing transformation of cultural values and political styles across the globe (Inglehart 2018), with major societal tensions existing around the power of different social, religious and ethnic groups. The Black Lives Matter movement, the Brexit Euroscepticist movement in the UK, and the insurrection attempt at the US Capitol are examples of this phenomenon. Many right-wing and populist candidates profit by these identity politics, promoting their anti-immigration positions (Pal et al. 2018), demonizing minorities and social groups, and arguing that dominant populations are being deprived of their rights and prosperity (Marchlewska et al. 2018).

An explicit tactic of such politicians is to propagate their ideas as much as possible both through news and social media, with the aim of getting additional exposure, promoting their agenda and reaching voters (Mazzoleni 2008). Consequently, the media plays a significant role in the formation of discourse related to identity politics. Prior research studies show that candidates such as Donald Trump or the German AfD attract disproportionate attention both on social media and news media (Lawrence and Boydstun 2017; Serrano et al. 2019) than other candidates. Since, they become the center of the public discourse, it is important to investigate whether the agendas they promote is also diffused into media reporting and how.

Media, Bias & Minorities

In order to evaluate any connections between politicians' agendas around identity politics and media reporting requires the understanding of how the media present the social groups involved in these identity politics and with what types of biases. First, media coverage of minorities is not proportional to their actual presence in society (Bleich, Bloemraad, and De Graauw 2015), leading to a representation bias. Second, the media consciously or unconsciously produces and reproduces intergroup biases. These biases refer to stereotypes associated with social groups, as well as attitudes towards the groups formulated in statements of prejudice (Hewstone, Rubin, and Willis 2002). Focusing in the US, stereotypes about immigrants, Asian Americans, African Americans, Jewish American, Latinos/as, women and non-binary populations are included in news stories (Wilson II, Gutierrez, and Chao 2012). Sometimes biases against the populations are subtle and not directly visible, but nevertheless lead to a distorted picture of the groups (Easteal, Holland, and Judd 2015). The type of stereotypes or prejudices might vary and can be explicitly harmful such as the association between African Americans and violent crime, or Latin populations to illegal migration (Bleich et al. 2015). Third, many media outlets produce partisan news, thus, they are not neutral intermediators between politics and the public (Groseclose and Milyo 2005). Such a behavior not only influences the issues the media chooses to cover, but also leads to content creation that favors certain political actors or groups and discriminates against others (Budak, Goel, and Rao 2016).

Media and Real World Effects

The discussed media representations and their related biases come with real world implications. Negative reporting on minorities might lead to minority isolation (Shaver et al. 2017). Furthermore, researchers argue that media reports that contain biases leads to their perpetuation in society (Schemer 2014). This bias reproduction can be expressed in multiple ways, such as the externalization of negative cues (Lambert and Githens-Mazer 2010), or the demand for stricter policy measures that target minorities (Kim, Harwood, and Xiang 2018). Going one step further, researchers provide evidence that the negative representation of minorities, or their linkage to events such as terrorist attacks, can result in hate-crime incidents (Hanes and Machin 2014). The effect of media on hate-crimes has been traced for traditional and social media, while there has been evidence of hate-crime diffusion (Müller and Schwarz 2019). Although the media might frame one minority negatively, this has the potential to lead to a general rise of minority-related hate-crime (Lambert and Githens-Mazer 2010).

Conceptual Framework

Between the time Donald Trump announced his nomination in June 2015 and his Election in November 2016, promoted three issues related to identity politics to support his campaigning: 1. supported 'white-identity politics', arguing that other social groups and minorities deprive the values of white Americans, 2. demonized Latin populations and used the blanket term "Mexicans" to refer to them, and 3. adopted anti-immigration rhetoric. To investigate how these issues influenced the media's agenda and to link them with real world events, we draw from the agenda setting, priming, and framing literature.

According to (Scheufele 2000), agenda setting theory assumes that issues that the media emphasizes become increasingly important for its audiences, while priming denotes that the specific issue salience will influence the behavior or attitudes of individuals. In our case, we measure media-agenda setting by investigating how frequently identity-politics, Latin populations, and immigration appear in online media articles. Furthermore, we investigate any priming effects by creating models that investigate the relation between media reporting intensity and hate-crime statistics in the US.

Similarly, (Scheufele and Tewksbury 2007) state that framing describes the phenomenon that how an issue is presented in media reporting can influence how it is understood by society, and consequently how society behaves according to it. In our case, we search for emphasis frames (Cacciatore, Scheufele, and Iyengar 2016) in media reporting, which correspond to how social groups, especially Latin populations, are presented in the media in terms of prejudice and stereotypes. Based on it, we investigate any framing effects, by testing the association of these representations to hate-crime incidents. Furthermore, we look into media reports across the media spectrum and by minority, in order to get a better understanding of the media's framing of social groups.

To connect agenda setting and framing to Donald Trump, we follow (Scheufele and Tewksbury 2007)'s work, which states that both agenda setting and framing is preceded by a phase of agenda and frame building, which is pushed by interest groups and individuals. By exploiting interrupted time series analysis, we investigate whether Trump's nomination, campaigning, and election, functioning as a proxy on the issues he promoted during his campaign, are linked to a change in media frames.

