Immigration Attitudes and Labor Market Conditions in the United States

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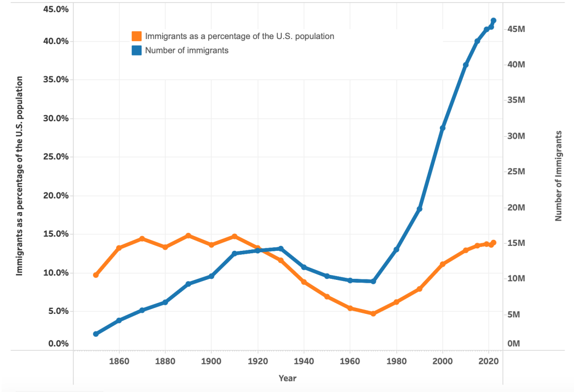
Disclaimer: This presentation is released to inform interested parties of ongoing research and to encourage discussion. Any views expressed are those of the authors and not those of the U.S. Census Bureau.

Motivation

- U.S. sees significant rise in foreign-born population, echoing pre-Great Depression trend [24, 20].
- Demographic shifts ([15]) and economic disruptions, including China's growth, the Great Recession, and US-China trade tensions, significantly impact labor market dynamics, prompting a reevaluation of public attitudes towards immigration ([10, 11, 2, 19, 13]).



Source: Migration Policy Institute

Research Question & Contributions

Research Question:

- How do labor demand shocks affect immigration attitudes?

Contributions:

- Identify a plausible causal relationship using shift-share instruments or Bartik shocks ([3]).
- Examine immigration attitudes over a long period (2000-2022).
- Leverage a novel, multifaceted data collection approach for immigration attitudes.

Source: Image generated by DALL.E, OpenAI.

Conceptual Framework

Impact of Labor Demand Shocks on Immigration Attitudes: Key Channels

- **Competition for Resources:**
  - Varying levels of substitutability and complementarity among incoming immigrants, existing immigrants, and the native-born population[1].
  - This competition, influenced by skills, education, occupation, and industry, varies over the short and long term and is affected by labor demand shocks.

- **Productivity and Wage Effects:**
  - Immigration can lead to productivity gains and innovation, potentially creating new jobs.
  - Conversely, an excess supply of labor may decrease wages, reducing consumption of goods and services and thus labor demand.

- **Misattribution and Group Identity:**
  - Labor demand shocks attributed to immigration due to other factors like automation, trade, or offshoring can foster scapegoating, frustration, and fear towards the immigrants.
  - This may lead to a group identity mindset that disfavors out-groups.

[1] This population is commonly referred to as "natives" in the economics literature as seen in this literature review paper [1]. We do not use it in any pejorative way.

Data Sources

Data I

Labor Market Data from IPUMS.com (see [21])

- The 1990 and 2000 Decennial Census Extracts
- Annual and 5-year American Community Survey (ACS) microdata, 2004 - 2020.
  - The 5-year ACS data are from 2018 and 2020.
- Sample restricted to non-institutionalized, civilian population, aged 18 and older.
- We examine employment by state, industry, and year.
- We use longitudinally consistent industries, based on 1990 Census Bureau industrial classification scheme and North American Industrial Classification System (3 & 4 digits).

Data II

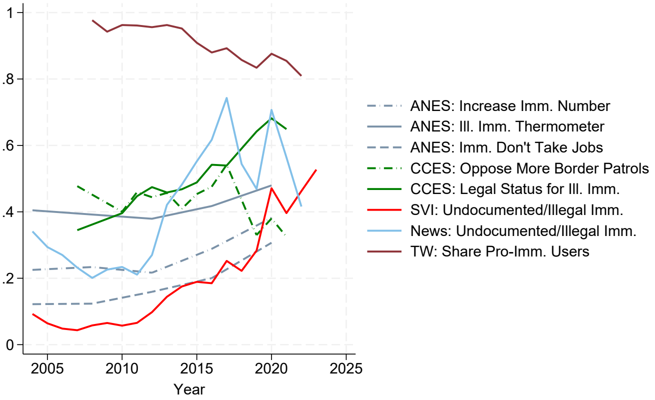
Immigration Attitudes Data

- Traditional Survey Data:
  - The American National Election Studies (ANES) ▸ Details
  - The Cooperative Congressional Election Study (CCES) ▸ Details
- Traditional Media:
  - Newspaper archives from newspapers.com and newslibrary.com ▸ Details
- Social Media and Digital Data Sources:
  - Google Trends (*i.e.*, Google Search Inquiries) ▸ Details
  - Tweets from Twitter (now X) ▸ Details

Immigration Attitudes Trends

National Time Trends in **Positive** Immigration Attitudes Across Measures and Sources

▸ More Trends (ANES) ▸ More Trends (Tweets) ▸ More Trends (Newspapers I) ▸ More Trends (Newspapers II)



Source: Authors' calculations using public data from the American National Election Studies, the Cooperative Congressional Election Studies, Google Trends, Newspapers, and Tweets, 2004 – 2022.

