Online Appendix

Contents

A.1 Methods

A.1.1 Search as Predictor of Offline Behavior

Here, we undertake a brief review of the search-as-prediction literature. While web search data has not yet been extensively used in political science as a measure of behavior, "nowcasting" behavior using web search has become a virtual cottage industry in economics and epidemiology. Here, we focus on three broad categories of studies that use behavioral data to validate the utility of web search as a measure of offline actions: economic behaviors, health behaviors, and political behaviors. This review is not exhaustive, and some behaviors are tested by multiple studies (for example, there appear to be at least a half-dozen papers validating the ability of web search to predict unemployment rates). We argue that the depth of this literature makes a strong case for the use of web search as a measure of offline behavior, even in cases where direct validation of specific search terms is not available.

Economic: Economic behaviors were among the first to be measured by web search data. Multiple papers use government unemployment data to validate searches for queries including the word "jobs" as a measure of unemployment (DâAmuri and Marcucci 2017; Tuhkuri 2016; Larson and Sinclair 2021; Askitas and Zimmermann 2009; Choi and Varian 2009; Fondeur and Karamé 2013). Interestingly, the inclusion of Google trends data substantially improves traditional economic models predicting unemployment. Baker and Fradkin (2017) takes this methodology a step further, using the American Time Use Survey to validate web search as a measure of job-seeking behaviors among Americans. ATUS is traditionally used to measure job search behaviors. Using web search data, Baker and Fradkin (2017) shows no effect of unemployment policy changes in 2008 or 2014 on Americans' job-seeking behaviors. In addition to measures of unemployment and job-seeking behaviors, scholars have been able to validate search as a measure of food stamp applications(Fantazzini 2014), credit demand (Zeybek and Uğurlu 2015), and bank runs (Anastasiou and Drakos 2021).

A second major category of validated web search data is consumption searches. Google trends data strongly correlates with the purchase of cars (Choi and Varian 2012), houses (Wu and Brynjolfsson 2015), and stocks (Preis, Moat and Stanley 2013; Da, Engelberg and Gao 2011). Even beyond durable goods, scholars have been able to measure movie box office revenues (Goel et al. 2010), video game sales (Goel et al. 2010), rank of songs on the Billboard Hot 100 chart (Goel et al. 2010), and other retail purchases (Vosen and Schmidt 2011). Google Trends can also be used to accurately measure gun purchases (Lam 2018), mortgage delinquencies (Askitas and Zimmermann 2011), and the spread of novel agricultural practices (Dos Santos 2018).

The final set of economic behaviors widely validated by search data are travel and immigration behaviors. Choi and Varian (2012) and Gawlik, Kabaria and Kaur (2011) show that searches for Hong Kong are correlated with tourist volume to that destination. Kim et al. (2016) takes this a step further and finds that web searches as strongly correlated with passenger demand for air travel. Finally, Bohme, Groger and Stohr (2020) shows that web searches can also be used to measure longer-term international migration.

Health: Validated web search data is also widely used in health research. A primary locus of interest is the measurement of infectious disease using web searches. Queries can be for disease symptoms ("loss of smell") or they can be for the disease itself. A wide range of diseases have been highly correlated with web search queries: COVID-19 (Lampos et al. 2020), dengue fever (Althouse, Ng and Cummings 2011), AIDS (Li et al. 2019), and other sexually transmitted infections (Johnson et al. 2020). It is important to consider the difference between "nowcasting" (measuring) versus "forecasting" (predicting future incidence) of a behavior, especially in the context of infectious diseases. The failure of Google Flu Trends (Lazer et al. 2014) highlighted the difficulty of out-of-sample prediction using web search in the infectious disease context. However, the GFT's errors in predicting future flu rates do not diminish the validity of search data to accurately describe *current* conditions.

Validated web search data has been used to measure other health conditions and behaviors. Scholars have used web search to predict cancer (Ofran et al. 2012), birth rates (Billari, D'Amuri and Marcucci 2016), obesity (Sarigul and Rui 2014), suicide (Parker et al. 2017; Kristoufek, Moat and Preis 2016), and deaths due to drug and alcohol use (Parker et al. 2017). A number of other health-related behaviors can also be measured by web search data: use of e-cigarettes (Ayers, Ribisl and Brownstein 2011), pharmaceuticals (Simmering, Polgreen and Polgreen 2014), cannabis (Steppan et al. 2013), and vaccines (Krupenkin, Yom-Tov and Rothschild 2021).

Political: Of the three categories within this literature review, the ability of search to predict political behaviors is the most understudied. However, scholars have successfully used web search data to measure a number of important offline political behaviors.

Street et al. (2015) shows that searches for voter registration are highly correlated with actual voter registration numbers, and uses this data to demonstrate the detrimental effects of early voter registration deadlines. Web search can also be used to predict turnout (Stephens-Davidowitz and Pabon 2017), as well as election outcomes in multiple countries (Swearingen and Ripberger 2014; Polykalas, Prezerakos and Konidaris 2013). Web search can also be used to measure more subtle political behaviors - Reilly, Richey and Taylor (2012) finds that ballot initiatives with more web search interest have lower rolloff rates than ballot initiatives with less.

A.1.2 Full Topic Model

To identify news segments on immigration, we used the following metric—any news segment with two or more mentions of our key strings ("immigr", "illegals", or "illegal alien") within 60 seconds of each other was considered an immigration segment. The segment began at the first mention of the keywords and ended at the last mention. Consecutive immigration segments[1] were

[1] For example, three mentions of keywords within 120 seconds, each no more than 60 seconds after the previous mention.

combined into a single longer segment. This procedure yielded 61,229 immigration segments with high precision, and possibly lower recall, as we relied on a fairly strict set of keywords to identify the segments. Furthermore, counting only text bounded by keyword mentions inevitably truncated the segments, making them as short as possible, since we did not count conversation before the first and after the last keyword and thus underestimated the total length of segments. However, since the focus of the paper is changes in media coverage over time, this truncation is not of major concern.