<table>
<tr><th>Regex Queries & No. retrieved articles</th></tr>
<tr><td>Immigration: 1,823,147 articles - alien entrant|alien migrant|anchor baby|anchor babies|boarders|chain migration|criminal alien|illegal alien|illegals|immigrant|refugee|undocumented migrant|undocumented immigrant</td></tr>
<tr><td>Identity politics: 2,703,095 articles - diversity|equality|feminism|feminist|gender|minority group|offend|political correctness|politically correct</td></tr>
<tr><td>African American: 596,572 articles - african american|african-american</td></tr>
<tr><td>Asian American: 52,047 articles - asian american|asian-american|american-asian|american asian</td></tr>
<tr><td>Jewish: 595,969 articles - jewish</td></tr>
<tr><td>Latinos/as: 753,971 articles - hispanic|latin</td></tr>
<tr><td>Mexican: 1,715,040 articles - mexican|mexico</td></tr>
</table>

Table 1: Overview of the Regex queries used to identify issues and social groups in the lower-cased corpus and the corresponding number of retrieved articles.

Data & Methods

Data

We use the open-source media analysis platform Media Cloud (https://mediacloud.org/) and analyze 54,650,532 Media articles between 2013 and 2019 from 900 US media sources across the political spectrum. We use the already existing categorization of these sources in left, center-left, center, center-right and right, performed by (Faris et al. 2017), who classified media based on their consumption by partisans on Twitter during 2016.[2] Sources that appeared in the media landscape after 2016 and were not already categorized are not taken into consideration in our study. We then run queries to measure the reporting magnitude of media on identity politics, immigration, and on four U.S. minority groups: Latinos/as, African Americans, Asian Americans, and Jewish Americans.

For locating articles related to each issue and social group, we use appropriate regex queries (table 1). Each regex query matches an article when any substring in the query appears in the article. For the four social groups, the queries correspond to general naming conventions of the groups. We create the query for immigration based on the work of (Ndulue et al. 2019), who explicitly investigated which issue-related concepts are used by the media during the period under investigation. The query for identity politics is based on the works of (Ely, Meyerson, and Davidson 2006; Bernstein 2005; Walters 2018), who point that issues such as gender, social diversity & equality, minority rights, political correctness and the tendency to "offend", are constitutive elements

[2]The list of sources can be found in https://sources.mediacloud.org/#/collections/936052X, where X = 0-4 depending category.

Social Group	Concepts	Token
African American	african-american(s) african american(s)	`african_american`
Asian American	asian-american(s) asian american(s) american asian(s) american-asian(s)	`asian_american`
Jewish	jewish	`jewish`
Latinos/as	latino(s), latina(s) latinx, latin	`latin`
Mexican	mexican	`mexican`

Table 2: Special tokens used to replace group-related concepts in the corpus for the creation of group-specific word embeddings

of the issue as perceived across the partisan spectrum. We do not claim that this query is exhaustive of all identity politics issues, but rather that it provides a plausible approximation of them. To ensure sample representativeness for immigration and identity politics queries, we read 200 randomly extracted stories from each query. The review concludes that 94% and 87% of stories are issue related respectively. Apart from Latinos/as, which is a key group in our analysis, we elect the other minorities based on their population size in the United States. African Americans and Asian Americans are the largest population groups after non-hispanic white and Latinos/as. Jewish American are the largest religious group after Christians. By calculating the articles including topic-related tokens we quantify, over time, the importance of the above issues and populations across the media spectrum, and we refer to it from now on as issue salience.

For training the embeddings we use the skip-gram model developed by (Mikolov et al. 2013). To generate group-specific word vectors, we replace group-related concepts with unique tokens, which we then used in our analysis when calculating prejudice and stereotypes (table 2).We set the window of neighbors to 10, and include words in our model that appear at least 50 times. For the calibration of the training process, we elect 10 negative samples for the noise contrastive estimation of the models' parameters. We train a word embedding dataset for each month between 2013 and 2019 and for each media political alignment category. Overall, we train 360 word embedding datasets with each dataset containing a corpus of 100,000 word vectors and each vector having 300 dimensions.

It is important to note that throughout the analysis we do not exclude articles that contain direct quotes of Trump about the issues. First, his ability to gain media exposure and being directly quoted reveals his agenda building power and is crucial for quantifying any agenda setting effects. Second, ethical journalistic conduct provides guidelines on how to deal with hateful and discriminatory speech, even in cases when it is included in third-party quotes (Steinberg 2020), in order to mitigate unwanted real-world outcomes. Despite this, the direct, uncritical and without special contextualization inclusion of Trump's problematic quotes was a prominent issue during his media coverage (openDemocracy 2017). Therefore, it is important to take it into consideration when investigating agenda setting and framing associations and effects.

Measuring Prejudice

For measuring the amount of media prejudice against minorities, we modify the word embeddings association test (WEAT) developed by Caliskan et al. (2017). WEAT transfers the idea of Implicit Association Test (IAT), used in psychology to measure implicit predispositions of individuals towards specific target concepts (Greenwald, McGhee, and Schwartz 1998), in the setting of word-embeddings. Intuitively, WEAT calculates the difference in distance between the embedding space of a concept word (e.g. Christianity) and two sets of attributes (e.g. pleasant - unpleasant) in comparison to another concept word (e.g. Islam). In our case, we want to calculate a prejudice score for each group independently from the others. Therefore, we use the equation

$$s'(w, A, B) = \sum_{a \in A} \cos(\vec{w}, \vec{a}) - \sum_{b \in B} \cos(\vec{w}, \vec{b}). \quad (1)$$

Vectors $\vec{a}$ and $\vec{b}$ correspond to the embeddings of words that belong in sets A and B, $\vec{w}$ the embedding of the target concept, cos the cosine distance between two vectors. The value s' gives the overall distance difference of a concept from two attribute sets, without weighing the amount of words in the attribute sets. We use the valence lexicon of (Hu and Liu 2004) to develop the two attribute sets of positive and negative words. For the score calculated in equation 1 to be comparable to the overall valence existing in a corpus of texts, we calculate, using the same equation, a score for a set of randomly sampled target concepts R. In this way, we calculate a baseline score to which we can compare the score calculated for our social group, resulting in the scoring equation

$$S'(A, B, x, R) = s'(x, A, B) - mean_{r \in R} s'(r, A, B) \quad (2)$$

, where x is a word vector for a single social group, A and B the sets of positive and negative sets of words, and R a set of randomly sampled words from the dataset. The above equation gives a valence word embeddings association score (WEAS) and is able to measure, in terms of valence, how positively or negatively media sources reported on a social group. For calculating scores for each social group, we use the vector corresponding to each special token defined in table 2. For the sets of positive and negative words, we use the total list of 2006 and 4873 positive and negative words existing in the selected sentiment dictionary of (Hu and Liu 2004). We report both the values s' and S', as value s' gives the direct valence bias when reporting on the social groups as perceived by article readers, while value S' represents the latent bias media outlets actually hold.