Empirical Framework

Empirical Framework

Objective:

- Estimate the causal effect of labor demand shocks on attitudes towards immigrants in the U.S.

Identification Challenge:

- Reverse causality: immigration attitudes may also influence Labor demand (*e.g.*, discrimination).

- Unobservability of Labor Demand: labor demand is not directly observable.

Our Approach:

- Employ Bartik shocks per [3] to isolate exogenous variation in labor demand.

Bartik Shocks

- Bartik shock for locations $l = 1, \ldots, L$ and year t can be expressed as:

$$B_{lt} = \sum_{n} (\underbrace{s_{lnt_0}}_{\text{Shares}} * \underbrace{g_{nt}}_{\text{Growth Rates}})$$

- Where s_{lnt_0} are industry shares in base year t_0 and g_{nt} are national industry growth rates since t_0.
  - We estimate Bartik shocks for both 1990 and 2000 base years. Orthogonality

Geographic Locations:

- 50 states and DC, and
- Commuting zones (CZ) (*i.e.*, clusters of counties that approximate local labor markets)
  - CZs are only possible for Twitter and CCES data.

Industries:

- Longitudinally consistent industries based on 1990 Census Bureau industrial classification scheme and North American Industrial Classification System (3 & 4 digits).

Fixed Effects Regression Model

$$y_{lt} = \alpha_l + \tau_t + \omega B_{lt} + X_{lt}'\gamma + \epsilon_{lt},$$

- y_{lt}: outcome variable of interest
- B_{lt}: Bartik shocks
- X_{lt}': a vector of time-varying location specific control variables (e.g., share of different ethnic and racial groups, different education groups, share of the foreign born population, and the share of those who don not speak English well or at all)
- α_l and τ_t: location and time effects
- ϵ_{lt}: stochastic error term

First-Differences Regression Model Individual-Level Regressions

Main Results

Preview of Main Results

- For comparability, sentiment measures and Bartik shocks are converted to standard deviations in regression models.
- Most measures (excluding CCES) indicate a positive relationship between positive labor demand shocks and positive immigration attitudes.
- Similar outcomes using first-difference and fixed effects models.

Fixed Effects Model, State Level, Every Four Years

	ANES			GT	NP	CCES		TW
	Number	Jobs	Therm	SVI Ratio	NP Ratio	Border Patrol	Legal Status	TW Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bartik	1.427**	1.266**	1.032*	1.625**	0.428	0.240	-0.156	1.133***
	(0.487)	(0.440)	(0.439)	(0.524)	(0.360)	(0.474)	(0.247)	(0.245)
N	216	216	216	185	234	153	153	204
R-Squared	0.701	0.680	0.667	0.716	0.826	0.874	0.944	0.932

Authors' calculations using public data from the 1990 Decennial Census, American Community Survey, American National Election Studies, Cooperative Congressional Election Studies, Google Trends, Newspapers, and Tweets. Four-year growth intervals are used, 2004 – 2020. Standard errors, clustered at the state level, are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

First-Differences Model, State Level, Every Four Years

	ANES			GT	NP	CCES		TW
	Number	Jobs	Therm	SVI Ratio	NP Ratio	Border Patrol	Legal Status	TW Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D.Bartik	1.221^{+}	1.360**	0.674	1.073**	1.019*	0.184	-0.112	0.488*
	(0.670)	(0.424)	(0.496)	(0.395)	(0.457)	(0.361)	(0.215)	(0.198)
N	159	159	159	138	186	102	102	153
R-Squared	0.336	0.227	0.271	0.542	0.602	0.691	0.541	0.697

Authors' calculations using public data from the 1990 Decennial Census, American Community Survey, American National Election Studies, Cooperative Congressional Election Studies, Google Trends, Newspapers, and Tweets. Four-year growth intervals are used, 2004 – 2020. Standard errors, clustered at the state level, are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Additional Results

Skip

CZ-Level Results, Twitter & CCES

Panel A. Fixed Effects

	Twitter: Pro-Immigration Share			CCES: Oppose More Border Patrols			CCES: Legalize Illegal Immigration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Bartik	0.462***	0.276***	0.289***	0.178**	0.115***	0.167***	0.0158	0.128***	0.136***
	(0.0573)	(0.0172)	(0.0197)	(0.0585)	(0.0162)	(0.0196)	(0.0540)	(0.0170)	(0.0186)
Observations	5383	2594	1337	3745	2094	1247	3745	2094	1247
R^2	0.767	0.626	0.588	0.421	0.197	0.279	0.542	0.415	0.415

Panel B. First-Difference

	Twitter: Pro-Immigration Share			CCES: Oppose More Border Patrols			CCES: Legalize Illegal Immigration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Bartik	0.234**	0.264**	0.257**	-0.00863	0.139	0.199	0.148	-0.143	0.0596
	(0.0887)	(0.0922)	(0.0846)	(0.164)	(0.161)	(0.153)	(0.179)	(0.201)	(0.147)
Observations	5314	2452	1160	2907	1224	840	2907	1224	840
R^2	0.140	0.160	0.224	0.062	0.084	0.203	0.031	0.064	0.084

Source: Authors' calculations using public data from the 1990 Decennial Census, the American Community Survey, tweets from Twitter and the Cooperative Congressional Election Studies.