To estimate topic proportions, we use a 30-topic structural topic model for the 61,229 immigration segments with an indicator variable for the time period relative to the 2016 election. The timeline is divided into three distinct periods: pre-campaign (before Trump announced his candidacy), campaign (between Trump's candidacy and his inauguration), and post-inauguration. We also include a variable for the channel (CNN, MSNBC, or Fox) and interact it with the time period variable. In addition to the standard English stop words, the model uses the words/phrases "immigrant", "immigrants", "immigrate", "immigrated", "immigrating", "immigration", "illegals", "illegal alien", and "illegal aliens" as stop words to prevent changes in language referring to immigrants from influencing the model.[2]

A.1.3 Search Info

Here, we provide additional details about the search data.

For Bing searches,[3] we define an immigration search as one that contains one of the following three strings: "immigr" (which includes words like "immigrant","immigration"), "illegals", and "illegal alien" (which would also capture any searches for "undocumented immigr*"). We

[2]Ndulue et al. (2019) found an increase in references to unauthorized immigrants as "illegals" or "illegal aliens" after Trump was elected. In theory, these terms are likely to have a positive association with anti-immigrant coverage, so an increase in these terms could spuriously suggest an increase in anti-immigrant crime coverage, even when the only change is in the way immigrants are referenced. In practice, including these terms in stop word lists has little to no substantive effect on the output of the model.

[3]We pull Bing searches from the en-US browser-based search market.

Table A1: Media Coverage of Immigration Topics Determined by the Structural Topic Model

Topic 1	**Highest Prob: crime, crimin, illeg, commit, murder, convict, time** **FREX: steinl, kate, rape, tibbett, pier, assault, crime** **Score: crime, murder, crimin, commit, kate, convict, steinl**	Topic 16	Highest Prob: job, worker, work, american, economi, econom, number FREX: wage, unemploy, worker, labor, farmer, growth, green Score: worker, wage, job, skill, economi, labor, econom
Topic 2	Highest Prob: democrat, open, left, california, want, liber, pelosi FREX: oakland, nanci, liber, jerri, pelosi, pawn, warren Score: democrat, pelosi, california, nanci, open, oakland, left	Topic 17	Highest Prob: presid, hous, white, trump, report, meet, tweet FREX: miller, lindsey, graham, white, stephen, kushner, jare Score: white, presid, hous, miller, graham, meet, stephen
Topic 3	**Highest Prob: illeg, two, kill, year, man, offic, charg** **FREX: twice, singh, crash, man, drunk, suspect, dominican** **Score: kill, man, polic, son, -year-old, suspect, illeg**	Topic 18	Highest Prob: question, ask, whether, tough, answer, get, can FREX: question, census, answer, tough, whether, ask, ramo Score: question, ask, answer, tough, whether, census, count
Topic 4	Highest Prob: law, polici, administr, trump, chang, enforc, general FREX: session, jeff, polici, administr, general, attorney, book Score: law, polici, administr, session, attorney, enforc, jeff	Topic 19	Highest Prob: need, system, reform, comprehens, fix, want, end FREX: lotteri, chain, system, comprehens, merit, migrat, broken Score: system, reform, comprehens, need, fix, lotteri, chain
Topic 5	Highest Prob: anti-, trump, rhetor, fear, peopl, group, racist FREX: brexit, anti-, manifesto, franc, nationalist, hatr, merkel Score: anti-, europ, racist, european, rhetor, germani, fear	Topic 20	Highest Prob: famili, children, separ, parent, kid, child, one FREX: reunit, parent, children, separ, kid, mother, zero Score: children, famili, separ, parent, kid, child, mother
Topic 6	Highest Prob: border, wall, mexico, secur, come, crisi, stop FREX: southern, crisi, fenc, caravan, border, tariff, barrier Score: border, wall, mexico, crisi, southern, patrol, cross	Topic 21	Highest Prob: citi, feder, law, sanctuari, communiti, enforc, state FREX: chicago, local, citi, sanctuari, counti, rahm, cooper Score: citi, sanctuari, feder, mayor, law, local, counti
Topic 7	Highest Prob: militari, full, street, north, war, michael, take FREX: maria, korea, russian, russia, hurrican, unusu, journal Score: militari, maria, michael, north, russia, full, russian	Topic 22	Highest Prob: secur, plan, includ, protect, homeland, new, propos FREX: homeland, dhs, secretari, memo, draft, includ, plan Score: homeland, secur, plan, depart, secretari, includ, propos
Topic 8	Highest Prob: illeg, peopl, countri, want, come, million, get FREX: jess, overstay, illeg, amnesti, million, greg, everybodi Score: illeg, million, peopl, amnesti, countri, want, dont	Topic 23	Highest Prob: court, judg, case, asylum, process, rule, will FREX: judg, court, suprem, asylum, seeker, circuit, lawyer Score: court, judg, asylum, suprem, process, case, facil
Topic 9	Highest Prob: peopl, just, that, dont, know, theyr, right FREX: theyr, cant, your, isnt, true, problem, understand Score: theyr, dont, that, peopl, problem, know, just	Topic 24	Highest Prob: money, busi, check, washington, emerg, guy, pete FREX: neil, charl, pete, machin, emerg, box, check Score: pete, emerg, busi, money, check, neil, obamacar
Topic 10	Highest Prob: legal, status, member, gang, came, countri, citizen FREX: ms-, anim, legal, gang, applaus, status, distinct Score: legal, gang, status, ms-, member, anim, applaus	Topic 25	Highest Prob: issu, republican, parti, think, elect, voter, vote FREX: cantor, poll, parti, voter, elect, won, win Score: republican, parti, voter, issu, poll, vote, elect
Topic 11	Highest Prob: presid, obama, execut, order, action, congress, will FREX: execut, action, unilater, defer, obama, permit, barack Score: execut, action, obama, presid, order, congress, constitut	Topic 26	Highest Prob: state, unit, nation, countri, refuge, ban, muslim FREX: ban, vet, terrorist, isi, syrian, refuge, terror Score: unit, muslim, nation, ban, state, refuge, vet
Topic 12	Highest Prob: talk, think, hes, said, thing, say, want FREX: talk, hes, bit, convers, term, littl, think Score: talk, hes, think, thing, said, lot, know	Topic 27	Highest Prob: ice, deport, enforc, crimin, undocu, agent, arrest FREX: custom, raid, ice, abolish, remov, oper, agenc Score: ice, raid, custom, agent, deport, arrest, enforc
Topic 13	**Highest Prob: care, health, state, benefit, undocu, school, pay** **FREX: health, tuition, insur, healthcar, care, medicaid, licens** **Score: care, health, licens, welfar, school, driver, healthcar**	Topic 28	Highest Prob: bill, senat, republican, democrat, deal, will, get FREX: mcconnel, mitch, compromis, senat, bill, ryan, negoti Score: bill, republican, senat, democrat, daca, hous, reform
Topic 14	Highest Prob: thank, join, new, good, news, tonight, now FREX: ainsley, fox, join, shannon, brian, thank, martha Score: thank, join, news, fox, morn, tonight, ainsley	Topic 29	Highest Prob: trump, donald, campaign, will, clinton, speech, undocu FREX: soften, cruz, hillari, clinton, ted, marco, donald Score: donald, trump, rubio, hillari, cruz, clinton, marco
Topic 15	Highest Prob: countri, america, peopl, american, come, tucker, world FREX: assimil, tucker, slave, societi, liberti, generat, statu Score: tucker, america, countri, american, assimil, peopl, world	Topic 30	Highest Prob: see, tri, now, make, come, back, get FREX: type, see, tri, put, continu, seen, make Score: see, type, tri, make, come, back, now