Measuring Stereotypes

An evaluation of stereotypes in text requires the existence of a list of group related concepts for which we can then investigate their appearance and importance in the dataset. Nevertheless, whether an attribute assigned to a group is regarded

African American	Asian American	Latinos/as Mexican	Jewish
drug	yellow	drug dealers	nose
watermelon	foreigner	border	hair
fried chicken	model	loud	greed
angry	industrious	illegal	usury
loud	studious	aliens	thrift
aggressive	intelligent	uneducated	mother
athlete	sexual	undocumented	princess
unintelligent	bad drivers	trafficker	materialistic
criminal	submissive	sexy	lawyer
violent	short	lazy	doctor
gangster	small eyes	illiterate	rich
tall	hardworking	unintelligent	crude
lazy	quiet	gang	
ghetto	asocial	macho	
sexual	education	fertility	
poor			
ugly			

Table 3: List of stereotypes generated by intersubjective comparison.

as a stereotype or not is dependent on the person who makes the inference. Thus, to overcome issues of objectivity we follow an intersubjective approach. We collect group related stereotypes from the scientific literature, Wikipedia, and Q & A websites. We use three sources for each social group and keep stereotypical words that appear at least in two out of three sources (Wikipedia 2020; Quora 2020; NLCTAP 2019; Reyes 2017; Ghavami and Peplau 2013; Gurock 1998; Diner 2004). The generated stereotype lists can be found in table 3. We generate a unique list for African American, Asian American and Jewish populations, while we use the same list when investigating stereotypes for Latinos/as and "Mexican."

To measure the importance of stereotypes quantitatively we exploit semantic properties of word embeddings. Researchers have demonstrated that mathematical manipulation of word vectors can reveal hidden associations between words (Ottoni et al. 2018; Papakyriakopoulos et al. 2020). For example, additive compositionality of vectors holds formally under specific assumptions (Gittens, Achlioptas, and Mahoney 2017). This denotes that, if a word appears very often in the context of another word, or if their meaning somehow is associated in the initial text, then the one word vector can describe, to some extent, the variance of the other. In the word embeddings context, the answer to the question about how prominent specific stereotypes are in describing a social group can be given by the amount of social group vector variance that the aggregate stereotypes vectors are able to explain. We perform this task by developing random forest models that take the set of word embeddings corresponding to the stereotypes as independent variables and the word vector of the social group as dependent variable. The vectors representing each social group are the ones calculated for the tokens existing in table 2. After running the models, we calculate the adjusted coefficient of determination R^2 for each fitted model. The score equation has the form:

$$S_A = R^2_{stereotypes,A} \tag{3}$$

, where A is the social group and $R^2_{stereotypes,A}$ the adjusted coefficient of determination for the model with the group specific stereotypes as inputs.

Interrupted Time Series Analysis

Next, given the time-series representing issue prevalence, social group stereotyping and prejudice, we use interrupted time series analysis (ITS) to investigate changes during the Trump campaign. Such an analysis has the advantage to both investigate changes at the level and the trend of variables, in cases that an external intervention takes place. Interrupted time series is used as a quasi-experimental design method, even in the absence of a control group (Tian and Chunara 2020; Siegel et al. 2021). In this way we can see whether media reporting behavior suddenly changes after Trump's nomination in May 2015, during his campaign, as well as after his election in November 2016. The model has the form:

$$\begin{aligned} Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 T + \beta_4 N + \beta_5 NT \\ + \beta_6 E + \beta_7 ET + u_t \end{aligned} \tag{4}$$

, where Y_t is the time-series under investigation, Y_{t-1}, Y_{t-2} are autoregressive components, T is the continuous time variable, N a binary variable that denotes the first intervention (Trump's nomination), E a binary variable that denotes the second intervention (Trump's election) and u_t the error term. The terms $\beta_4 N, \beta_6 E$ depict changes at the levels of the time-series depending on Trump's status change, while $\beta_5 NT, \beta_7 ET$ changes in time-series trends. Both changes in levels and trends are compared to the period prior to Trump's nomination (before June 2015). We create models taking into consideration all articles across the media spectrum, as well as create separate models for each media category. In this way, we uncover general and category-specific associations.