Standard errors, clustered at the CZ level, are in parenthesis. All specification in both panels include the following individual controls: age, dummies for male, single, white, and college-educated. The sample in Columns (1) and (3) include all years; In Column (2) it is two-year intervals, and in Column (3), the sample includes four-year intervals. + $p<0.1$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Individual-Level Immigration Attitudes Results, Repeated Cross-Sectional Data

Panel A. ANES State-Level Shocks

	Number	Jobs	Therm
	(1)	(2)	(3)
Bartik	0.175**	0.0572	0.0784
	(0.0557)	(0.0586)	(0.0622)
Observations	19385	19523	19135
R^2	0.117	0.125	0.143

Panel B. CCES State-Level Shocks

	Oppose More Border Patrols			Grant Legal Status		
	(1)	(2)	(3)	(4)	(5)	(6)
Bartik	0.0653	0.119	0.176	-0.325*	-0.288	-0.219
	(0.172)	(0.227)	(0.260)	(0.135)	(0.184)	(0.203)
Observations	396926	290302	179160	396955	290294	179152
R^2	0.079	0.069	0.077	0.097	0.099	0.090

Source: Authors' calculations using public data from the 1990 Decennial Census, the American Community Survey, the American National Election Studies, and the Cooperative Congressional Election Studies. Standard errors, clustered at the state level, are in parenthesis.

The sample in Columns (1) and (3) includes all years; In Column (2) it is four-year intervals, and in Column (3) it is two-year intervals. + $p<0.1$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Concluding Remarks

- Strong evidence suggests labor demand shocks impact immigration attitudes.
- Diverse measures and specifications yield different conclusions; reliance on a single measure may mislead, potentially overlooking a labor demand-immigration attitude link. ▸ Additional Results

Thank You

This is a work-in-progress, and we greatly value your comments and feedback.
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Please scan to download the presentation.

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Appendix

ANES

Overview ‣ Back

- Conducted during national election years since 1948 (mostly quadrennially, and sometimes biennially)
  - It's a collaboration between Duke University, University of Michigan, University of Texas at Austin, and Stanford University, with funding by the National Science Foundation.
- Nationally representative survey focusing on:
  - Electoral behavior and political participation.
  - Public opinion, and
  - Demographics for respondents.

Immigration-Related Data

- Questions featured within the Time Series Cumulative Data File:
  - Preferences for increasing or decreasing U.S. immigrant numbers (1992–2020). ‣ Details
  - Perceptions of recent immigration impacting job availability (2004–2020). ‣ Details
  - Attitudes towards illegal immigrants, measured via a "thermometer" scale (1992–2020). ‣ Details
- Extensively used in research, including studies by: [7, 17, 6, 23, 16, 5, 26, 22]

CCES I

Overview

▸ Back

- A national survey conducted annually since 2005 by YouGov
- Representative at the state level
- Consists of Common Content for all 50,000+ respondents and Team Content for subsets of 1,000, designed by participating teams. Teams may also collaborate on Group Content.
- It focuses on:
  - Electoral behavior and political participation,
  - Public opinion, and
  - Demographics for respondents.
- Frequently used in research, including studies by: [25, 12, 18, 9]

▸ List of Questions

CCES II

Immigration-Related Data ‣ Back

- Use 23 immigration-related questions, including a broad spectrum of topics such as:
  - Preferences for Border Control (2007, 2010 - 2017, 2019 - 2021) ‣ Details
  - Border Security and Wall Construction (2017-2018, 2020-2021) ‣ Details
  - Defense Funds for Wall Construction (2019) ‣ Details
  - Deportation Policies (2014 - 2017) ‣ Details
  - Employment Sanctions (2007, 2010, 2012 - 2017) ‣ Details
  - Suspicion-Based Questioning (2010 - 2015, 2017) ‣ Details
  - Federal Funding and Police Reporting (2017 - 2021) ‣ Details
  - Public Service Access (2012-2013) ‣ Details
  - Guest Worker Program (2007, 2010, 2015-2017) ‣ Details
  - Legal Immigration Reduction (2018 - 2020) ‣ Details
  - Legal Status for Illegal Immigrants (2006, 2007, 2010 - 2017, 2019-2021) ‣ Details
  - DACA Access (2018, 2021) ‣ Details
- Recode all variables to binary outcomes: ”1” indicating anti-immigration attitudes, ”0” otherwise.
- Calculate Z-scores for each variable to standardize responses. ‣ Details

Newspapers I

Data Collection
▸ Back

- Collect counts of newspaper articles from Newspapers.com for each state, annually from 2000 to 2022, mentioning **"illegal immigrants"** and **"undocumented immigrants"** distinctly[2].

- Download the first paragraph of newspaper articles from Newslibrary.com spanning 1980 to 2022, focusing on articles containing keywords: **"immigration," "immigrant,"** or **"migrant."** Coverage is sparse pre-2000.

