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Opinion Shift and Stability: The Information Environment and Long-Lasting Opposition to Trump's Muslim Ban

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Abstract
On January 27, 2017, President Trump signed executive order 13769, which denied citizens of seven Muslim-majority countries entry into the United States. Opposition to what was termed the "Muslim ban" quickly amassed, producing sudden shifts to the information environment and to individual-level preferences. The present study examines whether within-subject shifts against the ban lasted over an extended period of time. Evidence from a three-wave panel study indicates that individual-level opinions, once they shifted against the ban, remained fairly stable one year later. Analysis of a large corpus of cable broadcast transcripts and newspaper articles further demonstrates that coverage of the ban from February 2017 to January 2018 did not dissipate, remained largely critical, and lacked any significant counter-narratives to potentially alter citizens' preferences once again. Our study underscores the potential of capturing the dynamics of rapid attitudinal shifts with timely panel data, and of assessing the durability of such changes over time. It also highlights how mass movements and political communication may alter and stabilize citizens' policy preferences, even those that target stigmatized groups.

Keywords Public opinion · Muslim Americans · Race and ethnic politics · Immigration · American identity · Political communication

Authors are listed in reverse alphabetical order; authorship is equal. Data and code to reproduce the findings is available at: https://doi.org/10.7910/DVN/NNXBHP.

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How short-lived or long-lasting are rapid shifts in public opinion due to significant, real-world changes in the information environment? While some studies have detected externally valid, non-random, and rapid changes in mass attitudes using timely panel datasets (Collingwood et al. 2018; Christenson and Glick 2015a, b), they have rarely examined whether within-subject shifts remain stable over an extended period of time.[1] Inquiring into the stability of rapid changes in attitudes is important because if preferences regress back to the mean, the impact of political communication on opinions may be just temporary, fading away with time akin to experimental treatments that produce only momentary effects (Gaines et al. 2006). However, if opinions remain relatively stable once altered, fairly significant and one-sided changes in the information environment could have longstanding and substantively meaningful impacts on preferences, even towards policies targeting stigmatized groups.

To assess the question of opinion change and stability, we examine long-term within-subject changes in attitudes toward a timely and normatively important policy: President Trump's "Muslim ban." Despite the administration's repeated efforts to preserve the ban throughout 2017, previous research suggests that attitudes moved decisively against it. Using a two-wave panel design, Collingwood et al. (2018) find that panelists were fairly split on the issue just before the Executive Order (EO) announcement, but that a sizable portion of respondents shifted their attitudes less than one week after it went into effect. Rapid shifts in opinion are rare (Erikson et al. 2002; Page and Shapiro 1982), but are supported by the literature on political communication and priming (Krosnick and Kinder 1990; Tesler 2015). In the case of the ban, an influx of information in the media environment depicted it as distinctly un-American and in violation of the principle of American religious freedom, invoking meaningful and new evaluative criteria about the policy. This, in turn, provoked attitude change particularly among high American identifiers, who likely saw a clear incompatibility between American values and the ban.

The present research extends prior work by re-interviewing the same panel participants in January 2018, nearly one year after the first executive order was enacted. Our analysis of the three-wave panel dataset demonstrates that individual-level opinions remained largely stable once they had shifted against the ban. Valence analysis of a large corpus of transcripts from cable news broadcasts and four national newspapers further suggests that political communication between February 2017 and January 2018 did not present a significant counter-narrative in favor of the ban. In fact, the information environment over the ensuing year was largely critical of the ban, and did not bring about any new meaningful considerations to mind to alter citizens' preferences once again.

Our study makes both theoretical and methodological contributions to research on public opinion and on race and ethnic politics. Theoretically, it suggests that mass movements that successfully prime American inclusiveness can durably move individuals, especially high American identifiers, against new policies that target racial, ethnic or religious minority groups. Given that American identity is typically

[1] For an exception, see Christenson and Glick (2015b)'s use of a multi-wave MTurk panel design.

associated with anti-immigrant policy preferences (Citrin et al. 1990; Frendreis and Tatalovich 1997; Schildkraut 2003) and that group-centric attitudes tend to be highly crystallized and fixed (Nelson and Kinder 1996; Kinder and Sanders 1996), rapid and durable within-subject opposition toward the "Muslim ban" is particularly noteworthy. It indicates that policy attitudes related to highly disliked groups, such as Muslims, are perhaps more malleable than previously assumed. Methodologically, by focusing on within-subject opinion changes over a 1-year period, we provide an internally valid account of opinion change and stabilization around the "Muslim ban" EO. This type of panel design provides another blueprint for how timely and cost efficient panel studies on online marketplace platforms such as Amazon's Mechanical Turk (MTurk) can be used to examine the effects of imminent and unpredictable real-world events or exogenous shocks on public opinion in both the short- and long-term.[2]

In what follows, we first outline literature on attitude change and stability, paying specific attention to the circumstances under which rapid opinion change could endure. This section also provides a detailed accounting of the information environment, which enables us to make predictions about the durability of attitudinal change against the "Muslim ban." Next, we present our expectations and describe our dataset and methodological approach. We then detail our findings and conclude with a discussion of the study's limitations and contributions to the public opinion literature.

Temporary and Enduring Opinion Change

Even though public opinion is often resistant to change (Taber and Lodge 2006), political communication can prime citizens' underlying predispositions—such as American identity—and can change attitudes on non-crystallized preferences (Tesler 2015; Iyengar and Kinder 2010). More precisely, attitude change is likely to occur when policy positions are not yet ingrained (Collingwood et al. 2018), issues are salient (Krosnick and Kinder 1990), issues are not personally consequential (Krosnick 1988), information flows become intense and fairly one-sided (Zaller 1992), and cues or messages actually resonate with citizens (Harrison and Michelson 2017). While extant research has identified various conditions under which mass attitudes can shift, studies have rarely examined whether events in the news cycle or exogenous shocks in the information environment produce *temporary* or *enduring* effects.

Existing accounts suggest two divergent outcomes with respect to the durability of opinion change. On the one hand, public opinion research would predict momentary or fleeting effects since the impact of primed considerations usually dissipates over time (Gerber et al. 2011). For instance, previous work has shown that the public

[2] While many studies have relied on online platforms such as MTurk for various experiments, Christenson and Glick (2013) have shown that MTurk, primarily due to its speed and flexibility, also offers clear advantages for panel studies, especially those that require immediate implementation.

is willing to trade off civil liberties for greater security in the context of threat (Davis and Silver 2004), but that such preferences are only temporary, reflecting a momentary reaction that later subsides with a diminishing sense of threat (Davis 2007). Thus, with the passage of time, individuals may cease to remember or place less emphasis on the key evaluative criteria that nudged them to shift their attitudes in the first place.

This expectation is particularly applicable to issues linked to stigmatized populations such as the "Muslim ban." Previous work has demonstrated that the public evaluates Muslims much more unfavorably than most other racial, ethnic, and religious groups (Lajevardi and Oskooii 2018; Putnam and Campbell 2010; Edgell et al. 2006; Kalkan et al. 2009). Conspiracy theories about sharia law and the "dangers of Islam" are growing (Duss et al. 2015), and terrorist attacks committed by Muslim perpetrators are significantly more likely to receive news coverage than are attacks of similar types and fatalities committed by members of other groups (Kearns et al. 2018). As such, if primes of American inclusiveness and religious freedom were to lose their evaluative significance toward any group, and if attitudes were to settle back to their original levels on any policy, it would be toward one that directly impacts Muslims. In its place, citizens may revert back to their underlying psychological predispositions, such as partisanship or racial prejudice, when making subsequent evaluations (Tesler 2015).

On the other hand, attitudes can stabilize once changed (Christenson and Glick 2015a, b), even toward stigmatized populations. Broockman and Kalla (2016), for instance, find that a single perspective-taking conversation markedly reduced transphobia and increased support for anti-discrimination laws for at least three months. While our research question and design differs from prejudice reduction studies, two key reasons suggest that the observed attitudinal backlash against the "Muslim ban" likely persisted throughout Trump's first year in office. First, media coverage of the policy continued throughout 2017, rendering the issue relevant or "on the agenda" (McCombs and Shaw 1972; Scheufele and Tewksbury 2006; Althaus and Tewksbury 2002; Roberts et al. 2002). The salience of the issue likely reduced the possibility that individuals simply ceased to remember the evaluative considerations that moved them against the ban. Second, and more crucially, over the year that followed the initial EO announcement, no major countervailing messages or exogenous shocks entered the information environment to bring about any new and significant pro-ban considerations to mind. Thus, the initial framing of the ban around American identity and religious freedom may continue to hold explanatory power in understanding attitude change and stability one year later.

To examine whether the Muslim ban remained largely salient and anti-ban, we first collected all available broadcast transcripts from CNN, Fox, and MSNBC from January 1 to December 31, 2017 using the Lexis Nexis Academic platform. We then subsetted the transcripts to only those that included the terms "Muslim ban" or "Travel Ban." We found that transcripts from Fox and MSNBC were not uploaded consistently onto the Lexis Nexis platform over the time period studied and almost surely do not represent a random cross-section of media coverage. As such, we are unable draw any systematic valence-related conclusions with these two sources.

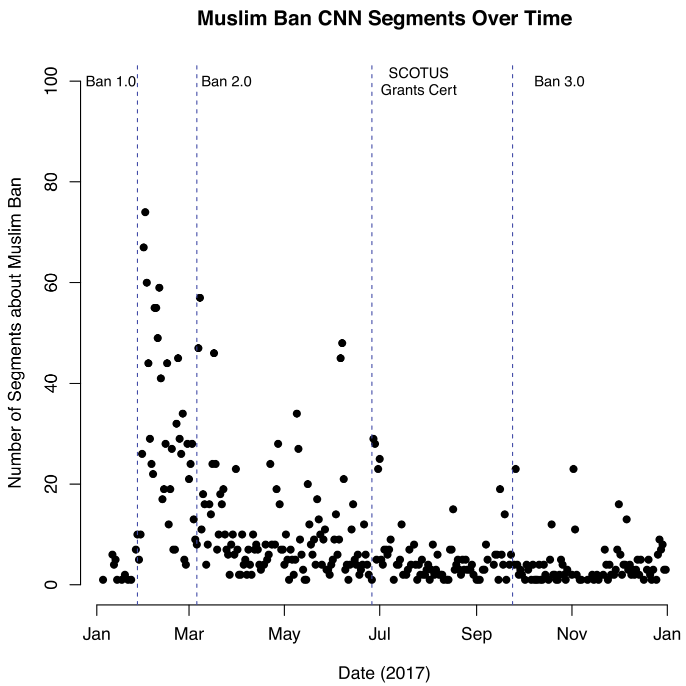

Fig. 1 CNN broadcast coverage of the "Muslim ban" over time

However, we carefully read these limited transcripts to provide a general overview of ban coverage, which we further elaborate on below and in "Appendix 3".