Vector Autoregressive Modeling

To measure the potential interconnectedness between media reports and to locate other drivers that result in media covering issues, we create vector autoregressive models (VAR) with time-asymmetric structures in order to fulfill the conditions of Granger-causality. We investigate whether the economic conditions in the U.S.A as depicted in the unemployment rates, or the immigrant flows influence media reporting. To achieve this, we include in the models the monthly US unemployment rate, as well as the monthly number of registered incoming immigrants in the US. In addition, we search for associations between media reporting on identity politics and on immigration, building on the results of the interrupted time-series analysis. The developed models consist of n=72 observations corresponding to each month between 2013 and 2019. We detrend time-series, to control for general trends on media reporting related to Trump's presidency. We run models on their differences, in order to fulfill conditions of stationarity and of normality. The final structural equation model has the form:

$$
\begin{aligned}
IM_t &= \beta_1 0 + \beta_{11} IM_{t-1} + ... + \beta_{1p} IM_{t-p} + \gamma_{11} ID_{t-1} \\
&+ ... + \gamma_{1p} ID_{t-p} + \sum_{j=1}^{n} \delta_{1j} V_{jt} + u_{1t} \\
ID_t &= \beta_2 0 + \beta_{21} IM_{t-1} + ... + \beta_{2p} IM_{t-p} + \gamma_{21} ID_{t-1} \\
&+ ... + \gamma_{2p} ID_{t-p} + \sum_{j=1}^{n} \delta_{2j} V_{jt} + u_{2t}
\end{aligned} \tag{5}
$$

, where IM_w , ID_w are the media reporting variables on immigration and identity politics respectively, V_{jt} the exogenous variables on unemployment and immigration rates, β, γ, δ estimators to be calculated, and u_w are error terms. Our models have lag=1, as proposed by the performed diagnostics tests.

Fixed-Effects Panel Data Analysis

We further investigate potential priming and framing effects of media reporting on hate crime. To achieve this, we collect hate crime statistics for each U.S. state between 2013 and 2018 (FBI 2019). We use the previously extracted time-series for media reporting (agenda-setting), as well as create and use monthly time-series containing the amount of prejudice on the 4 studied minorities (framing). We include other exogenous factors in the model, such as the flow of domestic and international migrants to each state and the ratio of local population belonging to a minority group. Because past research states that hate crime is associated with income inequality (FiveThirtyEight 2017), we control for economic asymmetries by including the economic inequality index at the state level. As we have both variables at the state and national level, we create a panel-data fixed effects model (FE, n=250). In this way, we can investigate the association between media reporting on the national level and hate-crimes at the state level. The model has the form:

$$H_{it} = s_i + f_t + X'_{it}\beta + u_{it} \tag{6}$$

, where H_{it} is the hate crime number by state and time point normalized by the total population of the state, s_i the state specific effect, f_t the time specific effect, X'_{it} is the matrix of exogenous variables, β the matrix of estimators and u_{it} is the time and state dependent error term.

Results

Immigration, Latinos/as, and Identity Politics: a Media Narrative Shift

The time-series analysis provides strong evidence that a media narrative shift took place during Trump's rise and consolidation to power (RQ1). Figure 1(a) shows that all related issues became more important from 2013, with a peak before the 2016 Elections. Mentions of immigration boomed, with media using migration related vocabulary in their articles in 2016 up to 10 times more in comparison to 2014. Comparing 2019 and 2013, the media reported on immigration 4 times more. Similarly, vocabulary related to identity politics became twice as prevalent. The interrupted time-series results (table 4) suggest that a major change in media reporting on these two issues happened at the same time as Trump's nomination in June 2015. Trump's nomination is statistically associated with a sudden doubling in immigration mentions in media reports ($\beta_{intercept} = 8.8e0e03, p < 0.05$) as well as with a 33 % increase on identity politics related articles ($\beta_{intercept} = 6.6e04, p < 0.01$). This increase in levels is followed by a steady rise of media articles on the issues during the Trump's campaign, with the model proposing statistically significant (identity politics) or non-statistically significant (immigration) trends. Comparing issue salience after Trump's election (Nov 2016) with the period prior to his nomination (before June 2015), the model suggests statistically significant differences in trends, as issue salience seems to decrease both for immigration and identity politics. This denotes that issue salience on the issues returned to its prior dynamics after the conclusion of Trump's campaign. The above associations provide strong evidence that during Trump's campaign the media shifted focus onto these issues, putting them in a more prevalent place in their agenda. Table 5 provides the interrupted time-series results across the media spectrum. It is visible that media outlets regardless of partisan stance participated in the described narrative shift. Issue salience on immigration increased either in terms of levels or in trends during Trump's campaign for all media categories. A similar behaviour is located in relation to identity politics, as the model suggests a non-statistically significant change only for left media.

Media narratives about Latin populations also changed, with Latinos/as being mentioned 2 times more in articles comparing 2019 to 2013, with a peak again in 2016. The model provides evidence for an association between reporting intensity dynamics to Donald Trump's campaign or election. Both media articles related to "Latinos/as" and "Mexicans" suddenly increased following Trump's nomination ($\beta_{intercept,Latin} = 3.6e03, p < 0.01$, ($\beta_{intercept,Mexican} = 6.8e03, p < 0.01$). This increase seems to diminish after Trump's election, similar to issue salience on identity politics and migration ($\beta_{slope,Latin} = -4e05, p < 0.01$, ($\beta_{slope,Mexican} = -6.7e02, p < 0.05$). Comparing media articles on the Latin population to aggregate articles on the three other populations in the study (Asian American, African American, Jewish), the model suggests different reporting dynamics. Not only is Trump's campaign not statistically associated to a change on the amount of generated articles on Asian American, African American and Jewish, either in levels or in trends, but also articles on these populations seem to further increase constantly after Trump's election. The specific dynamics provide evidence that Latinos/as were treated by media differently in terms of salience than the rest of social groups in the period under investigation. This behaviour was present for all media categories as table 5 shows, with issue salience related to "Latin" and "Mexicans" increasing during Trump's Campaign. On top of this, the model results suggest that Trump's campaigning period overlaps with a change in how the media framed the population in terms of prejudice and stereotypes (figures 1b,