▸ Sentiment Analysis

[2] "Illegal" and "undocumented" terms for describing immigration are loaded terms, and that is why they are selected in our examination of public sentiment instead of a more neutral term of "unauthorized."

Newspapers II

Sentiment Analysis

- Our initial method involves calculating the ratio of articles mentioning ”undocumented immigrants” to those using ”illegal immigrants” across each state and year, interpreting a higher ratio as a reflection of more pro-immigrant attitudes.
  - The Associated Press ceased using ”illegal immigrant” in 2013 (see [8]), aligning with studies like [9] which validate the term’s effectiveness in gauging anti-immigration sentiment.

- Our second approach involves applying natural language processing (NLP) to assign sentiment scores to the first paragraph of each downloaded article, following [9]’s finding that the sentiment of the first paragraph sufficiently represents the overall article’s tone. ▸ Details

▸ Theme Classification

Newspapers III

Theme Classification

- **Manual Classification:** Defined keywords for five topics: jobs, crime, border security, refugees, immigration policy. More on Jobs More on Crime More on Border Security More on Refugees More on Immigration Policy
  - Articles assigned topics based on these keywords, allowing multiple topics per article.

- **Unsupervised Machine Learning:** Use Latent Dirichlet Allocation (LDA) for theme and topic classification into 5 groups without predefined labels. Topics inferred from dominant keywords.

- Note: LDA results are not presented today. Back

Google Trends

▸ Back

- Utilize Google Trends data at national and state levels for the search queries **"illegal immigrants"** and **"undocumented immigrants."**[3].
  - Currently, we do not utilize the most detailed geography level, Designated Market Area, in our analysis.

- Google Trends provides Search Volume Indices (SVI), reflecting the relative search frequency of terms within specific times and places.
  - SVIs are normalized to be between 0 and 100.

- Assumption: "Illegal immigrants" is used more frequently by individuals with negative attitudes, while "undocumented immigrants" indicates more positive attitudes, based on [9] and other studies.

- The ratio of SVIs for these terms serves as an indicator of the overall area attitudes towards immigration at any given time.

[3] "Illegal" and "undocumented" terms for describing immigration are loaded terms, and that is why they are selected in our examination of public sentiment instead of a more neutral term of "unauthorized."

Tweets (from Twitter) I

Data Collection and Sentiment Analysis Methodology ▸ Back

- Collect tweets from 2008-2021 using the "snscrape" Python module, with limited data from 2008-2010.
  - Twitter (now X) was launched in 2006.
- Tweets were filtered for immigration-related keywords.
- User locations derived from tweet geo-coordinates or profile locations, matched to cities, counties, or states.
- Sentiment scores based on positive and negative term matches.
- Identified sentiment targets to distinguish between negative sentiments towards immigrants and policies/policymakers. ▸ Details

Tweets (from Twitter) II

Back **Identifying Immigration Sentiments and Targets**

- Classify sentiment targets using hashtags indicative of views on immigration. For example:
  - Pre-2016 anti-immigration hashtags: antiimmigrant, noamnesty, illegals.
  - Post-2016 anti-immigration hashtag: maga.
  - Pre-2016 pro-immigration hashtags: daca, weareallamericans.
  - Post-2016 pro-immigration hashtags: antitrump, resist.

  More on Pro-Immigration Hashtags More on Anti-Immigration Hashtags

- Utilize a random forest classifier for tweets without clear hashtags to assign sentiment targets.

- Average users' tweets to determine the share of anti-immigrant sentiment; users with over 50 percent anti-immigration tweets classified as anti-immigration.

- Calculate the share of anti-immigration users by state and year.

ANES Question 1

- The question text below is from 2004, with consistent wording across all other years.
- **Do you think the number of immigrants from foreign countries who are permitted to come to the United States to live should be increased a lot, increased a little, left the same as it is now, decreased a little, or decreased a lot.**
- Code 8: Don't know
- Code 9: Not applicable Back

ANES Question 2

- Question text: **How likely is it that recent immigration levels will take jobs away from people already here– extremely likely, very likely, somewhat likely, or not at all likely?**
- Code 8: Don't know
- Code 9: Refuse or not applicable Back

ANES Question 3

- The 1976 survey instructions for thermometer questions were clearly outlined, with subsequent years' guidance remaining notably similar.

- **We'd also like to get your feelings about some groups in American society. When I read the name of a group, we'd like you to rate it with what we call a feeling thermometer. Ratings between 50 degrees-100 degrees mean that you feel favorably and warm toward the group; ratings between 0 and 50 degrees mean that you don't feel favorably towards the group and that you don't care too much for that group. If you don't feel particularly warm or cold toward a group you would rate them at 50 degrees. If we come to a group you don't know much about, just tell me and we'll move on to the next one.**

- Code 98: Don't know or don't recognize

- Code 99: Not Applicable Back

CCES Question 1

- There may be veriation in
- Question Text: **What do you think the U.S. government should do about immigration? Increase the number of border patrols on the US-Mexican border.**
- Code 1: Yes
- Code 2: No
- Note: Question wording may vary across survey years, as seen in the example from one specific year. Back