Our cable broadcast valence analysis therefore consists of a total of 3050 CNN segments in the corpus. While CNN viewership leans left (relative to Fox), a 2017 National Tracking Poll found that 37 and 38% of adults who watch CNN identify as Independent and Republican, respectively.[3] Figure 1 presents the 2017 "Muslim ban" CNN coverage time series. Two takeaways about issue salience can be gleaned from Fig. 1. First, ban coverage was clearly most intense during the initial mass resistance to the policy (e.g., airport protests in early February 2017). Second, and more importantly, coverage continued throughout the year due to numerous court decisions and President Trump's issuance of two revised versions of the ban.

Search data from Google analytics provides corroborating evidence that the travel ban did not lose relevance in comparison to two other EOs that entered the political climate at the end of January 2017: the Mexico border wall and the Keystone pipeline. As Fig. 2 illustrates, citizens showed more interest in the ban compared to these two other hot-button issues. Moreover, this trend lasted throughout the year, although to a lower degree after the observed peak interest in late January and early February 2017.

[3] https://morningconsult.com/wp-content/uploads/2017/04/170404-crosstabs-Brands-v3-AG.pdf.

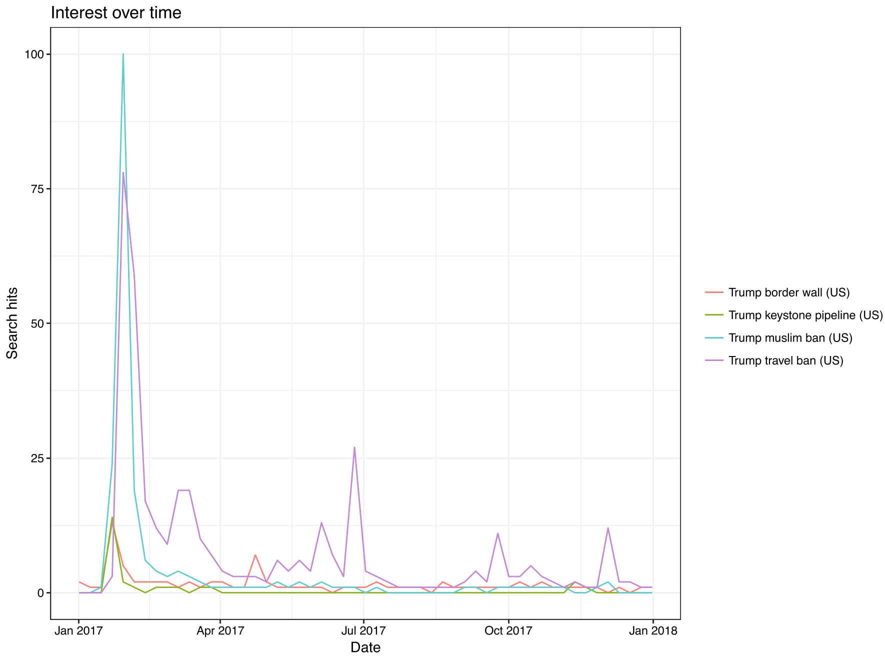

Fig. 2 Google trends searches over time. Y-axis is based on Google analytics normalizing, where 0 indicates no interest and 100 indicates most interest

While these trends suggest that the policy issue never disappeared from the political scene, they do not provide any evidence that the content of the coverage largely remained *anti-ban*. Examining the content of the available information is important when weighing whether opinions would have shifted back to their original position. On the one hand, if coverage remained anti-ban or neutral, attitudes could have remained stable. On the other hand, if coverage shifted and became pro-ban in response to new events (e.g., a domestic terrorist attack), then attitudes might have either regressed back to their original levels or turned even more decisively pro-ban.

To assess the content of the coverage, we used the same CNN transcript data as above and subsetted each media segment containing the terms "Muslim ban" or "Travel Ban" through a key word in context (KWIC) analysis. Within each segment, we examined the 25 words on either side of the term "Muslim" each time the word occurred. This yielded 5,626 observations. We then selected a random sample of 1200 observations and coded the segments for statements indicating the content opposed the ban, approved of the ban or presented neutral, informational, or balanced coverage.[4]

Content analysis of the broadcasts, displayed in Fig. 3, reveals that the valence of the coverage in 2017 was mostly neutral/informational and anti-ban. The dark solid

[4] Please see "Appendix 3" for a more detailed methodology. We relied on three trained coders, with an inter-coder reliability of 0.92 on 25% of the sample.

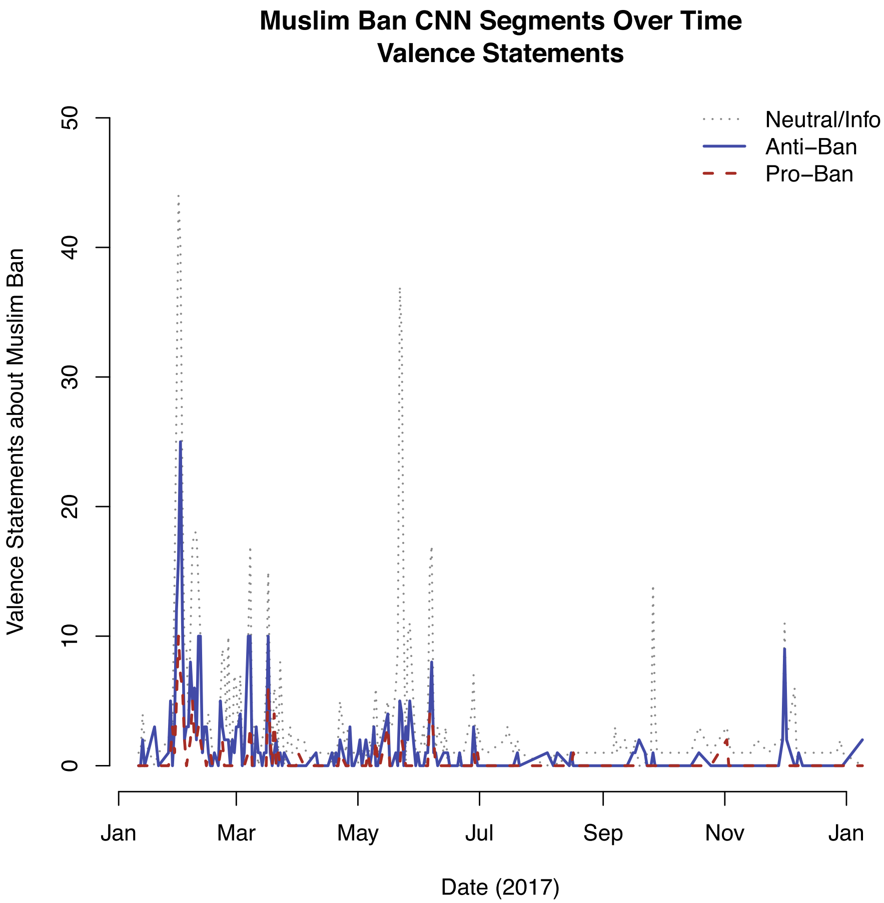

Fig. 3 Valence coverage of CNN media broadcasts over time

blue line represents anti-ban coverage, the dark red dashed line stands for pro-ban coverage, and the light gray dotted line indicates neutral/informational content. As illustrated, media activity was highest after the EO roll out, with valence significantly more anti-ban than pro-ban.

Following this intense period, valence references dropped significantly. However, at almost no point in the time series did the pro-ban valence supersede the anti-ban valence. Furthermore, our careful reading of randomly selected CNN, Fox, and MSNBC broadcast transcripts indicates that almost all of the coverage in support of the ban was fairly unidimensional, revealing that the travel ban was framed to be about border security, not religion—that is, "Not a Muslim ban." For instance, Fox News commentators in favor of the ban routinely made arguments such as: "... There's no mention of the words Muslim or Islam, and there are over 40 different Muslim-majority countries around the world that are not impacted or affected in any way by this executive order." In contrast, coverage against the ban appeared to be multidimensional, highlighting that it is: (1) a repudiation of America's commitment to religious freedom; (2) contrary to fundamental American values; (3) failing to enhance national security; (4) aiding ISIS and other terrorist organizations with recruitment efforts; and (5) hurting the U.S. tourism economy. In sum, the information environment, once changed, remained largely anti-ban or neutral/informational.

Since Fox and MSNBC transcripts were limited, we conducted a second set of analyses with data collected from leading national American newspapers covering the center-left (*New York Times* and *Washington Post*), the center (*USA Today*), and the center-right (*Wall Street Journal*). More specifically, we collected articles that reference either "Muslim ban" or "Travel Ban" from January 1 to December 31, 2017 and coded each article into one of three mutually exclusive categories: anti-ban, informational/balanced, and pro-ban. The corpus contains 1223 articles in total, with 48% of the articles coded as anti-ban, 3% pro-ban, and 49% balanced/informational. We provide an extensive technical discussion of our specific data collection and coding methodology in ″Appendix 3″.

Figure 4 reports over-time results from the combined corpora of text from all four newspapers. As with the CNN broadcast transcripts, the volume of articles peaked during the initial Muslim ban controversy in late January and early February 2017, then subsided. Fully 40% (494/1223) of ban coverage for the whole year appeared during the first two months of the year. Coverage increased again in June and July, as observed in Figs. 1 and 2, with 18% (223/1223) of the newspaper coverage on the ban occurring then. However, across the entire time frame, articles critical about the ban (blue solid line) dominate articles supportive of the ban (red dashed line). In total, 48% (583/1223) of articles were anti-ban, whereas just 3% (38/1223) were

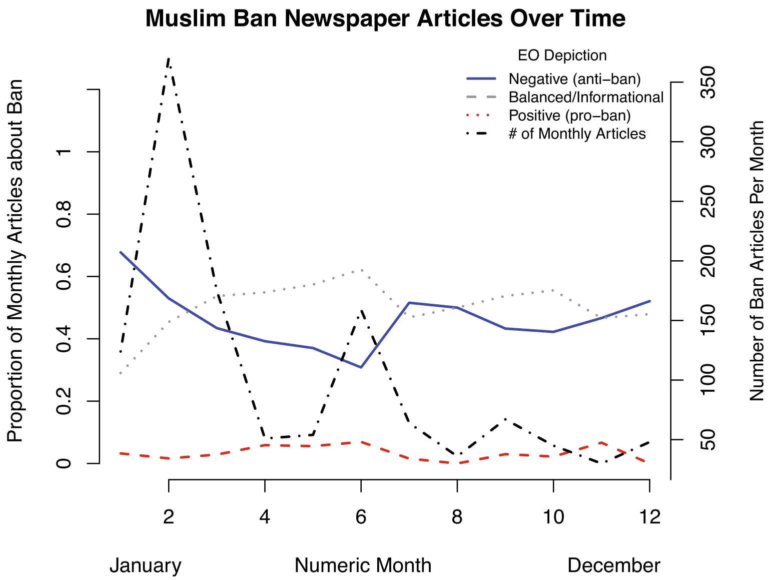

Fig. 4 Valence coverage of newspaper articles about the "Muslim ban/Travel ban" over time (Jan.–Dec. 2017). Source: *New York Times*, *Washington Post*, *Wall Street Journal*, *USA Today*