Notes: Topics of interest for this paper are in bold (Topics 1, 3, and 13). Topics 1 and 3 are coded as immigrant crime topics, and Topic 13 is coded as the immigrant welfare topic. Topics were generated using the R stm package.

define a “reporting” search as one that contains the word “report” and one of the immigration terms or a string that includes “to ice” (e.g., “how to report someone to ice”). A crime search is defined as a search that contains one of the listed immigration terms plus one or more of the following: “crime”,“criminal”, “kill”, or “murder”. Finally, a welfare search contains one of the immigration terms plus one of the following: “welfare”, “benefits”, or “cost”. These lists are not exhaustive but are intended to capture precisely a substantial proportion of searches related to reporting immigrants, immigration/crime and immigration/welfare.

For Google Trends, immigration reporting searches were represented by “report immigrant+report immigration+report illegals+report illegal alien+report to ice”. To measure immigration and crime searches on Google Trends, we pulled searches with the following string: “immigrant crime+immigrant criminal+immigrant murder+immigrant kill”. Immigration and welfare searches were represented by “immigrant welfare+immigrant cost+immigrant benefits”.

Google Trends displays searches at the daily (rather than weekly or monthly) level for only a few months at a time (it provides weekly data for five-year intervals). To generate a time series of daily Google searches, we used monthly and weekly data to normalize the searches to a single scale. The procedure was as follows: First, for each month, we took the mean weekly Google Trends value (mean search volume across the four weeks of each month). We used this average to calculate an adjustment value for each month, $adj = \frac{\text{monthly search}}{\text{mean weekly search}}$. We then multiplied each week by this adjustment value to get an adjusted weekly score for each week. We repeated the process with the adjusted weekly score and the daily score to get a final time series of adjusted daily scores.

This daily Google time series was moderately correlated with our daily Bing data from 2016 to 2019, with a correlation of 0.39 for crime, 0.51 for welfare, 0.32 for reporting, and 0.55 for weather. These correlations are especially notable given our limitations in generating Google Search strings compared to Bing. However, daily data in the early part of the Google daily time series (2004-2010) was extremely noisy, so we chose to use monthly data for our comparisons of

Table A2: Increase in anti-immigrant searches

Category	Google	Bing
Crime	2.45x	1.80x
Welfare	1.71x	1.72x
Report	1.36x	1.51x
Report (HSI)	–	1.41x

Notes: Bing and Google data showed similar increases in immigration searches during the Trump administration. This table displays the proportionate increase in searches for each category from the Obama administration to the Trump administration.

searches across presidential administrations.

Increases in anti-immigrant searches were highly consistent across Google and Bing, as shown in Table A2.

A.1.4 List of Removed Bing Terms

Some searches were identified as irrelevant or "botted". Searches in italics were identified as botted because they had a one-day spike of at least two orders of magnitude above the previous day and there was no similar spike in closely related searches (e.g., searches containing the same keywords but in a different order). For example, "california immigrants health benefits" had a extreme spike but "ca immigrant health benefits"and "immigrant health benefits california" did not. These searches were removed from the Bing data, including all searches that included the following strings (case-insensitive):

Crime: skill, deer were killed by predators, sweden immigrants crime, ice immigrant-crime hotline calls, criminal justice reform, "theodore roosevelt on race, riots, immigration, and crime book"

Welfare: low cost immigration law services, immigration benefits, costa rica immigration, immigrant costumes, benefits of illegal immigration, process and cost for immigrants coming to usa, benefits of immigrants, low cost immigration law services orange county ca, benefits of immigration, california immigrants health benefits

Report: “immigration commission report: report”, us news and world report, crime report, the parents report, summarizing a report, ig report, msnbc report, criminal illegal alien report, report on, sample report, thai immigration 90 day report, report from the government accounting office, intelligence report, responds to immigration report, center for immigration studies report

Table A3: Table 3 OLS

	Dependent variable:		
	Crime	Welfare	Report
Date	0.00000*** (0.00000)	0.00000*** (0.00000)	−0.00000*** (0.000)
Obama Admin	–	–	–
Trump Admin	0.0001** (0.00002)	0.00004** (0.00002)	0.00003*** (0.00000)
Constant	−0.002*** (0.001)	−0.002*** (0.0005)	0.0004*** (0.0001)
Note:			*p<0.1; **p<0.05; ***p<0.01

Notes: The results of this table replicate those presented in Table 3, which shows that Bing anti-immigrant searches were higher during the Trump administration.