CCES Question 2

- Question Text: **What do you think the U.S. government should do about immigration? Do you support or oppose each of the following? Increase spending on border security by $25 billion, including building a wall between the U.S. and Mexico.**
- Code 1: Support
- Code 2: Oppose
- Note: Question wording may vary across survey years, as seen in the example from one specific year. Back

CCES Question 3

- Question Text: **What do you think the U.S. government should do about immigration? Do you support or oppose each of the following? Overturn President Trump's order to use $6 billion of defense funds to pay for the construction of a wall.** Back

CCES Question 4

- Question Text: **What do you think the government should do about immigration? Identify and deport illegal immigrants.**
- Code 1: Yes
- Code 2: No
- Note: Question wording may vary across survey years, as seen in the example from one specific year. Back

CCES Question 5

- Question Text: **What do you think the government should do about immigration? Fine US businesses that hire illegal immigrants.**
- Code 1: Yes
- Code 2: No
- Note: Question wording may vary across survey years, as seen in the example from one specific year. Back

CCES Question 6

- Question Text: **What do you think the government should do about immigration? Allow police to question anyone they think may be in the country illegally.**
- Code 1: Yes
- Code 2: No
- Note: Question wording may vary across survey years, as seen in the example from one specific year. Back

CCES Question 7

- Question Text: **What do you think the U.S. government should do about immigration? Do you support or oppose each of the following? Withhold federal funds from any local police department that does not report to the federal government anyone they identify as an illegal immigrant.**

- Code 1: Support

- Code 2: Oppose

- Note: Question wording may vary across survey years, as seen in the example from one specific year. Back

CCES Question 8

- Question Text: **What do you think the U.S. government should do about immigration? Select all that apply. Prohibit illegal immigrants from using emergency hospital care and public schools.**
- Note: Question wording may vary across survey years, as seen in the example from one specific year. Back

CCES Question 9

- Question Text: **What do you think the U.S. government should do about immigration? Increase the number of guest workers allowed to come legally to the U.S.**

- Code 1: Yes

- Code 2: No

- Note: Question wording may vary across survey years, as seen in the example from one specific year. Back

CCES Question 10

- Question Text: **What do you think the U.S. government should do about immigration? Do you support or oppose each of the following? Reduce legal immigration by 50 percent over the next 10 years by eliminating the visa lottery and ending family-based migration.**
- Code 1: Support
- Code 2: Oppose
- Note: Question wording may vary across survey years, as seen in the example from one specific year. ▸ Back

CCES Question 11

- Question Text: **What do you think the U.S. government should do about immigration? Do you support or oppose each of the following? Grant legal status to all illegal immigrants who have held jobs and paid taxes for at least 3 years, and not been convicted of any felony crimes.**
- Code 1: Support
- Code 2: Oppose
- Note: Question wording may vary across survey years, as seen in the example from one specific year. Back

CCES Question 12

- Question Text: **What do you think the U.S. government should do about immigration? Do you support or oppose each of the following?** **Provide legal status to children of immigrants who are already in the United States and were brought to the United States by their parents. Provide these children the option of citizenship in 10 years if they meet citizenship requirements and commit no crimes. (DACA).**

- Code 1: Support

- Code 2: Oppose

- Note: Question wording may vary across survey years, as seen in the example from one specific year. Back

CCES III

Variable Creation

- Recode all variables to binary outcomes: ”1” indicating anti-immigration attitudes, ”0” otherwise.
- Calculate Z-scores for each variable to standardize responses.
- Average the Z-scores across all variables to form comprehensive index variables for analysis.
  - An index including all questions to observe overall trends in immigration attitudes.
  - An index excluding the border patrol question to assess its influence on the overall trend.
  - An index excluding both the border patrol and legal status questions to further isolate the impact of these specific issues on immigration attitudes.
  - Note: Questions on border patrol and conditional legal status are the most frequently asked.

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Sentiment Analysis with VADER

- Use VADER for our second sentiment analysis method, a lexicon and rule-based tool in NLTK Python library, optimized for social media sentiment.
- VADER analyzes lexical features (words), categorizing them as positive or negative based on semantic orientation.
- Provides scores ranging from -1 (extremely negative) to +1 (extremely positive), indicating sentiment intensity. Back

Keywords for Manual Jobs Theme Classification

- Keywrords for **jobs** theme: ”jobs”, ”employment”, ”work”, ”career”, ”profession”, ”occupation”, ”business”, ”industry”, ”hiring”, ”recruiting”, ”salary”, ”wage”, ”internship”, ”workforce”, ”staff”, ”employees”, ”worker”, ”unemployed”, ”unemployment”, ”jobless”, ”retired”, ”career fair”, ”job opening”, ”job posting”, ”position”, ”role”, ”vacancy”, ”layoff”, ”fired”, ”hired”, ”workplace”, ”employers”, ”full-time”, ”part-time”, ”freelance”, ”contract”, ”remote work”, ”job security”, ”economy”, ”economic growth”, ”GDP”, ”recession”, ”inflation”, ”deflation”, ”trade”, ”export”, ”import”, ”finance”, ”investment”, ”market”, ”stock”, ”fiscal policy”, ”monetary policy”, ”tax”, ”revenue”, ”stimulus”, ”debt”, ”credit”, ”budget”, ”financial crisis”, ”trade balance” Back