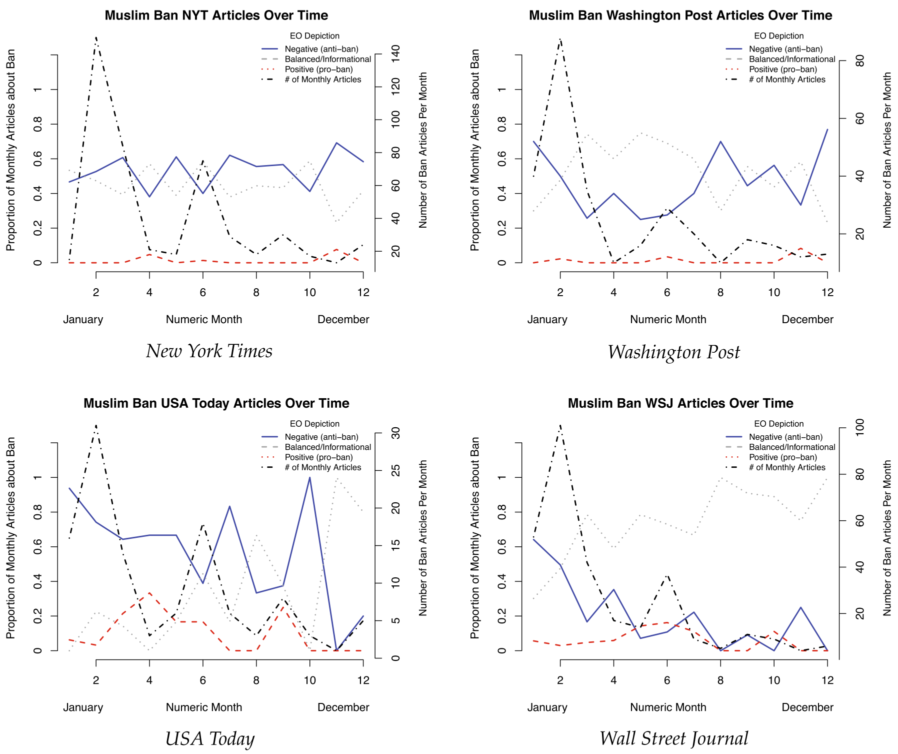

Fig. 5 Valence coverage of newspaper articles about the "Muslim ban/Travel ban" over time, by Source (Jan.–Dec. 2017)

pro-ban. We provide source breakout plots in Fig. 5, which generally conform to the combined-source plot. However, the general pattern observed in Fig. 4 varies somewhat based on source, with articles from NYT being more anti-ban and those from WSJ being slightly more mixed. Nonetheless, the results are broadly consistent with the CNN transcript findings.

Expectations

Based on extant literature and the initial analysis of the information environment, we derive three hypotheses about attitude change and stability and test them with a three-wave panel dataset. The baseline hypothesis is the regression to the mean expectation, which predicts momentary or fleeting effects of primed considerations:

H1: Regression to the Mean Panel respondents interviewed one year after the initial EO announcement (Wave 3) will hold ban opinions statistically indistinguishable from pre-EO ban opinions (Wave 1).

The opinion stability account, in contrast, expects opinions toward the ban to remain fairly stable after the initial mass resistance and controversy because ban coverage remained salient and the information environment did not noticeably change (i.e., remained primarily anti-ban) or bring to bear any significant new evaluative criteria:

H2: Opinion Stability Panel respondents interviewed one year after the initial EO announcement (Wave 3) will hold ban opinions statistically indistinguishable from post-EO ban opinions (Wave 2), but statistically distinguishable from pre-EO ban opinions (Wave 1).

Additionally, Collingwood et al. (2018) find that high American identifiers were particularly prone to shifting against the ban after the policy gained salience and was portrayed as distinctly "un-American." Indeed, as immigration lawyers at airports around the country filed writs of habeas corpus for the release of individuals affected by the ban, impromptu mass demonstrations erupted in cities and airports nationwide, receiving widespread media coverage and eliciting criticism from media pundits and politicians on both sides of the aisle. In a televised press conference, Senate Minority Leader Chuck Schumer, called the ban "mean-spirited" and "un-American," with Republican Senators John McCain and Lindsey Graham issuing the following joint statement in opposition to the ban: "Our government has a responsibility to defend our borders, but we must do so in a way that makes us safer and upholds all that is decent and exceptional about our nation."[5]

If the general argument about the stability of individual-level preferences is accurate (H2), one would not expect high American identifiers, who initially shifted their attitudes against the ban in wave 2, to alter their ban attitudes back towards their original position in wave 1 (i.e., revert back to being more pro-ban). This is because the information environment from wave 2 to wave 3 largely remained anti-ban or neutral across the full time period. As we will show in the ensuing section, coverage continued to be also framed around themes of American identity. Shifts among low American identifiers, however, are not to be expected. This is because primes linking American identity and the "Muslim ban" are unlikely to be as consequential to low identifiers who already opposed the policy in the first place. As previous research has noted, high American identifiers are more likely than their counterparts to be drawn to restrictive policies targeting ethnic, racial or cultural minorities (Citrin et al. 1990; Espenshade and Calhoun 1993; Frendreis and Tatalovich 1997; Huddy and Sears 1995; Schildkraut 2003). Therefore, our final hypothesis is focused on high American identifiers since only this subset of individuals moved in the direction of anti-ban shortly after it was portrayed as "un-American."

[5] https://www.mccain.senate.gov/public/index.cfm/press-releases?ID=587F2A2D-8A47-48F7-9045-CF30F0A77889.

H3: Opinion Stability and American Identity High American identifiersin Wave 2 will hold similar ban attitudes in Wave 3.

Panel Data and Analysis

The three-wave panel dataset was constructed as follows: the first wave interviewed respondents between January 24 and 27, 2017, in the days before the president signed the executive order. The same respondents were re-interviewed February 2–8, 2017, 5 days after the EO announcement. From January 8 to 14, 2018, we fielded a third wave and managed to secure 58% of wave 2 respondents, resulting in a fairly high response rate over a one-year span. [6] The panel consists of U.S. respondents aged 18 and older.[7] The data is unique in that it enables us to reliably compare within-subject shifts in attitudes from time 1 (T1), to time 2 (T2), and to time 3 (T3). We find no substantively significant demographic differences across waves 1 and 3, and across waves 2 and 3, indicating that attrition was largely random and not systematically related to ban attitudes (see Tables 4 and 5 in Appendix 2).[8]

While the dataset enables us to assess within-subject opinion change and stability over a span of one year, it is not a representative probability sample and thus does not extrapolate to the full U.S. adult population. As is illustrated in Appendix 2 Table 9, there are some differences between the MTurk sample and a representative sample from the 2016 Cooperative Congressional Election Study (CCES)[9] and the 2017 Current Population Survey (CPS).[10] These trends are in line with what others have found, particularly with respect to race, age, and education (Huff and Tingley 2015; Mullinix et al. 2015; Levay et al. 2016). As such, we augment the main analysis by weighting the data to CCES and CPS proportions for age, sex, education, race, and party identification, and re-estimating all of the models. Appendix 2 Table 15 presents the weighted findings and shows that the core results remain unchanged.[11]

The dataset contains three specific questions about President Trump's most debated executive orders. Respondents were asked the following question, which serves as the primary outcome variable: "President Trump's executive order

6 After matching respondents based on MTurk IDs and conducting data quality checks, the final dataset consists of $n = 422$ Wave 1, $n = 280$ Wave 2, and $n = 161$ Wave 3 respondents.

7 Variable summary statistics are provided in Appendix 2 Tables 6, 7, and 8 .

8 As an additional robustness check, we imputed the data using a $m = 5$ chained dataset, based on education, age, income, party identification, race, gender, and Trump approval. That is, we imputed the full (three wave) dataset for all wave 1 respondents and then again for just wave 2 and wave 3 respondents. In both imputed datasets, presented in Appendix 2 Table 13, mean ban attitudes shifted from wave 1 to wave 2, but not from wave 2 to wave 3. These results are substantively similar to the main findings detailed below.

9 https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910/DVN/GDF6Z0.

10 https://www.census.gov/cps/data/cpstablecreator.html.

11 We are also sensitive to the fact that MTurk respondents may be particularly aware of the news and more likely to be exposed to the Muslim ban backlash compared to the general population. If overly attentive respondents bias our results, those who reportedly watched the protests in wave 2 possibly gave different ban attitude responses than those who reported not watching the protests (presumably less attentive people). We tested this by conducting a χ^2 test between wave 2 ban attitude and "watched demon-

restricting immigration from Syria, Iran, Iraq, Libya, Yemen, Somalia, and Sudan—do you strongly agree (5), somewhat agree (4), neither agree nor disagree (3), somewhat disagree (2) or strongly disagree with this order (1)?"[12] Respondents were also asked about the Dakota Access Keystone pipeline and the Mexico border wall executive orders, which serve as placebo tests in the ensuing analyses.[13] Table 1 presents the outcome variable's distribution across all three wave. In general, middle responses (neither agree nor disagree) decline from wave 1 (14%) to wave 2 (8%) and hold in wave 3 (9%), and strongly disagree responses rise from wave 1 (30%) to wave 2 (41%) and hold in wave 3 (39%). Strongly agree responses also drop from wave 1 (29%) to wave 2 (23%) and to wave 3 (20%). While the survey did not include a "don't know" option in order to minimize satisficing (Krosnick 1991, 1999),[14] we note that movement out of the "neither" category from wave 1 to wave 2 matches similar movement out of the "don't know" option reported by two Quinnipiac Polls reported on January 12, 2017 (10% don't know) and February 7, 2017 (6% don't know), respectively.[15]

The key explanatory variable to test hypothesis 3 is American identity, which is defined as a subjective or internalized sense of belonging to the nation. National identity is a construct that emphasizes the importance of one's nationality in defining one's identity and the very basic idea that one can belong to a national 'us' (Gustavsson 2017). American identity is thus related to a sense of 'being' or 'feeling American' (Citrin et al. 2001; Huddy 2001; Huddy and Khatib 2007; Huddy 2015). Our measure of American identity consists of an additive scale of four items, with

Footnote 11 (continued)

strations" (1 = yes, 0 = no). We find no evidence of a statistically significant difference in wave 2 ban attitudes between the two groups (χ^2 =1.8, df = 4, p = 0.771), or even between the two variables when we subset to just respondents who completed the wave 2 survey (χ^2 = 2.6, df = 4, p = 0.617). This provides some evidence that an overly news attentive sample is not biasing our findings. We also located a 2016 probability-based representative Pew Research Center survey that asked questions about local news and national news consumption. We downloaded the data and calculated the percentage of respondents who reported watching television news. About 81% of respondents said they watched news, which is very similar to the percentage of our wave 2 respondents who reported watching local or national television news (78%). Thus, external evidence suggests our sample is not biased in the form of greater news consumption relative to the adult U.S. population. We provide greater discussion of the Pew sample in "Appendix 1".