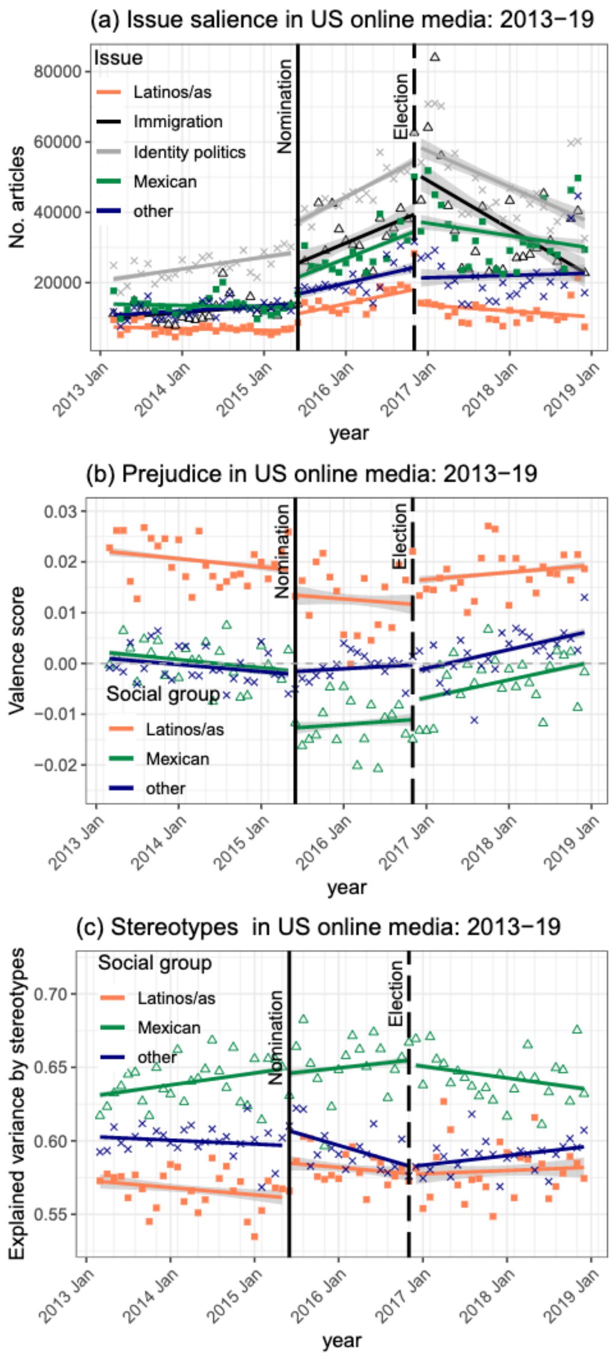

Figure 1: (a): Issue salience related to Latin populations, immigration and identity politics across time. (b) and (c): Valence and stereotype score in articles related to "Latinos/as", "Mexican" and other social groups across time. The variable *other* aggregates articles on Asian American, African American, and Jewish. Points represent the calculated scores in the data and lines the interrupted time-series analysis modeling.

1c).

After Trump's campaign announcement, media reports related to the blanket term "Mexican" obtained a negative valence, compared to neutral prior to this ($\beta_{intercept} = -9e03, p < 0.01$). Comparing the valence of articles related to "Mexicans" and to other populations, figure 1(b) shows that they were at the same level prior to Trump's nomination, but there was a significant divergence during his campaigning, which partly persisted after his election, providing evidence of a "Mexican" demonization. Media valence also changed in media articles related to "Latinos/as", with negative valence increasing during Trump's campaigning, albeit an effect that was non statistically significant ($\beta_{intercept} = -9e03, p > 0.05$). Investigating effects across the media spectrum (table 5), the decrease in valence in articles related to 'Mexican" was present for all media categories (not statistically significant only for right media), while center-left media had a statistically significant decrease also for articles referring to Latinos/as.

The interrupted time-series analysis also suggests an association between Trump's campaigning period and media framing in terms of stereotypes. Stereotyping of Latin populations increased suddenly after Trump's nomination ($\beta_{intercept} = 2.3e-02, p < 0.01$). This change remained persistent also after Trump's election. Comparing framing dynamics of articles related to "Mexican" and "Latinos/as" with those of other populations, it is visible that they followed diverging paths, with an increase in stereotypes for "Mexican" and "Latinos/as", and a minor decrease for the rest. Taking media categorization into consideration (table 5), center-left, left, and right media outlets increased stereotyping of Latinos/as, while left media decreased problematic language, with the change being nevertheless not statistically significant.

The above results show that the three issues at the center of Trump's 2016 electoral campaign were reproduced by the US media ecosystem, either by adapting their agenda or articles' framing. Immigration, identity politics and Latinos/as had a much higher salience during Trump's campaign, while Latin population representations became also more biased in terms of stereotypes and prejudice, as found in articles including terms related to "Mexican" and "Latinos/as".

Media Prejudice and stereotypes Against Minorities

To advance understanding of the narrative shift regarding immigration, Latinos/as, and identity politics, we decompose media representations across the media spectrum and four minorities: Latinos/as, African Americans, Asian Americans, and Jewish Americans (RQ2). Overall, media biases varied across the political spectrum, illustrating that the media held a partisan bias. Similarly, biases between minorities and concepts diverged, illustrating that the media did not treat all minorities equally, but largely followed Trump's "Mexican" demonization.