Keywords for Manual Crime Theme Classification

- Keywrords for **crime** theme: ”crime”, ”murder”, ”theft”, ”law”, ”police”, ”arrest”, ”felony”, ”misdemeanor”, ”robbery”, ”burglary”, ”assault”, ”fraud”, ”violence”, ”homicide”, ”manslaughter”, ”kidnapping”, ”rape”, ”domestic violence”, ”drugs”, ”weapon”, ”gang”, ”vandalism”, ”arson”, ”trespassing”, ”harassment”, ”stalking”, ”cybercrime”, ”embezzlement”, ”corruption”, ”bribery”, ”money laundering”, ”terrorism”, ”extortion”, ”smuggling”, ”trafficking”, ”prison”, ”jail”, ”probation”, ”bail”, ”conviction”, ”sentence”, ”warrant”, ”probable cause”, ”contraband”, ”incarceration”, ”custody” Back

Keywords for Manual Border Security Theme Classification

- Keywords for **border security** theme: ”border”, ”security”, ”fence”, ”wall”, ”patrol”, ”customs”, ”checkpoint”, ”surveillance”, ”guard”, ”border control”, ”immigration enforcement”, ”smuggling”, ”trafficking”, ”visa”, ”passport”, ”illegal entry”, ”border crossing”, ”protection”, ”national security”, ”inspection”, ”detection”, ”biometrics”, ”intelligence”, ”securitization” Back

Keywords for Manual Refugees Theme Classification

- Keywrords for **refugees** theme: ”refugee”, ”asylum”, ”asylum seeker”, ”displaced”, ”shelter”, ”persecution”, ”resettlement”, ”humanitarian”, ”internally displaced”, ”camp”, ”protection”, ”migration”, ”flee”, ”escape”, ”rescue”, ”deportation”, ”repatriation”, ”relocation”, ”UNHCR”, ”aid”, ”sanctuary”, ”status”, ”temporary protection” Back

Keywords for Manual Immigration Policy Theme Classification

- Keywrords for **immigration policy** theme: ”policy”, ”legislation”, ”reform”, ”visa”, ”citizenship”, ”naturalization”, ”green card”, ”permanent residency”, ”temporary visa”, ”work visa”, ”family reunification”, ”quota”, ”law”, ”regulation”, ”amnesty”, ”deportation”, ”detention”, ”integration”, ”sponsorship”, ”guest worker”, ”pathway to citizenship”, ”dual citizenship”, ”consulate”, ”embassy”, ”immigration court”, ”appeal”, ”status adjustment”, ”DACA” Back

Hashtags Indicating Pro-Immigration Sentiment in Tweets

- Hashtags for classifying **anti-Trump/pro-immigration** sentiments: #antitrump #resist #liar #notmypresident #resistance #impeachtrump #notrump #nobannowall #resisttrumptuesdays #theresistance #nevertrump #dumptrump #lovetrumpshate #boycotttrump #fucktrump #trumpprotest #trumpmemes #trumpisajoke #daca #abolishice #familiesbelongtoghether #faketrumpemergency #trumpshutdown #nowall #indicttrump #trumplies #trumpliesmatter #cult45 #moroninchief #dumpchump #closethecamps #daca #defundhate #statueofliberty #publiccharge #smartnews #beto2020 #warren2020 #dontdeportmelania #racistinchief #derangeddonald #racist #racism #xenophobia #moscowmitch #standwithiraqirefugees #iceraids #trumpcamps #keepfamiliestogether #publicchargerule #25thamendmentnow #saynotoxenophobia #powerofinclusion #trumpisawhitesupremacist #detention #humanrights #asylumseekers #knowyourrights #undocumented #cuccinelliresign #stephenmiller #deportmelania #refugeeswelcome #bernie2020 #concentrationcamps #dontlookaway #trumpisaracist #jewsagainstice #neveragainisnow #tuckfrump #enoughisenough #racisttrump Back

Hashtags Indicating Anti-Immigration Sentiment in Tweets

- Hashtags for classifying **pro-Trump/anti-immigration** sentiments: #maga #fakenews #buildthatwall #buildthewall #makeamericagreatagain #protrump #trumpsupporters #trumptrain #trumppence #republicansfortrump #blacksfortrump #latinosfortrump #womenfortrump #americafirst #draintheswamp #trump2020 #enforceourborders #illegalimmigrants #illegals #illegalimmigration #illegalaliens #maga2020 #kag2020 #dems #recallgavinnewsom #wethepeople #closetheborder #sanctuarycities #sanctuarystate #wakeupamerica #socialism #liberalismisamentaldisorder #finishthewall #deportthemall #democratsaredestroyingamerica #openborders #sendthemback #noamnesty Back