[12] Due to the administration's executive order ban changes, the wave 3 ban question read: "President Trump's executive order restricting immigration from Syria, Iran, Libya, Yemen, Somalia, and Chad—do you strongly agree (5), somewhat agree (4), neither agree nor disagree (3), somewhat disagree (2) or strongly disagree with this order (1)?" These changes are minor, and given citizens' low state of political knowledge, are unlikely to produce attitudinal effects due to question wording alone (Schuman and Presser 1996).

[13] Question wording of all the variables used in the analyses is presented in "Appendix 1".

[14] Krosnick et al. (2002) examine whether no-opinion options (e.g. "don't know") may discourage some respondents from cognitively engaging in work necessary to report the true opinions they do have. They find that the inclusion of no-opinion options may not enhance data quality and instead may preclude measurement of some meaningful opinions. This is particularly applicable in a context where online survey respondents may be motivated by speed and might not deeply engage with the survey questions when "don't know" options are present. Based on this line of research, we precluded no-opinion options.

[15] https://www.washingtonpost.com/blogs/plum-line/wp/2017/02/07/a-new-poll-shows-a-surprisingly-big-public-swing-against-trumps-muslim-ban/?utm_term=.9d1ee0984a47.

Table 1 Distribution of the outcome variable across waves

	Str. disagree	Smw. disagree	Neither	Smw. agree	Str. agree	Total
Wave 1 prop.	0.30	0.14	0.14	0.14	0.29	1.00
N	122	59	56	56	118	411
Wave 2 prop.	0.41	0.11	0.08	0.16	0.23	1.00
N	116	30	23	46	65	280
Wave 3 prop.	0.39	0.13	0.09	0.19	0.20	1.00
N	63	21	14	31	32	161

President Trump's executive order restricting immigration from Syria, Iran, Libya, Yemen, Somalia, and Chad—do you strongly agree (5), somewhat agree (4), neither agree nor disagree (3), somewhat disagree (2) or strongly disagree with this order (1)?"

values ranging from 4 to 20. The scale is internally valid, with a Cronbach's alpha reliability coefficient of 0.90.

In order to evaluate the presence or absence of opinion stability one year after the EO was announced, we also account for the same control variables used in the initial study by Collingwood et al. (2018).[16] These variables include: partisanship, dummies for race, gender, age, income, education, Trump approval rating in T1, and a Muslim affect scale also in T1.[17] We employ ordinary least squares (OLS) regression to assess our last hypothesis. Given the ordinal nature of our travel ban wording, we also estimate the models with an ordered logistic regression. Results are presented in Appendix 2 Table 12, and are consistent with the OLS findings.

To begin, we compare ban attitudes in T1, T2, and T3. This initial statistical test evaluates the competing "regression to the mean" (H1) versus "opinion stability" (H2) hypotheses. Table 2 shows clear support for the opinion stability hypothesis. The mean ban attitude in wave 1 (on a 1–5 scale) is 2.97. However, the wave 2 mean decreased to 2.69, a statistically significant drop ($p < 0.05$), indicating increased opposition to the ban. Wave 3 attitudes ($\mu = 2.68$), measured one year later, are essentially unchanged from wave 2. Our initial test thus supports the hypothesis that ban attitudes, once shifted, remained fairly stable.[18]

[16] We excluded a dummy variable for Trump vote from the three-wave regression analysis due to a high number of missing cases. However, we do include a Trump favorability variable, which is highly correlated with Trump vote at 0.831.

[17] For more details refer to "Appendix 1".

[18] A concern is that our respondents vary in how much attention they pay to the survey, and that this might impact the reliability of our results. One way to test this possibility is to examine whether answers to factual questions about the political environment correlate with how long it takes the respondent to complete the survey. Respondents who take the survey more quickly may be giving random responses and thus may be more likely to get the factual questions incorrect. We test this possibility by correlating political knowledge with survey time completion. First, political knowledge is completely uncorrelated with length of survey completion. Second, respondents who took longer to answer the survey (above the mean length) were no different in political knowledge than those who did not take as long (below the mean length), as measured by a chi-square test. We find similar results between reported Wave 1 Muslim ban attitudes and survey length ($\chi^2 = 5.66$, $p = 0.22$); Wave 2 Muslim ban attitudes and survey length ($\chi^2 = 4.373$, $p = 0.348$); Wave 3 Muslim ban attitudes and survey length ($\chi^2 = 3.09$, $p = 0.541$).

Table 2 Difference of means T-tests of ban attitudes between T1, T2, and T3

	Mean	Mean	t-stat	p-value
Wave 1 v. Wave 2	2.97	2.69	2.20	0.03
Wave 1 v. Wave 3	2.97	2.68	1.98	0.05
Wave 2 v. Wave 3	2.69	2.68	0.10	0.92

One possible explanation for the observed shift and subsequent durability of ban attitudes is that evaluations toward President Trump became more negative during his first year in office. If this is the case, we might find that ban attitudes are shifting alongside the two other major EOs announced around the same time as the "Muslim ban." To assess this possibility, we examined attitudes between T1 and T3 on the Keystone pipeline and the Mexico border wall EOs. Appendix 2 Table 14 presents the t-test comparisons and demonstrates no statistically significant movement on these other issues over the last year (Keystone, $t = -0.755$, p-value = 0.451; Mexico border wall, $t = 1.124$, p-value = 0.262).[19] Thus, this long-lasting within-subject opposition to the ban is likely not attributable to a general dissatisfaction with President Trump, but rather due to the information environment portraying the policy at odds with core American values.

Lastly, we evaluate hypothesis 3 to examine whether high American identifiers continued to remain relatively less supportive of the ban from T2 to T3. Appendix 2 Table 10 reports three separate identically specified OLS regression models from the three waves. Row 1 shows that the American identity coefficient moves from 0.052 (T1) to 0.021 (T2) to 0.037 (T3). While the coefficient in T3 does increase somewhat, the slope change is primarily due to low American identifiers slightly shifting more so against the ban one year later. For ease of interpretation, Fig. 6 presents Monte Carlo simulations predicting ban attitudes among low American identity respondents compared to high American identity respondents for all three waves. As illustrated, high American identifiers' ban attitudes in T2 and T3 are nearly identical, and less supportive of the travel ban than in T1. Thus, these findings provide support for hypothesis 3. We should note that while high American identifiers appear to have shifted against the ban, they are still less likely than low identifiers to display opposition for the EO, which is consistent with previous research on the relationship between American identity and restrictive policy preferences toward ethnic, racial or cultural minorities (Citrin et al. 1990; Espenshade and Calhoun 1993; Frendreis and Tatalovich 1997; Huddy and Sears 1995; Schildkraut 2003).

Since our findings rest on the argument that individuals responded to the changing information environment between wave 1 and wave 2, we provide an additional set of robustness checks. We conducted two separate analyses where we: (1) subset our data to respondents who reported in wave 2 that they watched television or consumed print media since January, 27, 2017 (the day the EO was announced), and (2)

[19] Support for the border wall appears to have dropped somewhat, but the difference is not statistically significant. That said, to the extent the drop may be realized with a larger dataset, the change is sensible given the continued discussion and criticism of the border wall throughout the year.

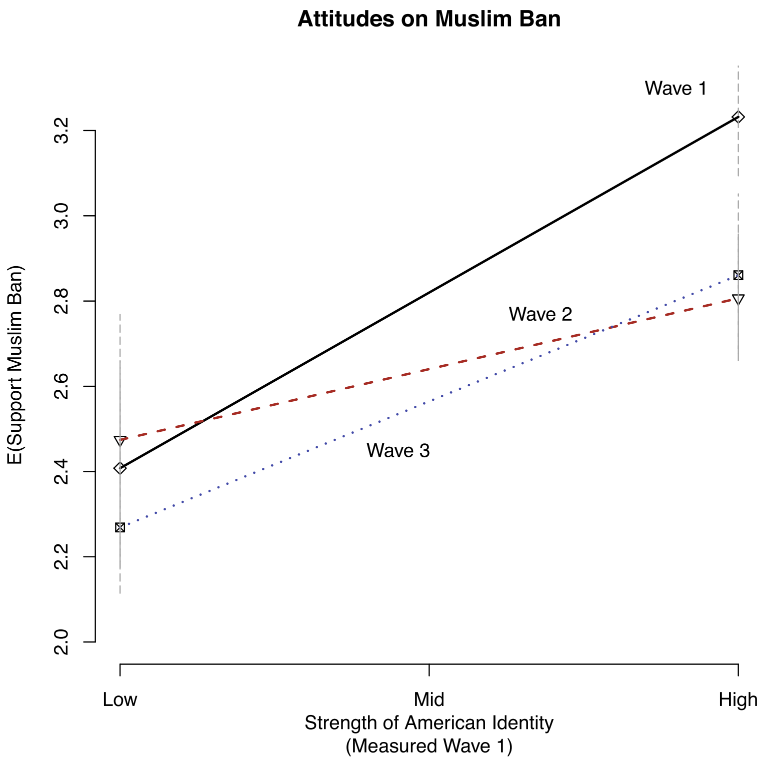

Fig. 6 Strength of American identity and attitudes toward the "Muslim Ban." Expected values with 90% confidence bands based on OLS models in Appendix 2 Table 10

people who reported watching demonstrations and protests on television or the internet against the travel ban.[20] Both analyses assume that respondents fitting these criteria are disproportionately likely to have received the media messages characterized by calls to American identity and anti-ban, as discussed above. If the general findings hold among this subset, we can have greater confidence that media effects are activating how individual-level American identity relates to Muslim ban attitudes, as opposed to some statistical anomaly. Appendix 2 Table 11 presents findings of these subset models, which are consistent with our main findings.

Given the well-documented and continued partisan divide (Mason 2013; Klar 2013, 2014), one concern may be that the observed American identity effects on ban support are conflated with partisanship. That is, because citizens take cues from political elites (Zaller 1992; Gilens and Murakawa 2002; Levendusky 2010; Lenz 2013), a plausible alternative explanation is that Republican identifiers shifted in the

[20] We are cognizant that self-reported media consumption may be subject to social desirability. We note here again that our share of respondents reporting they watched local or national news is about 78%, whereas the comparable number from Pew is 81%. This provides added confidence that our respondents are answering truthfully.

direction of pro-ban (following their GOP president), and that Democrats shifted in the opposite direction (following the positioning of Democratic elites). If the former is the case, we should expect to see Republican identifiers shifting in a pro-ban direction from wave 2 to wave 3 and Democrats the reverse. We test this possibility below and find no support for a partisan polarization explanation of ban attitude change.

Before delving deeper into this analysis, it is imperative to distinguish American identity from partisanship to justify the expectation that appeals to American identity in the context of the ban should operate in a separate conceptual space than should partisan cues and appeals. American identity, unlike patriotism, is not tinged with political ideology (Huddy and Khatib 2007), which is closely linked to party identification. Thus, feelings of closeness or pride in one's country and its symbols (Ashmore et al. 2001) can be held by citizens from all partisan stripes. In the data, the correlation between American identity and party identification is .20, .18, and .19 in the three waves, respectively. This indicates that American identity and party attachment are not the same construct.