Table A4: Table 4 OLS

	Dependent variable:		
	Crime	Welfare	Report
Immigration Segments	−9e-09 (6e-09)	8.7e-09*** (3.1e-09)	1.3e-09*** (3e-10)
Immigr + Crime Coverage	8.21e-07*** (1.45e-07)	9.09e-08** (4.61e-08)	1.1e-08** (4.9e-09)
Immigr + Welfare Coverage	1.78e-07 (1.39e-07)	3.32e-07* (1.73e-07)	−3.9e-09 (7.5e-09)
Trump Admin	−3.7e-07* (1.92e-07)	−6.3e-09 (1.33e-07)	2.5e-07*** (2.1e-08)
Date	1.7e-09*** (3e-10)	1e-09*** (2e-10)	−2e-10*** (0e+00)
Day of Week FE	X	X	X
Month FE	X	X	X
Constant	−2.64e-05*** (4.31e-06)	−1.48e-05*** (3.13e-06)	3.32e-06*** (4.55e-07)
Note:			*p<0.1; **p<5e-02; ***p<1e-02

Notes: The results of this table replicate those presented in Table 4, which shows that Bing anti-immigrant searches were higher on days with higher coverage of immigrant + crime and/or immigrant + welfare.

A.2 Robustness to Model Specification

A.2.1 Results with OLS

In this section, we show that our Bing results from the body of the paper are substantively identical whether we use OLS (this section) or logistic regression (body of the paper). In the case of OLS, the dependent variable is the proportion of all Bing searches for a particular set of terms (e.g., immigrant+crime). In both cases, standard errors are clustered by date.

Table A5: Table 5 OLS

	Dependent variable:		
	Crime	Welfare	Report
Immigration Segs	$-$0e+00 (0e+00)	0e+00 (0e+00)	$-$0e+00 (0e+00)
Immigr + Trump Segs	$-$3e-08*** (0e+00)	$-$0e+00 (0e+00)	0e+00 (0e+00)
Immigr + Crime Coverage	8e-07*** (1e-07)	1e-07** (5e-08)	2e-08*** (0e+00)
Immigr + Welfare Coverage	1e-07 (1e-07)	3e-07* (2e-07)	$-$0e+00 (0e+00)
Trump Admin	$-$9e-07*** (3e-07)	$-$3e-07** (1e-07)	2e-07*** (2e-08)
Date	0e+00*** (0e+00)	0e+00*** (0e+00)	$-$0e+00*** (0e+00)
Trump Segs x Trump Admin	4e-08** (2e-08)	3e-08*** (0e+00)	0e+00*** (0e+00)
Day of Week FE	X	X	X
Month FE	X	X	X
Constant	$-$2.82e-05*** (4.5e-06)	$-$1.67e-05*** (3e-06)	2.8e-06*** (4e-07)
Note:			*p<0.1; **p<5e-02; ***p<1e-02

Notes: The results of this table replicate those presented in Table 5, which shows that the relationship between anti-immigrant searches and anti-immigrant coverage persisted even after controlling for news coverage of Trump's statements and actions on immigration.

A.3 Additional Analysis

A.3.1 Structural Topic Model Results Over Time

Here, we present additional information about the topic model used. In the body of the paper (Figures 3 and 4), we show the overall amount of daily news coverage of immigrant crime and immigrant welfare, which is the sum of the daily topic proportions, $DailyCoverage_{jk} = \sum_i CrimeProportion_{ijk}$ over all news segments i on channel j on date k. This measure captures the overall volume of ant-immigrant coverage. Here, we present regressions that estimate the effect of the different time periods on the daily mean of topic proportions, which covers the proportion of immigration coverage on a particular topic.

Table A6 presents the estimates for topic prevalence by time period and by channel. During the campaign and the post-inauguration period, there was a significant increase in coverage of immigrant crime. On the other hand, the overall proportion of coverage of immigrant welfare declined during this period, likely because anti-immigrant programs significantly increased messaging about crime.

Table A6: Structural Topic Model Results - Immigration Coverage by Topic

	Dependent variable:		
	Topic Proportion		
	Crime (1)	Crime (3)	Welfare (13)
CNN	-	-	-
Fox	0.008^{***} (0.002)	0.010^{***} (0.002)	0.014^{***} (0.002)
MSNBC	-0.002 (0.003)	-0.001 (0.003)	0.003^{***} (0.002)
Campaign	0.026^{***} (0.002)	0.005^{***} (0.002)	-0.006^{***} (0.002)
Campaign x Fox	0.008^{***} (0.003)	0.003^{***} (0.003)	-0.004^{***} (0.003)
Campaign x MSNBC	-0.010^{***} (0.003)	-0.0002^{***} (0.003)	-0.001^{***} (0.003)
Post-Inaug	0.016^{***} (0.002)	-0.002^{***} (0.002)	-0.002^{**} (0.002)
Post-Inaug x Fox	0.008^{***} (0.002)	0.005^{***} (0.002)	-0.003^{**} (0.002)
Post-Inaug x MSNBC	-0.001 (0.003)	-0.001 (0.003)	-0.002 (0.003)
Constant	0.006^{***} (0.002)	0.020^{***} (0.002)	0.020^{***} (0.002)
Observations	61,213	61,213	61,213

*p<0.1; **p<0.05; ***p<0.01

Notes: Immigrant crime coverage increased significantly as a proportion of all immigration coverage during the campaign and the post-inauguration period. Immigrant welfare coverage, however, declined as a proportion of overall immigration coverage.