State-Level Correlation Trends Between ANES and Measures from Other Sources

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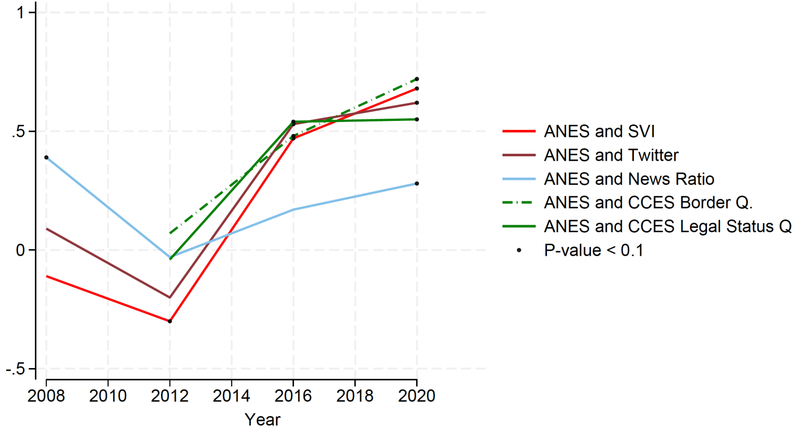

Source: Authors' calculations using public data from the American National Election Studies, the Cooperative Congressional Election Studies, Google Trends, Newspapers, and Tweets.

State-Level Correlation Trends Between Tweets and Measures from Other Sources

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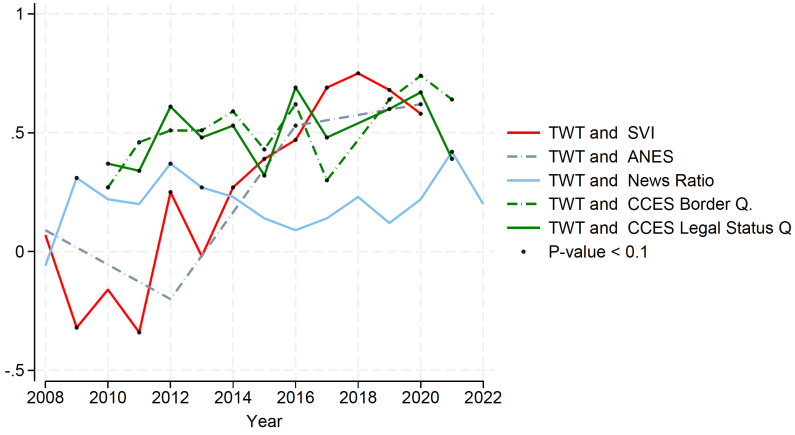

Source: Authors' calculations using public data from the American National Election Studies, the Cooperative Congressional Election Studies, Google Trends, Newspapers, and Tweets.

Trends in Share of Immigration Articles from Newslibrary.com by Topic

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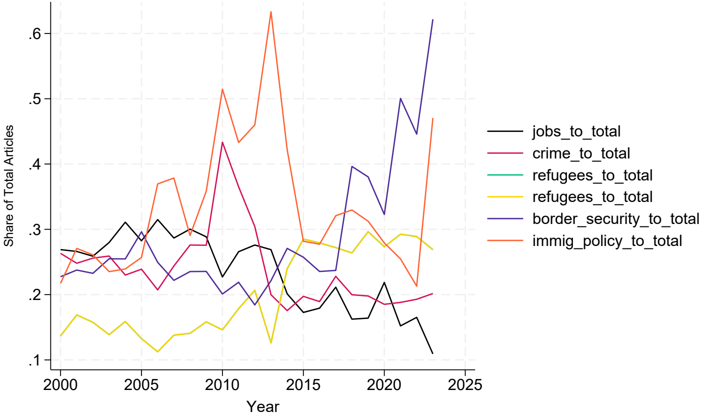

Source: Authors' calculations using newspapers collected from Newslibrary.com (public-use data).

Trends in Share of Positive to Negative Immigration Articles from Newslibrary.com by Topic

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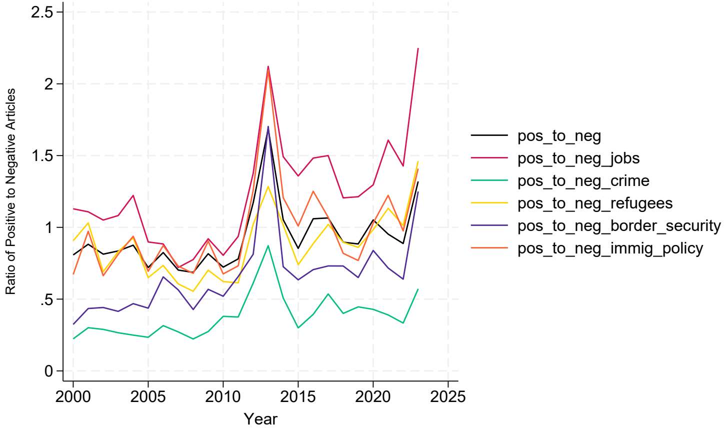

Source: Authors' calculations using newspapers collected from Newslibrary.com (public-use data).