Figure 7 further reveals that while Republicans score the highest on American identity, both Independents and Democrats also skew towards the right side of the American identity scale. Importantly, this relationship holds across survey waves. That is, the bivariate American identity and partisan distribution does not change as respondents drop out of the data from wave 1 to wave 3. Additionally, the coefficients for the party identification variables presented in Appendix 2 Table 10 do not change considerably across the three waves, which suggests that the observed attitudinal change is not driven by Democrats or Republicans shifting in different directions.[21]

To provide further verification that attitude change is not driven by partisan polarization in response to the executive order and subsequent protests, we conducted post-estimation simulations similar to those presented in Fig. 6. However, this time we simulated different values of partisanship and its effects on reported support for the "Muslim ban" by survey wave. The results presented in Fig. 8 provide clear support for our argument that attitude change is driven by American identity and not by partisan polarization. The plot reveals that between waves 1 and 2, both Republicans and Democrats dropped in support of the ban at fairly similar levels. If attitude change was being driven primarily by partisanship we would then observe one party's ban support drop further than the other, or one party becoming more supportive of the ban, and the other less so. Overall, this figure demonstrates an intercept drop across party rather than a party polarization effect. The plot also reveals that the simulated outcomes for Democrats and Republicans in wave 3 are virtually no different than those reported in wave 2. Together, the evidence suggests that the observed attitude change is not driven by party identification—that is, primarily Democrats becoming anti-ban after Wave 1.

We also assessed the possibility that attitude change is driven by partisan elites cuing the public. Stories during the aftermath of the ban roll-out suggested Republican elites might be presenting the public with mixed policy cues. For instance, an

[21] One may observe that the Republican coefficient slightly increases from wave 1 to wave 2, but this is due to a comparison of a slightly larger drop in ban support among independents (the comparison group).

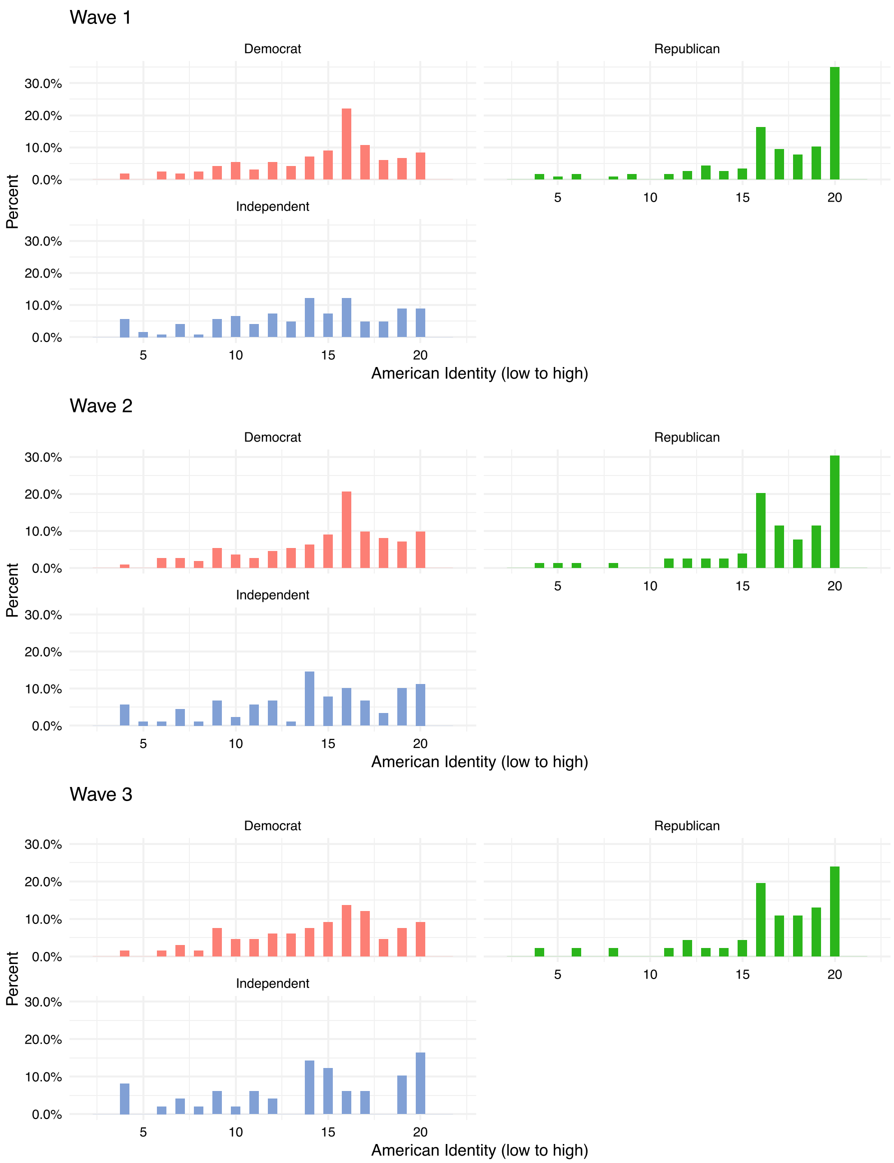

Fig. 7 Distribution of American identity by party identification across survey waves

article published in *Vanity Fair* on January 30, 2017, entitled, "Republicans Break with Trump as Backlash Over "Muslim Ban" Grows," discussed Republican elite polarization on the issue.[22] Meanwhile Democratic elites stood firmly in opposition

[22] https://www.vanityfair.com/news/2017/01/republicans-trump-muslim-ban.

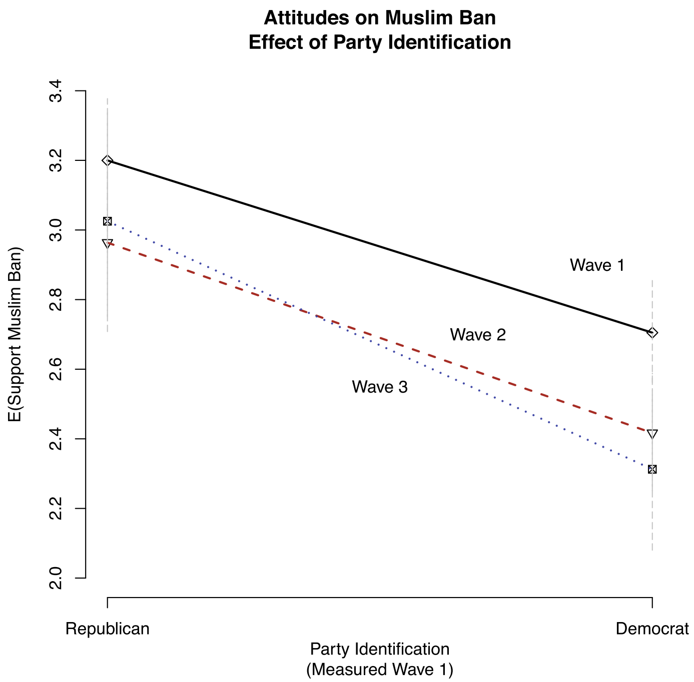

Fig. 8 Party identification and attitudes toward the "Muslim Ban." Expected values with 90% confidence bands based on OLS models in Appendix Table 10

to the ban. One way to assess this alternative explanation is to examine ban attitude standard deviations shifts among high attention respondents from wave 1 to wave 2.

Table 3 reports ban attitude standard deviations for "high attention" and college educated respondents across wave 1 and wave 2.[23] Row 1 reports results among Republicans; row 2 reports results among Democrats. Using either news attention or education as our proxy for "attentiveness," Republicans' ban attitude standard deviation grew larger from wave 1 to wave 2, whereas Democrats' ban attitude standard deviation declined. This is suggestive of a partisan cue story consistent with plausible elite behavior (i.e., Democratic coalescence, and GOP mixed cues).

Nonetheless, we offer reasoning that provides stronger support for an American identity account rather than a partisan or partisan cues account. First, due to sample limitations, our wave 1 survey included only 73 four-year college plus respondents. Cell sizes for college educated Democrats and Republicans are relatively small, so

[23] Our wave 2, but not wave 1, survey included measures of attention to news. We asked respondents if they "watched local or national television news" (1 = No, I have not done that, 2 = Yes, once or twice, 3 = Yes, several times), and whether they "read print or digital news stories" (1 = No, I have not done that, 2 = Yes, once or twice, 3 = Yes, several times). We combined answers to the two questions, then divided them into high attention (5 or 6 on the scale) and lower attention on the scale (2–4). It is possible that the protests stimulated citizens' interest in the news and so this is not such a great baseline political attention measure. To attempt to compensate for this, we proxy for attention with education measured in wave 1.

Table 3 Muslim ban standard deviations across waves for "high attention" and college educated citizens

	Attention W1 SD	Attention W2 SD	Att diff	College W1 SD	College W2 SD	College diff
1	0.84 (62)	1.25 (62)	0.40	0.81 (20)	1.27 (17)	0.46
2	1.12 (73)	1.01 (73)	− 0.10	1.06 (31)	0.75 (25)	− 0.31

Row 1 reports results for Republican identifiers; row 2 reports results for Democratic identifiers. Cell sample size is reported in parentheses

we caution over-interpretation. Second, just because we observe attitude movement potentially consistent with a partisan cues story does not mean that citizens are shifting due to partisan elites conveying information. Just as plausibly—or in consonance with elite partisan cues—activists, protesters, and heightened media attention could drive these observed partisan trends. In other words, appeals to American identity and media coverage of protests could drive high American identity Democrats to shift in a more anti-ban direction (in line with the Democratic base), thereby reducing Democrats' ban attitude standard deviation. At the same time, appeals to American identity conveyed in protests and in media discourse (i.e., the information environment) could also drive high American identifying Republicans (and independents) toward an anti-ban direction, which would widen Republicans' ban attitude standard deviation (away from the Republican base).

Figure 9 provide suggestive evidence that a mixed partisan cues argument is less plausible than a protest/American identity explanation. Using the same newspaper corpus that generated Fig. 4, we searched for weekly terms appearing in our corpus related to six themes: (1) Democrats; (2) Republicans; (3) Trump; (4) Protests; (5) Mixed GOP elite cues, (6) Democratic leader cues, and (7) American identity.[24] We focus on the first 3 months of 2017 because that is where the bulk of the articles reside to enable weekly measurement, and because that is where we can most clearly compare a mixed-cues argument (Trump vs. McCain/Graham) against a protest (that activated American identity) argument.

Figure 9 presents a count of the number of times each theme appears during the week. The ban was first initiated at the end of week 4. Comparatively then, week 5 was the most media intense period in the time series, where mentions of Trump dominate everything else. One noteworthy point to highlight is that the only other themes that surpass 500 references are American identity and/or protests and airports. In stark contrast, the discussion of the Lindsey Graham and John McCain joint statement is minimally covered, and is completely dwarfed by general references to the Republican and Democrat themes. Overall, this analysis suggests that protests and discussion about airports and issues related to American identity played a more consequential role in the media landscape during the critical opinion change time period.