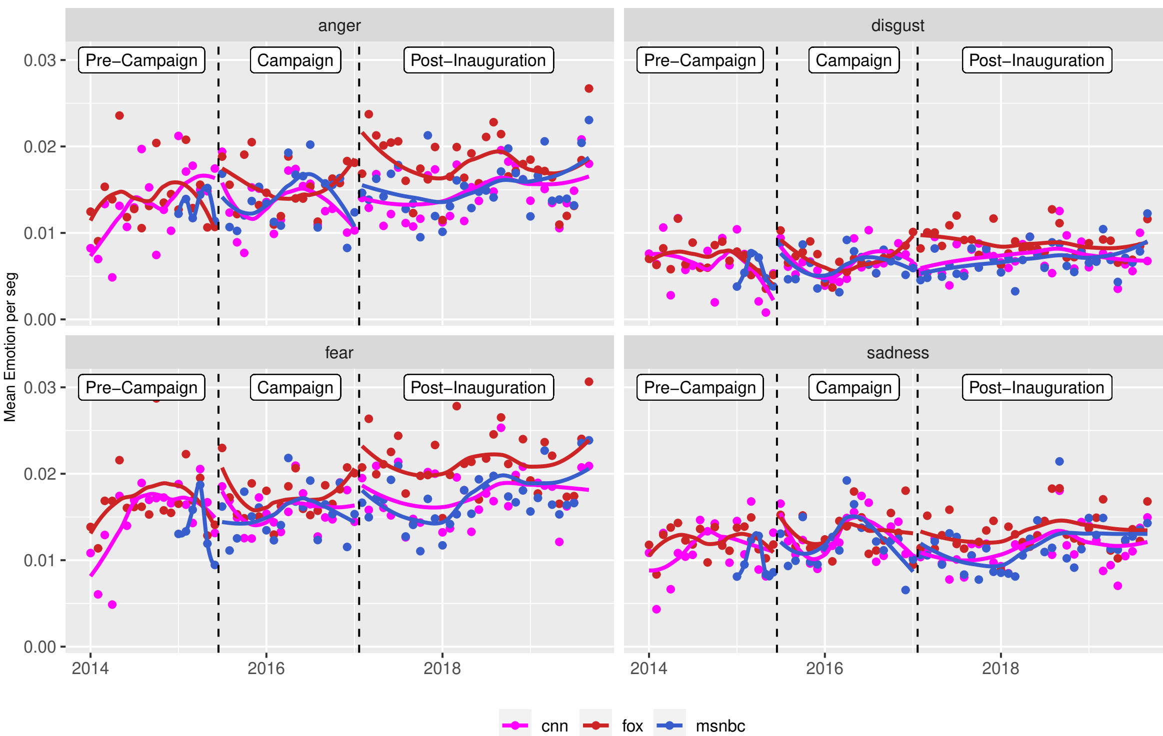
A.3.2 Emotion Analyses Over Time

In this section, we look at the emotional valence of news content about immigration over time. We see that the average anger and fear in immigration segments increased over after the inauguration, while the average level of disgust and sadness did not. Because the overall number of immigration segments increased post-inauguration, we see an increase in the overall amount of negative emotional cues around immigration after the inauguration.

A.3.3 Crime and Welfare Search Results

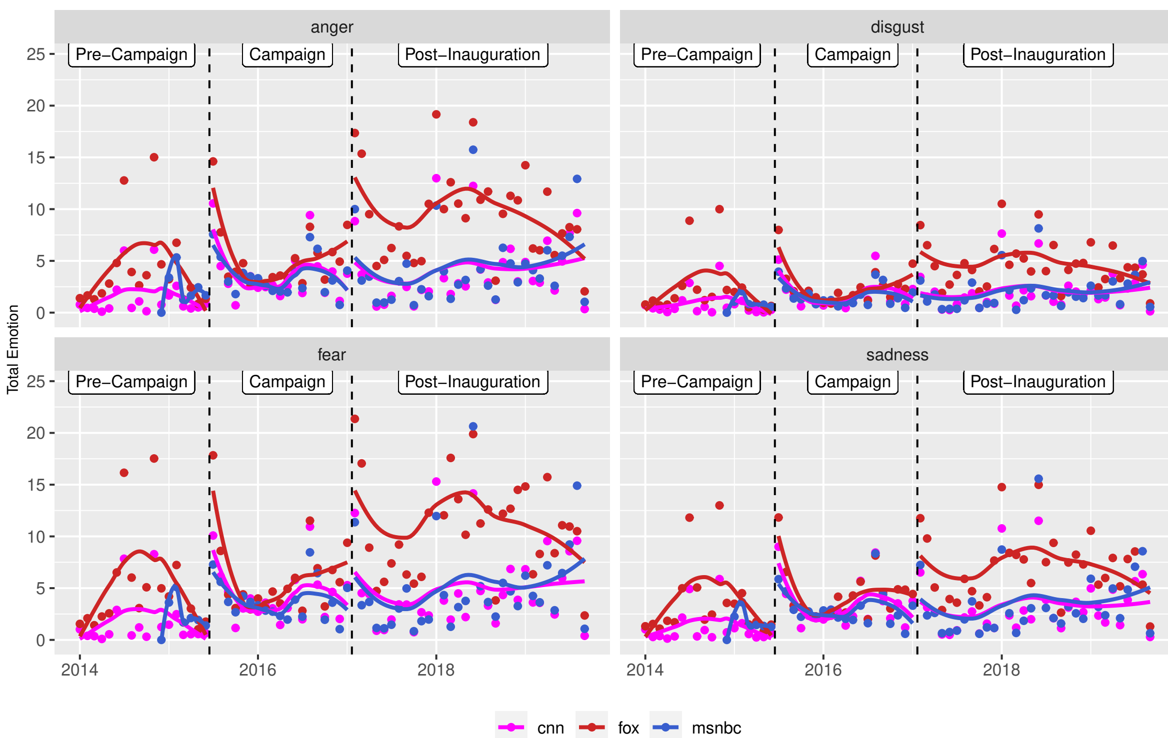
Here, we replicate the results of Table 4 in the body of the paper with crime and welfare searches. We find very similar patterns for crime, welfare, and reporting searches.

Figure A1: Emotionality of Mean Immigration Segment



Notes: Plot shows mean proportion of emotional words per segment for all segments designated as immigration segments. There was an increase for fear and anger, but little change for sadness or disgust.

Figure A2: Total Monthly Emotion by Channel



*Notes:*Notes: Plot shows sum of proportions of emotional words for all segments designated as immigration segments. Ther largest increase was in anger and fear.