Orthogonality of Bartik Shocks

- Orthogonality condition of Bartik shocks may be achieved through either of the following:
  1. National employment growth rates' orthogonality (see [4]), ▸ Details
  2. Employment shares's orthogonality (see [14])

- In our context, the orthogonality of national employment growth rates is more plausible due to a large number of growth rates.

- Adopting [4] approach:
  - Re-estimate main specification at growth rates level (*i.e.*, industry level) to obtain exposure-robust standard errors. ▸ Equivalency Results for First Differences ▸ Equivalency Results for Fixed Effects

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National Growth Rates' Orthogonality

- National growth rates must be as-good-as-randomly assigned (conditional on growth rates level observables, if needed).([4]).
- Orthogonality requires numerous, mutually uncorrelated growth rates. ▸ Results
- Based on [4], orthogonality of national industry-specific growth rates is equivalent to orthogonality of location-specific Bartik shocks and residuals.
- This equivalency suggests:
  - Equal coefficients in location and industry-level analyses.
  - Industry-level standard errors are necessary, as location-specific errors may be inappropriate. ▸ See Industry Clustering Level

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Growth Rates Summary Statistics

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	Growth Rates, Base 1990	Growth Rates, Base 2000
Mean	0.287	0.147
S.D.	0.577	0.354
IQR	0.537	0.289
Effective Sample Size		
Across detailed industries & periods	220.1	199.2
Across industry groups	34.8	24.4
Largest s_{nt} Weight		
Across detailed industries	0.016	0.018
Across industry groups	0.080	0.092
Observation Counts		
# Shocks	884	876
# Detailed industries	221	219
# Industry groups	76	56

Source: Authors' calculations using public Decennial Censuses and the American Community Survey data. The specifications in both columns correspond to Column (1) of Table 1 in [4].

Growth Rates Intra-Class Correlations (ICC)

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	Growth Rates, Base 1990		Growth Rates, Base 2000	
	Estimate	SE	Estimate	SE
Shocks ICC				
2-digit Industries	0.060	0.074	0.084	0.127
3-digit Industries	0.007	0.017	0.037	0.026
Detailed Industries	0.818	0.062	0.700	0.102
Period Means				
2006	0.169	0.102	0.089	0.068
2010	0.136	0.122	0.076	0.078
2014	0.157	0.159	0.147	0.103
2018	0.256	0.221	0.297	0.147

Source: Authors' calculations using public Decennial Censuses and the American Community Survey data. This table is adapted from Table 2 in [4].

Equivalency Results, First-Differences Model, ANES & CCES

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	State Level			Industry Level		
	ANES	CCES		ANES	CCES	
	Number	Legal Status	Border Patrol	Number	Legal Status	Border Patrol
dbartik	1.737*	-0.0972	0.159			
	(2.32)	(-0.52)	(0.51)			
dbartik2				1.737***	-0.0972	0.159
				(3.55)	(-0.80)	(0.51)
N	102	102	102	442	442	442

Authors' calculations using public data from the 1990 Decennial Census, the American Community Survey, the American National Election Studies, and the Cooperative Congressional Election Studies. Four-year growth intervals are used, 2012 – 2020. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Equivalency Results, Fixed Effects Model, ANES & CCES

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	State Level			Industry Level		
	ANES	CCES		ANES	CCES	
	Number	Legal Status	Border Patrol	Number	Legal Status	Border Patrol
bartik	1.819*	-0.144	0.192			
	(2.42)	(-0.63)	(0.51)			
bartik2				1.819***	-0.144	0.192
				(4.71)	(-1.00)	(0.84)
N	153	153	153	663	663	663

Authors' calculations using public data from the 1990 Decennial Census, the American Community Survey, the American National Election Studies, and the Cooperative Congressional Election Studies. Four-year growth intervals are used, 2012 – 2020. *t* statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(Stacked) First-Differences Regression Model

- Preferred estimation method due to **possible** serial correlation in immigration attitudes (attitudes in year t correlated with year $t-1$).

- To examine robustness to model specification, we estimate both models.

$$\Delta y_{lt} = \tilde{\tau}_t + \tilde{\omega}\Delta B_{lt} + \Delta X'_{lt}\tilde{\lambda} + \Delta \varepsilon_{lt},$$

- All variables are as previously defined.
- Δ denotes first differences (*e.g.*, $y_{lt} - y_{lt-1}$).

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Individual-Level Regressions

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- Since one of the aims of this study is to examine comparability of various immigration attitudes measures, we mainly estimate state-year level outcomes where all measures are available.
- Concern arises that observed changes in average attitudes may stem from demographic shifts rather than genuine attitudinal changes.
- To mitigate this concern, we use individual-level outcomes from ANES and CCES, allowing for control over individual characteristics.

$$y_{ilt} = \alpha_l + \tau_t + \omega B_{lt} + X'_{ilt}\gamma + \epsilon_{ilt},$$

  - i denotes an individual.

- CCES also provides a smaller individual panel in some years, allowing for control over unobserved individual heterogeneity.

$$\Delta y_{ilt} = \tau_t + \omega \Delta B_{lt} + \Delta X'_{ilt}\lambda + \Delta\varepsilon_{ilt},$$