[24] Search terms: (1) democrat, democrats; (2) republican, republicans; (3) trump; (4) protest, protesters, protests, airport, airports; (5) graham, mccain; (6) schumer, pelosi; (7) American, unamerican, un-american, core values, religious freedom, religious test, liberty, violation, nation of immigrants.

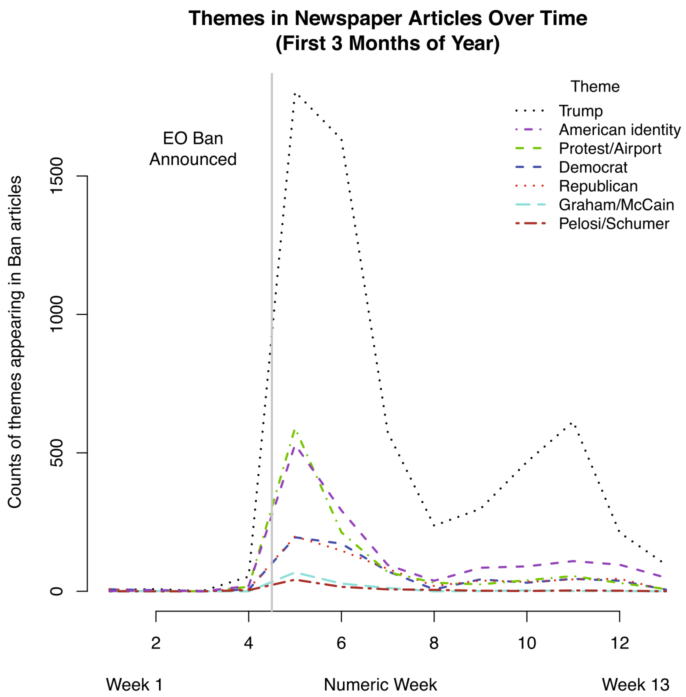

Fig. 9 Newspaper coverage of the Muslim Ban/Travel Ban

Discussion and Conclusion

The results presented in this article provide a roadmap for examining the impact of significant real-world events on policy attitudes. While prior research has demonstrated the utility of various cues and treatments in altering mass attitudes toward different issues and groups, only a few studies have assessed the durability of such attitudinal changes (Christenson and Glick 2015a, b; Broockman and Kalla 2016). We complement this literature and use a three-wave panel study to demonstrate that the enactment of the "Muslim ban" is one instance in which individual-level opinions shifted rapidly (within 5 days), and remained fairly stable up to nearly one year later. Absent stimulating and powerful exogenous shocks to the information environment, it is unlikely that individuals who oppose the ban will, once again, shift back and support it.

Several important takeaways for the public opinion literature can be gleaned from our study. First, we highlight the strength of timely panel datasets in capturing rapid within-subject public opinion shifts as real-world events unfold. The public opinion literature contends that attitudes are either unstable, unreliable, and unstructured (Zaller 1992; Converse 1964) or that aggregate public opinion is generally stable (Page and Shapiro 2010). However, we suggest that attitudes toward a variety of non-crystallized topics may be undergoing constant shifts as issues move in and out of the news cycle, attracting varying degrees of attention, and that these fluctuations are a reasonable response to significant events. Intermittent cross-sectional data may not reliably capture such fluctuations and may fail to account for specific, real-world events that may durably alter attitudes.

The processes of opinion change and stability outlined in our study may also inform scholars interested in developing, refining, and testing theories about the impact of political communication on policy attitudes related to a host of issues ranging from immigration to criminal justice reform, gun control, and border security. Importantly, we note that it is not simply enough for exogenous shocks or significant events to increase the importance or salience of an issue. Rather, for meaningful attitudinal change to take place, citizens need to be confronted by fairly significant, one-sided political communication. When contending sides on a given issue can easily and convincingly interpret and communicate events in ways beneficial to their position, citizens may rely on their underlying predispositions and fail to update their priors with new considerations.

Finally, the findings presented herein go beyond an illustration of how changes to the information environment can alter citizens' policy preferences. We demonstrate that previously held policy attitudes toward even *Muslims*, a stigmatized group, suddenly and durably shifted due to fairly one-sided political communication that highlighted the incompatibility of the "Muslim ban" EO with egalitarian principles of American values and notions of religious liberty. Considering that citizens are often psychologically motivated to maintain and support their existing evaluations even in the face of disconfirming information (Redlawsk 2002), the fact that Muslims are one of the most disliked and distrusted groups in American politics (Kalkan et al. 2009; Lajevardi and Oskooii 2018), and the state of partisan polarization, capturing long-lasting attitude change against Trump's "Muslim ban" is noteworthy. It offers some hope that citizens are still open to considering new evaluative criteria that may challenge their priors, even those high American identifiers who tend to support policies that adversely impact ethnic, racial or cultural minorities.

Certainly, our research is not without limitations. First, our panel dataset is not representative of the national population, which restricts our ability to generalize the findings to the country, writ large. This limitation is counterbalanced by the panel's high degree of within-subject internal validity and additional analyses with the data weighted to different population benchmarks. Second, our sample size is relatively small, making it hard to conduct discrete subgroup analysis. Third, our design does not randomly assign respondents to a treatment condition. Instead, we use time to proxy treatment. This limitation is primarily an issue for precisely estimating the size of the treatment effect, not for making a type I error. Fourth, we cannot precisely detect the information stimulus that is responsible for ban attitudes to change. Future research could potentially account for this limitation by developing a controlled experiment that attempts to separate out the different aspects of the treatment.

Despite these limitations, we provide compelling evidence in favor of the opinion stability account that is robust to alternative explanations and model specifications. We demonstrate that respondents in our sample are not more likely than the rest of the population to have consumed news media about the protests and demonstrations. Additional analyses also suggest that the observed relationship between American identity and ban support are not conflated with partisanship. As such, our study provides compelling evidence of rapid attitudinal change and stability toward the "Muslim ban" with important implications for the literature. Most prominently, our findings imply that one-sided political communication that resonate with citizens can play an important role in altering policy attitudes. Furthermore, our research suggests that timely, easy to implement, and cost-efficient online panels can be beneficial to public opinion scholars interested in examining and explaining long-term temporal variations in individual attitudes before and after exogenous shock to the information environment.

Acknowledgements We would like to thank the past and current editorial team of Political Behavior and the three anonymous reviewers for their helpful feedback and suggestions. Special thanks is also extended to Erin Cassese, Seulgi Lee, Charles Mills, Emily Tohma, Ali Valenzuela, and participants at the UCSD PRIEC, UCR Mass Behavior Brown Bag Series, Princeton Center for the Study of Democratic Politics workshop, and APSA panel on the racialization of Islam and Muslims.

Appendix 1

Survey Question Wording

- DV: President Trump's executive order restricting immigration from Syria, Iran, Iraq, Libya, Yemen, Somalia, and Sudan (wave 2: Syria, Iran, Libya, Yemen, Somalia, and Chad). Strongly disagree (1); Somewhat disagree (2); Neither agree nor disagree (3); Somewhat agree (4); Strongly agree (5).
- President Trump's executive order allowing for the Keystone and Dakota Access Pipelines. Strongly disagree (1); Somewhat disagree (2); Neither agree nor disagree (3); Somewhat agree (4); Strongly agree (5).
- President Trump's executive order to build a wall on the southern border. Strongly disagree (1); Somewhat disagree (2); Neither agree nor disagree (3); Somewhat agree (4); Strongly agree (5).
- Income: What is your family's annual income? Under $20,000 a year (1); Between $20,000 and $40,000 a year (2); Between $40,000 and $60,000 a year (3); Between $60,000 and $80,000 a year (4); Between $80,000 and $120,000 a year (5); Over $120,000 a year (6). $60K or less = 1; else = 0.
- Education: What is the highest level of education you have completed? No High School Degree (1); High School Degree (2); Some College (3); 2-Year College Degree (4); 4-Year College Degree (5); Post Graduate Degree (6). Some College or less = 1; else = 0.
- Which political party do you most align with? (1 = Democrat; else = 0; 1 = Republican; else = 0; Independent/other = base category)
- American Identity (additive scale): To what extent do you agree or disagree with the following statements—strongly disagree (1), somewhat disagree (2), neither agree nor disagree (3), somewhat agree (4), or strongly agree (5)? The scale runs from 4 (no American identity) to 20 (high American identity):
  - My American identity is an important part of my "self."
  - Being an American is an important part of how I see myself.

  - I see myself as a typical American person.
  - I am proud to be an American.

- The Muslim affect scale, developed in Lajevardi (2017) and tested extensively in Lajevardi and Abrajano (2018), consists of nine questions that scale at an alpha of 0.91: with respect to Muslim Americans, how much do you agree or disagree with the following statements—strongly disagree, somewhat disagree, neither agree nor disagree, somewhat agree, strongly agree? (statements (re)coded so that high values indicate positive affect)

  - Muslim Americans integrate successfully into American culture.
  - Muslim Americans sometimes do not have the best interests of Americans at heart.
  - Muslims living in the US should be subject to more surveillance than others.
  - Muslim Americans, in general, tend to be more violent than other people.
  - Most Muslim Americans reject jihad and violence.
  - Most Muslim Americans lack basic English language skills.
  - Most Muslim Americans are not terrorists.
  - Wearing headscarves should be banned in all public places.
  - Muslim Americans do a good job of speaking out against Islamic terrorism.

- Age: In what year were you born (2016—answer)
- Female: What is your gender? Male (0) or Female (1)
- White: What racial group best describes you? White (1), else = 0.
- Do you approve of the way President Trump's is handling his job as President? 1 = Approve, else = 0.

2016 Pew Research Center's American Trends Panel Wave 14

Pew fielded a survey from January 12 to February 8, 2016. The survey is a mixed mode national, probability-based panel of adults in the United States. The survey sample size is 4654 (4339 by web and 315 by mail), with a margin of error of ± 1.95 percentage points. The data come with survey weights that account for differential probabilities of selection into the panel as well as issues related to non-response. Survey weights were used to calculate the reported percentages. The three questions we used are posted below:

And how often do you...

- Watch local television news?

  - Often (1)
  - Sometimes (2)
  - Hardly ever (3)
  - Never (4)

- Watch national evening network television news (such as ABC World News, CBS Evening News, or NBC Nightly News)?

- Often (1)
- Sometimes (2)
- Hardly ever (3)
- Never (4)

- Watch cable television news (such as CNN, The Fox News cable channel, or MSNBC)?
    - Often (1)
    - Sometimes (2)
    - Hardly ever (3)
    - Never (4)

Appendix 2

See Tables 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 and 15.