Table A7: Media Coverage and Anti-Immigrant Searches

	Dependent variable:			
	Crime		Welfare	
	Bing	Google	Bing	Google
Immigration Segs	0.0003 (0.001)	0.081*** (0.031)	0.003*** (0.001)	0.190*** (0.025)
Immigr + Crime Coverage	0.126*** (0.013)	4.542*** (0.451)	0.022** (0.010)	0.265 (0.366)
Immigr + Welfare Coverage	0.025 (0.028)	−0.672 (1.169)	0.082** (0.035)	0.123 (0.950)
Trump Admin	−0.018 (0.086)	20.149*** (3.045)	0.039 (0.060)	6.113** (2.474)
Date	0.001*** (0.0001)	−0.007** (0.003)	0.0005*** (0.0001)	0.007*** (0.003)
Day of Week FE	X	X	X	X
Month FE	X	X	X	X
Constant	−23.421*** (1.404)	142.177*** (51.822)	−20.998*** (1.221)	−89.987** (42.100)

*p<0.1; **p<0.05; ***p<0.01

Notes: The volume of immigrant crime coverage and overall immigrant-related coverage was positively associated with higher search rates for immigrant crime, and welfare. The volume of immigrant welfare coverage is positively associated with immigrant+welfare searches. Bing Regression is binomial logit with standard errors clustered by date. Google Regression is OLS on daily Google data.

A.3.4 Emotion and Search Results

In this section, we replicate the analysis for table 6 for the crime and welfare searches. We find that crime searches are associated with anger cues, while welfare searches are more strongly associated with fear cues.

A.3.5 Homeland Security Investigations (HSI) Search Results

We use two measures of "reporting" searches on Bing. These measures represent a trade-off between precision and recall. The first measure, described in the body of the paper, very precisely measures intent but misses a large portion of people who are interested in reporting immigrants.[4]

To understand which searches lead to immigrant reporting behavior, we looked at search

[4] Only 34% of clicks to the HSI tip form came from a reporting search.

Table A8: Emotional Cues and Anti-Immigrant Searches

	Dependent variable:			
	Crime		Welfare	
	Bing	Google	Bing	Google
Anger	0.291*** (0.096)	9.686** (4.720)	0.028 (0.080)	0.900 (3.690)
Fear	0.087 (0.104)	3.469 (4.726)	0.197*** (0.074)	15.911*** (3.695)
Sadness	0.706*** (0.110)	10.642** (5.160)	0.200** (0.078)	8.828** (4.034)
Disgust	0.190 (0.139)	−3.632 (6.181)	−0.203* (0.116)	−13.565*** (4.832)
Immigration Segs	−0.009*** (0.001)	−0.030 (0.054)	0.0004 (0.001)	−0.063 (0.043)
Trump Admin	0.026 (0.076)	22.233*** (3.141)	0.027 (0.058)	6.374*** (2.456)
Date	0.0005*** (0.0001)	−0.011*** (0.003)	0.0005*** (0.0001)	0.005** (0.002)
Constant	−20.939*** (1.352)	203.653*** (52.585)	−21.439*** (1.239)	−62.850 (41.111)
Day of Week FE	X	X	X	X
Month FE	X	X	X	X

*p<0.1; **p<0.05; ***p<0.01

Notes: This table is the equivalent of Table 6 in the body of the paper, except looking at the relationship between emotional cues, crime searches, and welfare searches. Anger cues were associated with immigrant crime searches, and fear cues were associated with immigrant welfare searches.

queries that resulted in at least one click to the HSI tip form page.[5] HSI terms were much more popular than direct "reporting" terms. On the average day, there were 1,465% as many HSI searches as there were "reporting" searches. The most popular term that led to an HSI click was "ice", followed by "hsi tip form". While this measure has less precision than the previously described "reporting" measure it has higher recall. Together, these measures present a clear picture of searches on reporting immigrants. Unfortunately, due to Google Trends' inability to pull searches for a specific fixed string (Google Trends for "ice" would give searches for both "ice tip line" and "ice cream"), we were unable to pull the equivalent results for HSI searches.

Table A10 and Figure A3 are the HSI equivalents for Table 3 and Figure 4 in the body of the paper, respectively. Figure A3 confirms an increase in searches on reporting immigrants after Trump was inaugurated. Table A10 shows that while there was no significant association between

[5]There are two ways to report immigrants to ICE: the HSI phone tipline and the HSI online tip form. Direct clicks on the online tip form from the search results are relatively rare, since the form is not clearly labelled in the search results as a form to report immigrants. Presumably, most people who report immigrants to ICE first click on the ICE website and then make their way to the tip form. Alternatively, they may use the phone number. Due to the rarity of direct clicks on the tip form, we chose to use search queries that led at least one user to click directly on the tip form, with the rationale that those search queries represent intent to report immigrants.

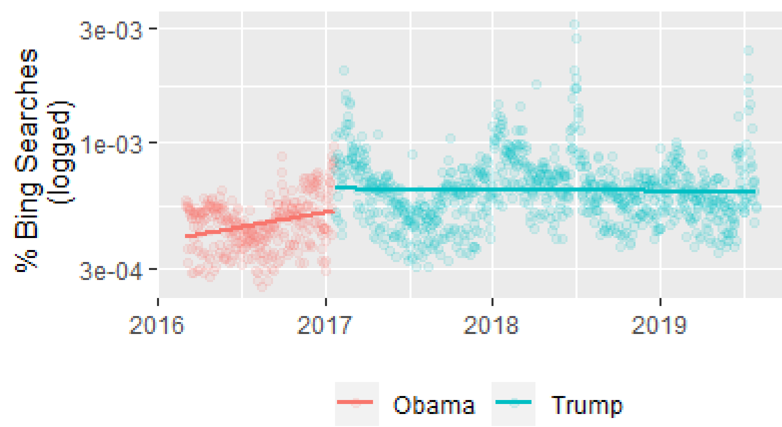
Table A9: Top 10 Terms Resulting in Direct Clicks on the HSI Tip Form

HSI
ice
hsi tip form
www.ice.gov/tips
report illegal immigrants anonymously
ice tip line
www.ice.gov/webform/hsi-tip-form
ice report
ice reporting illegal immigrants
ice.gov
immigration and customs enforcement

Notes: This table shows the top 10 searches resulting in a direct click on the HSI tip form.

immigrant crime coverage and HSI searches, there was a strong association between total coverage of immigration and HSI searches. The HSI search findings replicate the immigrant reporting results from the body of the paper, providing powerful evidence that searches for reporting immigrants increased after Trump was inaugurated and that this increase was associated with more media coverage of immigration.