Media Prejudice Against Minorities The statistical processing shows that news media across the spectrum reported differently on the groups in terms of prejudice (Fig 2, a):

Time-series	Variable	Event	Slope	Intercept
Issue salience	Latin	Nomination	3.5e02	**3.6e03****
		Election	**-4e02***	3.6e04
	Mexican	Nomination	**4.7e02***	**6.8e03****
		Election	**-6.7e02***	1.4e04
	Other	Nomination	2e02	2e03
		Election	-3e02	3.6e04
	Immigration	Nomination	2.5e02	**8.8e03***
		Election	**-1e03***	2.6e04
	Identity politics	Nomination	**4.3e02***	**6.6e04****
		Election	**-1.e03***	**2.5e04**
Prejudice	Latin	Nomination	-7.4e-05	-3.9e-03
		Election	3e-04	3.7e-04
	Mexican	Nomination	2e-04	**-1e-02****
		Election	2e-04	-2.5e-04
	other	Nomination	2.9e-04	-5.6e-06
		Election	1.8e-04	-5.6e-03
Stereotypes	Latin	Nomination	9.8e-05	**2.3e-02***
		Election	5.2e-04	-8.8e-03
	Mexican	Nomination	-2e-04	-4e-03
		Election	1.2e-03	**2.1e-02****
	other	Nomination	**-1e-02***	1e-02
		Election	**2e-02****	**-4e-02****

Table 4: Interrupted time-series analysis results. The variable *other* aggregates articles on Asian American, African American, and Jewish. Significance codes: ** p≤0.01, * p ≤0.05.

Issue Salience						
Variable		**L**	**CL**	**C**	**CR**	**R**
Latin	I	3.31e02	**3.4e04****	**2.4e02***	3.7e01	-2.53e02
	S	**8e01****	-6.7e01	**4.8e02***	**1e03***	**1.5e02**
Mexican	I	5.8e02	**6.4e03****	6.15e02	5.5e02	-1.5e02
	S	**1.6e02****	**-2.2e02****	**8.1e01***	**1.3e02***	**2.4e02***
Other	I	-4.7e01	**3.5e03****	6.4e01	4e02	-7.5e02
	S	4.5e01	**-2.3e02****	3.7e01	**1.8e02***	**1.6e02***
Immigr.	I	**1.1e03****	**6.1e03***	**2.5e01***	**8.3e02***	4.1e01
	S	5.9e01	-2.85e02	-1.7e01	**9.7e01***	**3.1e02***
Identity politics	I	1.2e02	**6.1e04***	**7.8e01***	**1e03***	**-4.4e02**
	S	8.5e01	**-4.2e02***	1.8e01	**2.3e02***	**3.9e02**
Prejudice						
Variable		**L**	**CL**	**C**	**CR**	**R**
Latin	I	-1.2e-03	**-1.1e-02****	-9e-05	-6.1e-03	-5e-03
	S	4.3e-05	7e-04	-3.5e-04	1.2e-05	6e-04
Mexican	I	**-1.4e02****	**-7.8e-03****	**-1.5e-02****	**-1.2e-02****	-4e-03
	S	-1.4e-04	**-3.9e-04**	4e-04	3e-04	4e-04
Other	I	**4.5e-03***	-2.7e-04	-4e-03	3.7e-03	-2e0-3
	S	1e-04	**3.1e-04**	4e-04	-3.5e-05	1e-04
Stereotypes						
Variable		**L**	**CL**	**C**	**CR**	**R**
Latin	I	-4e-03	**6.1e-02****	**2.1e-02****	2e-02	**2e-02***
	S	3e-03	**2.3e-03****	-1.2e-03	-1e-03	-2e-03
Mexican	I	-2e-04	**-2e-02****	1e-01	1.5e-02	-1.4e-03
	S	-4e-04	8e-04	-1e-03	-7e-04	-6.8e-04
Other	I	8e-03	-3e-03	9.4e-03	3e03	7e-03
	S	-9e-04	-1e-04	-9.6e-04	**-1e-03***	**-2.7e-03***

Table 5: Interrupted time-series analysis results. Intercept (I) and slope (S) parameters across the media spectrum after Trump's nomination. The variable *other* aggregates articles on Asian American, African American, and Jewish. L: Left, CL: Center-Left, C: Center, CR: Center-Right, R:Right. Significance codes: ** p≤0.01, * p ≤0.05.

right wing media spread a much more negative valence than the rest of the media. In addition, increasing liberal reporting correlated with more positive evaluations of the four minority groups. On average, center and left media sources made positive descriptions of the minorities, while right media was explicitly negative. This behavior reveals a direct partisan bias of the media when mentioning minorities. Nevertheless, the above media evaluations also include how said media generally views the world. The latent valence metric controls for this behaviour. Figure 2(a) shows that center-left and center media sources generally generated more positive valence in articles on minorities than the average. In contrast, left-wing, center-right and right-wing sources associated a more negative valence toward minorities.

Besides the prejudice across the media spectrum, media sources generated unique evaluations for each minority. Figure 2(b) illustrates the framing of the four minorities in terms of valence. As expected, there is a divergence between the concepts for "Latinos/as" and "Mexicans." The first identity label was usually included in stories with an overall positive valence, while the latter had negative framing, mostly because of the position of immigration as the epicenter of political discussions. Stories including "Latinos/as" related terms were not always politically relevant, but included a lot of articles related to lifestyle, food, and culture, resulting in a more positive evaluation of the concept. African Americans were represented marginally positively by the media. A plausible reason for that is the extremely cautious reporting on the population, because of the America's history and politics regarding race and slavery. The media also created an overall neutral representation of Asian-Americans, with articles referring to the issues and achievements of the minority. The most negatively framed population between 2013 and 2019 were Jewish American people. However, a potential reason for that isn't that the media necessarily speaks negatively about the population, but because the issues associated with Jewish American are generally of a negative nature. For example, a significant amount of articles mentioning the population are related to news stories about Israel's war conflicts. Furthermore, focusing in the period of Trump's campaign, articles related to the label "Mexican" contained much more negative valence than that of Jewish American (-0.012 against -0.007, Mann-Whitney U p-value < 0.01), with the population being the most negatively