Table 4 Wave 1 to Wave 3 balance table

	Wave 1	Wave 3	T-Stat	P-value
White	0.82	0.82	− 0.02	0.98
Female	0.47	0.47	0.01	0.99
Age	38.73	41.96	− 2.63	0.01
Education	0.83	0.80	0.87	0.39
Income	0.60	0.59	0.15	0.88
Party ID	2.12	2.12	0.01	0.99
Trump approval	0.45	0.40	0.94	0.35
American identity	14.98	14.86	0.30	0.77

Demographic difference of mean comparisons across respondents

Table 5 Wave 2 to Wave 3 balance table

	Wave 2	Wave 3	T-Stat	P-value
White	0.82	0.82	0.04	0.97
Female	0.45	0.47	− 0.25	0.80
Age	39.92	41.96	− 1.56	0.12
Education	0.81	0.80	0.40	0.69
Income	0.57	0.59	− 0.31	0.76
Party ID	2.12	2.12	− 0.08	0.94
Trump approval	0.44	0.40	0.80	0.42
American identity	15.13	14.86	0.64	0.52
Watched demonstrations	0.80	0.76	1.11	0.27

Demographic difference of mean comparisons across respondents

Table 6 Summary statistics, Wave 1

	Minimum	Maximum	Mean	Median	Std. Dev
Muslim ban	1	5	2.97	3.00	1.62
American identity	4	20	14.98	16.00	4.20
Some college or less	0	1	0.83	1.00	0.38
Income less than $60	0	1	0.60	1.00	0.49
Democrat	0	1	0.40	0.00	0.49
Republican	0	1	0.28	0.00	0.45
White	0	1	0.82	1.00	0.39
Female	0	1	0.47	0.00	0.50
Age	18	82	38.73	36.00	13.11
Trump approval	0	1	0.45	0.00	0.50
Muslim scale	9	45	33.31	35.00	8.42

Table 7 Summary statistics, Wave 2

	Minimum	Maximum	Mean	Median	Std. Dev
Muslim ban	1	5	2.69	2.00	1.67
American identity	4	20	15.13	16.00	4.18
Some college or less	0	1	0.81	1.00	0.39
Income less than $60	0	1	0.57	1.00	0.50
Democrat	0	1	0.40	0.00	0.49
Republican	0	1	0.28	0.00	0.45
White	0	1	0.82	1.00	0.38
Female	0	1	0.45	0.00	0.50
Age	18	82	39.92	37.00	13.06
Trump approval	0	1	0.44	0.00	0.50
Muslim scale	9	45	33.77	35.00	8.18

Table 8 Summary statistics, Wave 3

	Minimum	Maximum	Mean	Median	Std. Dev
Muslim ban	1.00	5.00	2.68	2.00	1.61
American identity	4.00	20.00	14.86	16.00	4.34
Some college or less	0.00	1.00	0.80	1.00	0.40
Income less than $60	0.00	1.00	0.59	1.00	0.49
Democrat	0.00	1.00	0.41	0.00	0.49
Republican	0.00	1.00	0.29	0.00	0.45
White	0.00	1.00	0.82	1.00	0.39
Female	0.00	1.00	0.47	0.00	0.50
Age	21.00	82.00	41.96	39.00	13.32
Trump approval	0.00	1.00	0.40	0.00	0.49
Muslim scale	9.00	45.00	34.22	35.00	8.34

Table 9 Comparison of unweighted Mechanical Turk (MTurk), Cooperative Congressional Elections Survey 2016 (CCES), and Current Population Survey 2017 (CPS) data

Demographic	MTURK	CCES '16	CPS '17	MTurk-CCES	MTURK-CPS
Gender					
Male	54.14	48.00	49.00	− 6.14	− 5.14
Female	45.86	52.00	51.00	6.14	5.14
Race					
Non-White	15.75	28.00	39.00	12.25	23.25
White	84.25	72.00	61.00	− 12.25	− 23.25
Education					
College plus	16.85	26.00	24.20	9.15	7.35
Some college or less	83.15	74.00	75.80	− 9.15	− 7.35
Age					
18–35	46.69	31.00	31.60	− 15.69	− 15.09
36–50	31.49	23.00	24.60	− 8.49	− 6.89
51+	21.82	46.00	43.80	24.18	21.98
Party					
Rep	30.19	32.00		1.81	
Ind	26.87	33.00		6.13	
Dem	42.94	35.00		− 7.94	

Table 10 Predictors of Muslim ban attitudes (OLS)

	Dependent variable: strongly disagree–strongly agree		
	Ban attitude	Ban attitude	Ban attitude
	Wave 1	Wave 2	Wave 3
	(1)	(2)	(3)
American identity Wave 1	0.052***	0.021	0.037
	(0.013)	(0.015)	(0.019)
Some college or less	0.001	0.069	− 0.106
	(0.134)	(0.153)	(0.189)
Income less 60K	− 0.018	0.010	− 0.198
	(0.102)	(0.123)	(0.159)
Democrat	− 0.419***	− 0.416**	− 0.502*
	(0.121)	(0.149)	(0.197)
Republican	0.073	0.132	0.215
	(0.146)	(0.177)	(0.231)
White	− 0.197	0.166	0.086
	(0.126)	(0.157)	(0.200)
Female	0.017	− 0.033	0.111
	(0.096)	(0.117)	(0.150)
Age	0.008*	0.007	− 0.0001
	(0.004)	(0.005)	(0.006)
Trump approval Wave 1	1.363***	1.554***	1.142***
	(0.139)	(0.171)	(0.246)
Muslim Favorability Scale	− 0.065***	− 0.063***	− 0.072***
	(0.007)	(0.009)	(0.012)
Constant	3.783***	3.503***	4.361***
	(0.410)	(0.504)	(0.629)
Observations	402	275	157
R^2	0.671	0.685	0.702
Adjusted R^2	0.662	0.673	0.682
Residual Std. Error	0.943 (df = 391)	0.952 (df = 264)	0.913 (df = 146)
F statistic	79.694*** (df = 10; 391)	57.495*** (df = 10; 264)	34.404*** (df = 10; 146)

Standard errors in parentheses *p < 0.05; **p < 0.01; ***p < 0.001

Table 11 Predictors of Muslim ban attitudes (OLS) subset to those who read news or watched local or national news (Models 1:3) and those who reported watching demonstrations on TV or reading about them on the internet (Models 4:6)

	Dependent variable					
	Ban	Ban	Ban	Ban	Ban	Ban
	News W1	News W2	News W3	Watch Demon W1	Watch Demon W2	Watch Demon W3
	(1)	(2)	(3)	(4)	(5)	(6)
American identity Wave 1	0.043*	0.012	0.004	0.043**	0.009	0.035
	(0.018)	(0.019)	(0.026)	(0.016)	(0.016)	(0.022)
Some college or less	0.014	0.059	− 0.090	0.169	0.124	− 0.068
	(0.163)	(0.169)	(0.228)	(0.157)	(0.160)	(0.224)
Income less 60K	− 0.022	− 0.153	− 0.189	− 0.046	− 0.016	− 0.219
	(0.135)	(0.140)	(0.196)	(0.129)	(0.131)	(0.189)
Democrat	− 0.371*	− 0.391*	− 0.438	− 0.500**	− 0.470**	− 0.620*
	(0.177)	(0.184)	(0.254)	(0.156)	(0.159)	(0.237)
Republican	0.458*	0.223	0.389	0.496**	0.043	0.257
	(0.201)	(0.209)	(0.282)	(0.186)	(0.189)	(0.278)
White	− 0.556**	− 0.0002	− 0.307	− 0.192	0.067	0.176
	(0.186)	(0.193)	(0.255)	(0.171)	(0.174)	(0.252)
Female	0.007	− 0.187	0.140	− 0.094	− 0.176	0.019
	(0.131)	(0.136)	(0.184)	(0.124)	(0.126)	(0.186)
Age	0.008	0.010	0.001	0.007	0.007	0.003
	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)	(0.008)
Trump approval Wave 1	1.286***	1.747***	1.354***	1.171***	1.652***	0.822***
	(0.201)	(0.209)	(0.293)	(0.183)	(0.186)	(0.307)
Muslim Favorability Scale	− 0.060***	− 0.055***	− 0.069***	− 0.054***	− 0.060***	− 0.077***
	(0.010)	(0.011)	(0.015)	(0.010)	(0.010)	(0.014)

Table 11 (continued)

	Dependent variable					
	Ban	Ban	Ban	Ban	Ban	Ban
	News W1	News W2	News W3	Watch Demon W1	Watch Demon W2	Watch Demon W3
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	3.875***	3.287***	4.901***	3.450***	3.672***	4.525***
	(0.569)	(0.592)	(0.801)	(0.533)	(0.541)	(0.768)
Observations	179	179	99	221	221	119
R^2	0.731	0.741	0.743	0.696	0.713	0.685
Adjusted R^2	0.715	0.726	0.713	0.681	0.699	0.656
Residual Std. Error	0.856 (df = 168)	0.889 (df = 168)	0.883 (df = 88)	0.893 (df = 210)	0.907 (df = 210)	0.945 (df = 108)
F statistic	45.732*** (df = 10; 168)	48.103*** (df = 10; 168)	25.385*** (df = 10; 88)	48.006*** (df = 10; 210)	52.055*** (df = 10; 210)	23.529*** (df = 10; 108)

*p < 0.05; **p < 0.01; ***p < 0.001

Table 12 Predictors of Muslim ban attitudes (ordered logit)

	Dependent variable: strongly disagree–strongly agree		
	Ban attitude	Ban attitude	Ban attitude
	Wave 1	Wave 2	Wave 3
	(1)	(2)	(3)
American identity Wave 1	0.124***	0.046	0.090
	(0.030)	(0.038)	(0.046)
Some college or less	0.006	0.172	− 0.274
	(0.296)	(0.367)	(0.444)
Income less 60K	0.176	0.010	− 0.432
	(0.225)	(0.283)	(0.374)
Democrat	− 0.769**	− 0.841*	− 1.301**
	(0.256)	(0.336)	(0.462)
Republican	0.442	0.323	0.212
	(0.325)	(0.367)	(0.505)
White	− 0.353	0.569	0.419
	(0.279)	(0.386)	(0.486)
Female	− 0.004	− 0.157	0.132
	(0.215)	(0.272)	(0.353)
Age	0.019*	0.020	− 0.010
	(0.008)	(0.011)	(0.014)
Trump approval Wave 1	2.024***	2.272***	1.871***
	(0.304)	(0.376)	(0.519)
Muslim Favorability Scale	− 0.169***	− 0.161***	− 0.168***
	(0.020)	(0.024)	(0.031)
Cut 1	− 4.560***	− 3.652***	− 5.904***
	(0.999)	(1.223)	(1.615)
Cut 2	− 3.198**	− 2.594*	− 4.493**
	(0.981)	(1.210)	(1.570)
Cut 3	− 1.961*	− 1.794	− 3.630*
	(0.973)	(1.211)	(1.562)
Cut 4	− 0.618	0.012	− 1.734
	(0.973)	(1.219)	(1.568)
Observations	402	275	157
Log likelihood	− 410.5143	− 258.6502	− 149.6274
AIC	849.0285	545.3003	327.2548