Figure A3: HSI Bing Searches by Time



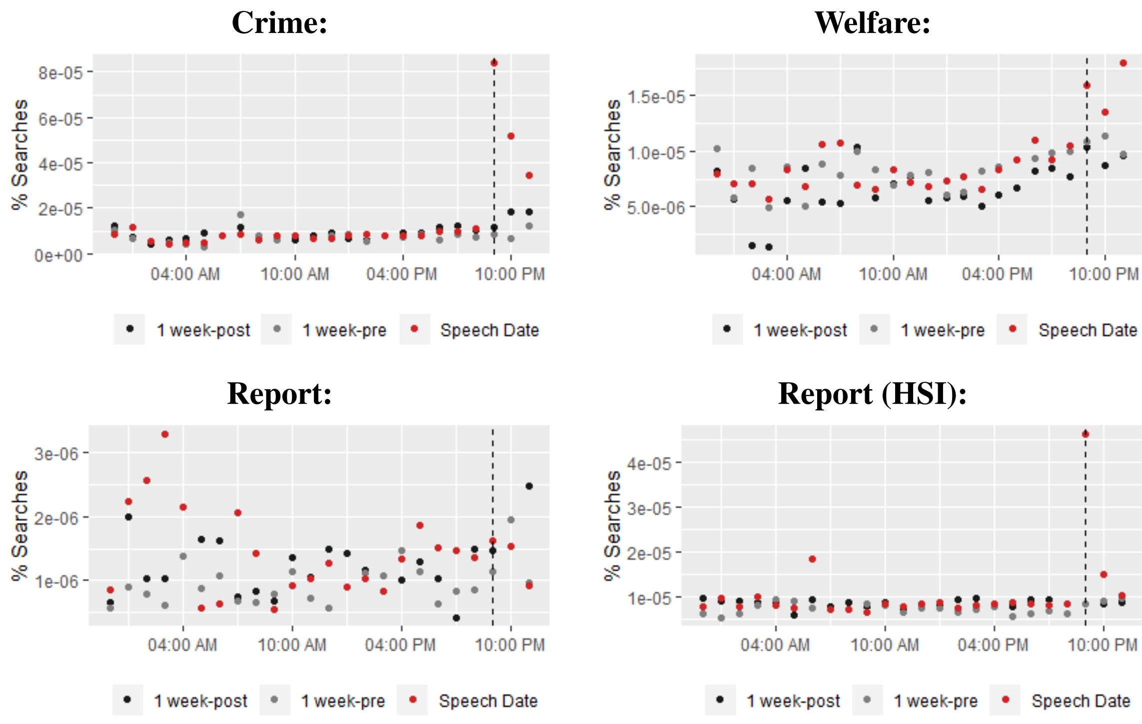
Notes: Searches for reporting immigrants increased after Trump was inaugurated. This figure is the counterpart to Figure 4 in the body of the paper.

Table A10: Immigration Coverage and HSI Searches

	Dependent variable:
Immigration Segs	0.002*** (0.0003)
Immigr + Crime Coverage	−0.00004 (0.004)
Immigr + Welfare Coverage	−0.027** (0.013)
Trump Admin	0.299*** (0.026)
Date	−0.00003 (0.00003)
Day of Week FE	X
Month FE	X
Constant	−11.598*** (0.583)
Note:	*p<0.1; **p<0.05; ***p<0.01

Notes: There was a strong correlation between daily immigration coverage and searches for how to report immigrants using the HSI measure. This table is the counterpart to Table 4 in the body of the paper.

Figure A4: Bing Immigration Searches During Trump Speeches



Notes: Searches for immigrant crime, immigrant welfare, and reporting immigrants (HSI) increased sharply during Trump's televised speeches. The dataset includes the 2018 and 2019 SOTUs and a 2019 Oval Office address on immigration. For crime and reporting (HSI), the increases were consistent across all three speeches whereas for welfare, the increase occurred only during the Oval Office address. This figure is the Bing counterpart to Figure 5 in the body of the paper.

A.3.6 Bing Speech Results

While we were unable to compare Trump's and Obama's speeches with Bing data due to limitations (Bing data were available only after Trump's first SOTU), we present the Bing data used to analyze Trump's speeches in Figure A4 and Table A11. The data clearly replicate the Google Trends data presented in the body of the paper, with clear increases in anti-immigrant searches during broadcasts of Trump's speeches.

Table A11: Bing Immigration Searches During Presidential Speeches

	Dependent variable:			
	Crime	Welfare	Report	Report (HSI)
Speech Date	0.240 (0.173)	0.141 (0.094)	0.138 (0.090)	0.026 (0.045)
Speech Hour	0.357 (0.233)	0.332^{***} (0.084)	0.242 (0.185)	0.135 (0.113)
Speech Date x Speech Hour	1.433^{**} (0.558)	0.077 (0.403)	−0.048 (0.259)	1.318^{***} (0.314)
Constant	-11.754^{***} (0.041)	-11.816^{***} (0.040)	-13.751^{***} (0.052)	-11.726^{***} (0.029)

*p<0.1; **p<0.05; ***p<0.01

Notes: There was a significant spike in Bing searches for crime and reporting immigrants (HSI) during Trump's speeches. Regression is binomial logit with standard errors clustered by date-hour. The Speech Date variable is 1 if the search was performed on the date of the speech and 0 otherwise (i.e., the search was performed one week before or after the speech). The Speech Hour variable is 1 if the search was performed during the hours of 9pm or 10pm EST (with the exception of the Oval Office speech, which was only 9pm EST). This table is the Bing counterpart to Table 7 in the body of the paper.

A.3.7 Weather Placebo Results

To ensure that the search results were not due to larger shifts in web search behavior, we replicated our analysis using searches for the word "weather", as there should be no effect of media or the Trump administration on weather searches.

We repeated the analysis by administration for Bing and Google searches for the placebo search term of "weather". The results are shown in Figure A5. Google Trends showed an unusual overall pattern for this search, with searches for weather increasing at a steady rate throughout the time series. However, there appeared to be no discontinuity during the Trump administration for Google searches; instead, there was a substantial bump in searches around mid-2018. There was also no discontinuity in Bing weather searches although there was a slight upward time trend similar to the Google data. These findings suggest that the observed shifts in immigration searches were not the result of an overall shift in search patterns.