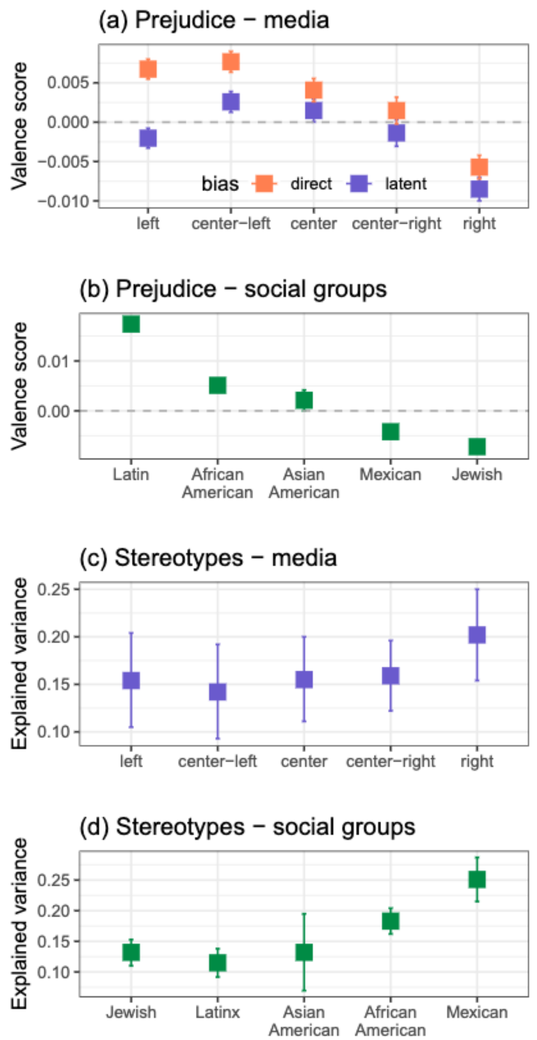

Figure 2: (a), (b): Valence score across the media spectrum and by minority. (c), (d): stereotype prevalence across the media spectrum and by minority.

framed of all.

Media Stereotypes Against Minorities We find similar results for stereotypes as with prejudice. Figure 2 (c) shows that right-wing outlets over-proportionally included stereotypical representations of minorities in their articles when comparing them to the rest. On the other hand, center-left and left-wing outlets used the most unbiased language when reporting on minorities in terms of stereotypes. Close to them were media outlets of center, and center-right, who included biased descriptions more or less of the same degree. That does not mean that left and center-left media did not reproduce stereotypes at all. Although right-wing media sources had a higher amount of stereotypes in their minority descriptions, left-wing sources also reproduced stereotypical representations of groups. While the incidence of stereotypes was less common, left media also reproduced some stereotypes - consciously or unconsciously - for example when choosing to link a minority with a specific issue or not. In many cases stereotypes were used to point out the unfair treatment of groups in the society, by associating the populations with existing stereotypes.

We found not only a divergence in stereotypical representations between media outlets, but also between social groups. The results in Figure 2(c) suggest, in terms of word embeddings associations, that the most stereotyped group concept in media were the "Mexicans," who were usually reported in articles on migration, trafficking and cartels. The opposite pattern held when the media used the term "Latino", "Latina" or "Latinx", with stories having diverse content and a lower incidence of common stereotypes in portraying the population. "Latinos/as"-related terms were much more rarely associated with migration and drugs, and mentions in media presented features and issues of the Latin population. The next most intensive stereotyping was experienced by African Americans. Although the vocabulary on the minority group was usually very carefully chosen, avoiding negative evaluations of the population, it also reproduced typical stereotypes associated with them. Media associated Asian-Americans with stereotypes only moderately, presenting them usually as a "model-minority", hard-working and educated. Media reproduced almost no typical stereotypes about Jewish American populations, such as being intelligent, or linked to professions such as lawyer or doctor.

Media Associations to Hate-Crime

The connection between a narrative shift in media agenda-setting and Donald Trump's campaigning period, together with the media's framing of minorities, led us in investigating potential framing and priming effects. The vector autoregressive modeling supported us in understanding the relation of narratives to real-world indications. The model (Table 6) showed that media attention on identity politics and media attention on immigration were structurally coupled. News sources across the spectrum simultaneously generated stories on immigration and identity politics at proportional amounts with associations between the issues being beyond a simple correlation (r = 0.79). News articles generation on identity politics granger caused the generation of news articles on immigration (F test: $p = 0.012, \beta_{lag1} = 0.58; p = 0.02$). Similarly, the χ^2 test on instantaneous statistical coupling was also significant (p=0.001), providing evidence that either the generation of news on one issue was caused by the generation of news on the other, or that a third variable exists that confounds their behavior.

The analysis also showed that economic changes as depicted in unemployment rates did not influence media attention on immigration ($\beta = 350; p = 0.52$) nor on identity politics ($\beta = -442; p = 0.3$). The same applies for the influence of immigration flows (on $News_{IMM} : \beta = -0.01; p = 0.32$, on $News_{ID} : \beta = -0.12; p = 0.12$). The latter findings suggest that the described media narrative shift was partly decoupled from real-world events, taking place primarily in the virtual sphere of political and media discourse. The above results are helpful for evaluating the statistical associations between media reporting and hate

Test	Statistic
$News_{ID} \xrightarrow{GC} News_{IMM}$	F: **3.92***
$News_{IMM} \xrightarrow{GC} News_{ID}$	F: 1.68
Instantaneous statistical coupling	χ^2: **10.00****

Table 6: F-tests (Granger causality) and χ^2 test results for the association between media attention on identity politics and media attention on immigration. Significance codes: ** p≤0.01, * p ≤0.05.