Standard errors in parentheses *p < 0.05; **p < 0.01; ***p < 0.001

Table 13 Difference of means t-tests of ban attitudes between T1, T2, and T3

	Mean Diff	SD of Diff	T-Stat	P-value
Impute W1: Wave 1 v. Wave 2	0.28	1.01	4.66	0.00
Impute W1: Wave 1 v. Wave 3	0.19	1.08	2.93	0.00
Impute W1: Wave 2 v. Wave 3	− 0.09	1.15	− 1.36	0.18
Impute W2: Wave 1 v. Wave 2	0.24	1.34	3.69	0.00
Impute W2: Wave 1 v. Wave 3	0.18	1.44	2.58	0.02
Impute W2: Wave 2 v. Wave 3	− 0.06	1.90	− 0.64	0.54

Based off imputations from Wave 1 and Wave 2

Table 14 Placebo tests

	Mean Wave 1	Mean Wave 3	T-Stat	P-value
Placebo: keystone pipeline	2.56	2.68	− 0.76	0.45
Placebo: border wall	2.65	2.47	1.12	0.26

Keystone pipeline and Southern border wall attitudes. Difference of means t-tests (no statistically significant change from T1 to T3)

Table 15 Predictors of Muslim ban attitudes (generalized linear model maximum likelihood estimation), weighted to Cooperative Congressional Election Studies 2016 (CCES) and Current Population Survey (2017) demographics: age, sex, race, education, and party identification

	Dependent variable: strongly disagree–strongly agree					
	Ban	Ban	Ban	Ban	Ban	Ban
	CCES W1	CCES W2	CCES W3	CPS W1	CPS W2	CPS W3
	(1)	(2)	(3)	(4)	(5)	(6)
American identity Wave 1	0.057**	0.019	0.018	0.064***	0.011	0.013
	(0.018)	(0.021)	(0.018)	(0.018)	(0.021)	(0.019)
Some college or less	− 0.039	0.077	− 0.225	− 0.089	0.047	− 0.263
	(0.136)	(0.183)	(0.216)	(0.161)	(0.214)	(0.220)
Income less 60K	− 0.005	0.032	− 0.240	0.015	0.005	− 0.298
	(0.113)	(0.135)	(0.150)	(0.124)	(0.150)	(0.156)
Democrat	− 0.511***	− 0.488*	− 0.485*	− 0.479**	− 0.519*	− 0.427*
	(0.153)	(0.223)	(0.199)	(0.164)	(0.240)	(0.196)
Republican	0.157	0.103	0.483	0.145	0.115	0.440
	(0.172)	(0.201)	(0.260)	(0.185)	(0.224)	(0.281)
White	− 0.116	0.164	0.084	− 0.131	0.207	0.140
	(0.163)	(0.185)	(0.204)	(0.150)	(0.170)	(0.174)
Female	− 0.114	− 0.100	0.082	− 0.152	− 0.081	0.103
	(0.123)	(0.151)	(0.162)	(0.134)	(0.170)	(0.169)
Age	0.003	0.003	− 0.002	0.001	0.001	− 0.007
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)

Table 15 (continued)

	Dependent variable: strongly disagree–strongly agree					
	Ban	Ban	Ban	Ban	Ban	Ban
	CCES W1	CCES W2	CCES W3	CPS W1	CPS W2	CPS W3
	(1)	(2)	(3)	(4)	(5)	(6)
Trump approval Wave 1	1.333***	1.649***	1.084***	1.247***	1.496***	1.167***
	(0.188)	(0.271)	(0.284)	(0.196)	(0.299)	(0.296)
Muslim Favorability Scale	− 0.060***	− 0.059***	− 0.072***	− 0.065***	− 0.064***	− 0.074***
	(0.009)	(0.011)	(0.014)	(0.010)	(0.012)	(0.014)
Constant	3.781***	3.567***	4.811***	4.033***	4.012***	5.129***
	(0.529)	(0.590)	(0.828)	(0.595)	(0.683)	(0.829)
Observations	402	275	157	402	275	157
Log likelihood	− 586.269	− 411.261	− 220.421	− 609.186	− 434.024	− 223.202
Akaike Inf. Crit.	1194.537	844.523	462.842	1240.372	890.048	468.404

*p < 0.05; **p < 0.01; ***p < 0.001

Appendix 3: Media Content Analysis

Media Transcript Valence Content Analysis Description

All CNN, Fox News, and MSNBC broadcast transcripts from January 1 to December 31, 2017 were downloaded from Lexis-Nexis academic. However, the unit of analysis is the media segment, which typically lasts 5–10 min in a typical television program. Below we review our technical coding procedure for CNN. There were not enough FOX and MSNBC transcripts to accurately represent media coverage of the Muslim ban.

CNN Media Transcripts

In total, the CNN corpus consists of 40,287 segments. All transcript text were converted to lower case, then run through a filter based on whether the segment included at least one occurrence of the terms “Muslim ban” or “Travel ban.” In total, 3050 segments matched our criteria.

Within each segment, we further split the data based on a key word in context (KWIC) search on the term “Muslim,” to assess how anchors and guests talked about Muslims in specific. We selected 25 words on either side of the term “Muslim,” which we refer to as a *snippet*. The snippet is empirically large enough to content analyze how the word “Muslim” is used, and small enough to not conflate the utterance with other themes.

Next, we randomly sampled n = 1200 snippets from all “Muslim” snippets. Each snippet was then hand-coded for valence: anti-ban, balanced/informational, and pro-ban. Pro-ban snippets are those where the discussant advocates support for Trump’s

Muslim ban policy. Anti-ban snippets are the converse: the discussant criticizes the Muslim ban and advocates opposition to the policy. Balanced or informational segments do not express an opinion one way or the other, such as an anchor announcing a court decision, or include rare situations where the snippet is both pro and anti-ban.

For this specific analysis, three trained coders independently coded the same 300 snippets, reaching an inter-coder reliability of 0.92. The remaining 900 snippets were then divided evenly among the three coders. Upon completion of the snippet coding, daily valence scores were calculated based on the number of anti-ban, pro-ban, and informational (balanced) occurrences in all Muslim ban segments appearing on that day. We thus have three daily count measures of Muslim ban media valence across the full year time series. For example, on February 1, 2017, one of the most active days exhibited in Fig. 3, we observed 25 anti-ban snippets spread across the full day's programming, 40 balanced/informational snippets, and 7 pro-ban snippets.

FOX and MSNBC Media Transcripts

Unfortunately, both FOX News and MSNBC do not provide Lexis-Nexis with their full array of media segment transcripts over the time period studied. In our search with the exact same date criterion, we only managed to locate 2321 Fox News media segments, with just 370 segments matching the "Muslim ban"/"Travel Ban" filter criteria. MSNBC transcripts exhibit a similar pattern. We located just 1,627 MSNBC total segments from the Lexis Nexis broadcast transcripts database for the time period January 1, 2017–December 31, 2017. Of these, just 340 segments were about the "Muslim ban"/"Travel Ban." As with the CNN analysis, we further split both corpora by a KWIC search on the term "Muslim," selecting 25 words on either side of the the term. This resulted in n = 818 snippets referencing the term "Muslim" for FOX News and n = 802 for MSNBC. We coded all of these snippets using the same criteria we employed for CNN, resulting in three categories: anti-ban, balanced/informational, pro-ban. However, given the low sample size, we immediately noticed many repeat snippets. Due to this issue and the fact that both FOX and MSNBC transcripts were not routinely or systematically uploaded, we are unable to make any reliable valence-related inferences of the ban coverage throughout 2017.

Newspaper Valence Content Analysis Description

New York Times

To produce the *New York Times* (NYT) corpus, we interfaced with the NYT Application Programming Interface (API) "article search." Given the technicalities of the API, we submitted searches to download any article containing the phrase "Muslim ban" or "Travel ban" between January 1, 2017 and December 31, 2017. We combined the resulting observations into one corpus. We then removed any duplicate articles—those that appeared more than once since some articles include both "Muslim ban" and "Travel ban."

This produced a corpus containing 710 news articles across the full year. We then coded each article for positive (pro-ban), balanced/informational, or negative (anti-ban). Positive articles portray the "Muslim ban" EO in an overall favorable light, negative articles in an overall negative light, and balanced/informational as either strictly informational or an even mix of negative and positive with no clear takeaway. For NYT, WSJ, WAPO, and USAT articles, three coders read 20% of all articles, achieving an inter-coder reliability of 89%. One coder then separately coded the rest of the corpus.

Upon deeper inspection, 30% of the NYT articles were not about the Muslim ban or executive order but included the search terms. These articles were subsequently dropped from the analysis. This type of article is typified by an article appearing in the Book Review section on April 21, 2017, entitled "American Poets Refusing to Go Gentle Rage Against the Right." The article is wide ranging and focused on poets' criticisms of modern politics. The only reference to a travel ban occurs here: "In March the Poetry Coalition which includes 25 organizations in the United States held readings around the country focused on the theme of migration with some programs put together partly in response to the Trump administration's attempted travel bans. At City Lights Bookstore in San Francisco the Poetry Society of America held a reading and discussion about the plight of Syrian refugees." Thus, while the article does reference "Muslim ban," it is not about the "Muslim ban;" the term simply turns up in passing.

Our final NYT corpus includes 496 articles. Of these articles, 263 (53%) were coded as negative towards the order (anti-ban), 230 (46%) balanced/informational, and only 3 (1%) positive towards the order (pro-ban). Figure 5 shows the corpus's over-time valence distribution.

Wall Street Journal

For the *Wall Street Journal* (WSJ), we accessed ProQuest, an academic database program that archives many media sources. We submitted a search for "Travel ban" or "Muslim ban" for any articles between January 1, 2017 - December 31, 2017. This produced 545 total articles. Of the articles appearing in the corpus, as with the NYT search, 236 were not about the Muslim ban or controversy surrounding the executive order. Thus, these articles were dropped, leaving us with a total of 308 articles. The articles were then hand-coded in the same manner as those in the NYT corpus. This left us with 106 (34%) anti-ban/negative articles, 183 (59%) balanced/information articles, and 19 (6%) pro-ban/positive articles.

Washington Post

We also accessed ProQuest to download *Washington Post* (WAPO) articles, containing the search terms "Travel ban" or "Muslim ban" between January 1, 2017 and December 31, 2017. This produced 569 total articles. Of the articles appearing in corpus, 262 were not about the Muslim ban or controversy surrounding the executive order. Thus, these articles were dropped, leaving us with a total of 307 articles. The articles were then hand-coded in the same manner as those in the NYT and WSJ corpora. This left us with 143 (47%) anti-ban/negative articles, 160 (52%) balanced/information articles, and 4 (1.3%) pro-ban/positive articles.

USA Today

To acquire *USA Today* (USAT) articles, we accessed Access World News' NewsBank, an academic database program that archives many media sources including USAT. We submitted a search for "Travel ban" or "Muslim ban" for any articles between January 1, 2017 and December 31, 2017. This produced 154 total articles. Of the articles appearing in database, as with the other searches, 40 were not about the Muslim ban or controversy surrounding the executive order. Thus, these articles were dropped, leaving us with a total of 114 articles. The articles were then hand-coded in the same manner as those in the NYT, WSJ, and WAPO corpora. This left us with 73 (64%) anti-ban/negative articles, 29 (25%) balanced/information articles, and 12 (10.5%) pro-ban/positive articles.

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