Table A12 shows the results of the "weather" placebo test on immigration media coverage. Searches including the term "weather" should have no clear relationship with immigration cov-

Table A12: Media Coverage and Weather Searches (Placebo)

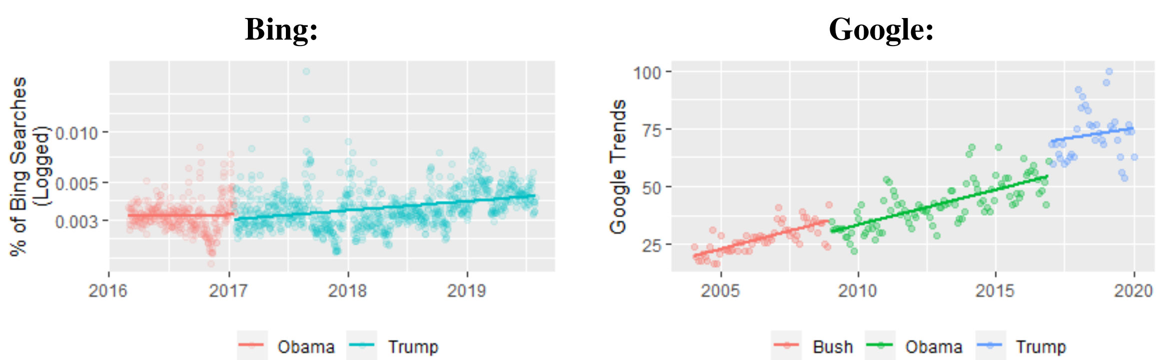
	Dependent variable:	
	Bing	Google
Immigration Segs	0.0003 (0.0003)	0.018 (0.014)
Immigr + Crime Coverage	-0.011^{**} (0.005)	-0.254 (0.200)
Immigr + Welfare Coverage	-0.003 (0.007)	-0.733 (0.518)
Trump Admin	-0.117^{***} (0.032)	7.024^{***} (1.350)
Date	0.0003^{***} (0.00003)	0.014^{***} (0.001)
Dow FE	X	X
Month FE	X	X
Constant	-11.324^{***} (0.582)	-168.512^{***} (22.980)
Note:		*p<0.1; **p<0.05; ***p<0.01

Notes: There was no consistent relationship between immigration coverage and weather searches for either Bing or Google. Bing regression is binomial logit with standard errors clustered by day; Google regression is OLS.

erage. As expected, there was no consistent relationship between immigration coverage and weather searches on either Google or Bing. This suggests that the observed relationship between immigration coverage and anti-immigrant searches was not the result of general patterns in search volume.

Finally, to check that the observed search spikes were not the result of overall shifts in search patterns, we used searches for "weather" during the same periods as a placebo. Figure A6 shows that on both Google and Bing, there was no spike in searches for weather during speech times for Obama or Trump. In sum, the results of these three tests indicate that the observed change in immigration searches is not the result of broader shifts in search behavior.

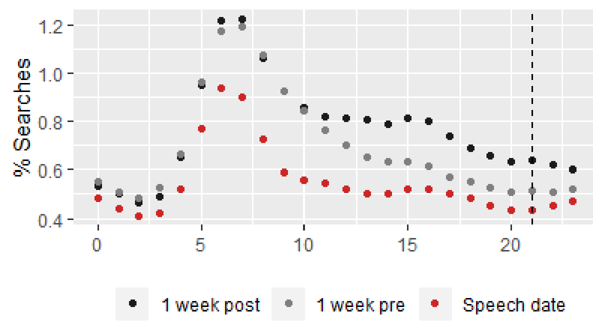
Figure A5: Weather Placebo Searches and Presidential Administrations



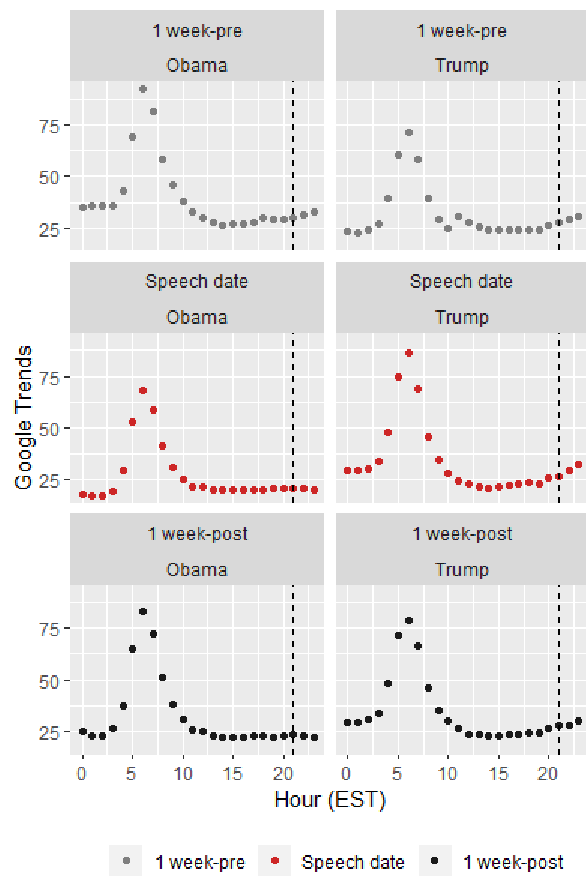
Notes: There was no clear Trump administration effect on weather searches. Bing searches showed no discontinuity between the Obama and Trump administrations. While Google weather searches did appear to be higher during the Trump administration, there was no clear discontinuity during the first few months of the administration, and the clear upward trend of the Bush and Obama administrations in weather searches continued.

Figure A6: Weather Searches During Presidential Speeches

Bing:



Google:



Notes: Neither Bing nor Google showed any spike in weather searches during any televised speeches. For Google searches, for each plot, Y-axis is comparable within, but not between, days. A rating of 100 represents the hour with the most searches on that specific date but is not comparable with searches on other dates.

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