Predicted:	Hate Crime Ratio	
	Estimate	**Std. Error**
Inequality index	-6.4e-04	6.4e-04
International immigration	3.2e-04	7.5e-04
Domestic immigration	4.3e-04	3.8e-04
White population	**1.1e-05***	4.7e-05
$News_{ID}$	**8e-10***	3.7e-10
$valence_{minorities}$	**-2.5e-07****	6.00e-08
Balanced Panel	n = 50, T = 5, N = 250	**F = 4.1****

Table 7: Results for the model with panel data and fixed effects for predicting the magnitude of Hate Crime on the US state level. Significance codes: ** p≤ 0.01, * p ≤0.05.

crime: First, due to multicollinearity and statistical coupling, we included only news reporting on identity politics in the model that describes hate-crime incidents on the state level. Second, we included economic variables and immigration flows for measuring their effect on hate-crime.

The results of the model with panel data and fixed effects are found in table 7. For the period between 2013 and 2018, international and domestic immigration were not statistically associated to the hate crime ratio by state ($\beta_{int.imm.} = 3.2e-04; p > 0.1, \beta_{dom.imm.} = 4.3e-04; p > 0.1$). The Inequality Index was statistically associated to hate-crime incidents initially ($\beta_{inequality} = 9.82e-04; p < 0.01$), but the effect vanished when controlling for media prejudice ($\beta_{inequality} = -6.4e04; p > 0.1$). Overall, three independent variables of the model were statistically significant when predicting hate-crime incidents: the ratio of the White-American population by state, the amount of news on identity politics at the federal level, as well as the average prejudice included in media articles. Higher hate-crime was measured in areas with a higher percentage of White Americans ($\beta_{white} = 1.1e-05; p < 0.05$). Media attention on identity politics also relates to hate-crime statistics. The higher the number of articles on identity politics by year, the larger the amount of hate-crime cases reported at the state level ($\beta_{news} = 8e-10; p < 0.05$). Similarly, increasingly negative valence in media articles was associated with an increase of hate-crime at the state level ($\beta_{valence} = -2.52e-07; p < 0.01$).

The results of the econometric models shows an association between media framing (amount of prejudice) and agenda setting (identity politics salience) and hate-crime incidents (RQ3). This correspondence does not per se denote a causal relation. Nevertheless, the fact that media attention on the issues was not related to other real-world events, that the associations are between media attention on the federal level and hate-crime on the state-level, and that the framing of the articles is also associated with the hate-crime incidents, provides insights on how media reporting can cause hate-crime variations, providing evidence that support the existence of priming and framing effects. Overall, the model results show that media discourses and narratives can have transformative effects on minorities, with narratives having implications that influence the lives of populations.

Discussion & Conclusion

The study provided important insights on the role and behavior of the media during the consolidation of Donald Trump in the political landscape. We found strong evidence that supports the thesis that media agenda-setting followed Trump's agenda related to immigration and identity politics. The same applies for media's framing of Latin populations, which replicated Trump's "mexican" demonization during his campaign. Furthermore, we did not find any association between real world drivers such as immigration flows or economic welfare and media reporting. These findings support the thesis that the US online media ecosystem became amenable to Trump's political performances. The specific media transformation raises questions about the actual role of media as communication gatekeepers, since issue salience and content should actually correspond to events that take place in the world and not replicate political actors' positions.

The second important insight of the study is that both the prevalence of identity politics in media, as well as negative framing of minorities was statistically associated to hate crime incidents. By performing an analysis that investigates the associations between federal and state level and controlling for other indicators such as economy, ethnic composition of regions, and immigration flows, we found that media reporting between 2013 and 2018 was related to real-world outcomes, suggesting the existence of priming and framing effects. This reveals how problematic media reporting can have unforeseen consequences in the society directly or indirectly, consciously or unconsciously.

These two insights also provide evidence on how politicians' agenda and frame building can be step-wise translated into media narrative changes, which itself alters social behavior. It would be irresponsible to say that Trump caused the specific chain of events, since media and social reality is highly complex, with multiple factors influencing how and why specific incidents will take place. Instead, the study advances the understanding of the amenability of the media ecosystem, and the interconnectedness of the content generated to real world incidents.

It is important therefore to reevaluate how the media should get involved in political discourse, how and under what conditions they can become impartial to political actors' attitudes, and how they should report on social groups in order to fulfill conditions of diversity and inclusivity. A step towards that direction includes media outlets taking into consideration that reporting always comes with conscious and unconscious biases against social groups. It is a challenge therefore for the media not only to find the appropriate language when referring to minorities, but also to consider what is necessary to report and which issues they should associate them with. Media needs to be cognizant of the language it's using, being careful not to internalize a politicians' agenda, or to further stereotyping the politician might be engaged within. In the wake of the experience with Trump, news organizations should review their own language usage to ensure they're not experiencing slippage driven by candidate language. The understanding of such features can lead to the generation of more inclusive news for populations, in ways that actually promote social diversity and acceptance and not marginalization. A more inclusive reporting can contribute to the integration of immigrants and other social groups into society, and the reduction of tension points, such as hate-crime incidents.

Since the news is a cornerstone of political discourse, further steps should be taken to ensure a politically neutral media landscape that actually contributes to informing the public, regardless of the cultural and political values it supports. Our study contributed to understanding the features of the US media ecosystem during the rise and consolidation of Trump, which is be valuable for evaluating and improving media function. We described narrative dynamics, specific media behaviors, and real-world associations that can be used as examples for problematic media functions and serving as a base for social change. We also developed word-embeddings methods for quantifying prejudice and stereotypes in text, which can be useful to the research community when dealing with similar case-studies.

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