

EFFECT OF THE ECONOMY ON SENTIMENT ABOUT IMMIGRATION

by Carol Rangel and David Shou

Background

- Anti-immigration sentiment rose steadily during the Biden presidency and reached the highest in two decades in 2024
- Border crossing reached record-level under Biden
- Immigration is intrinsically an economic issue
 - Argument used by both sides



REUTERS/Eduardo Munoz

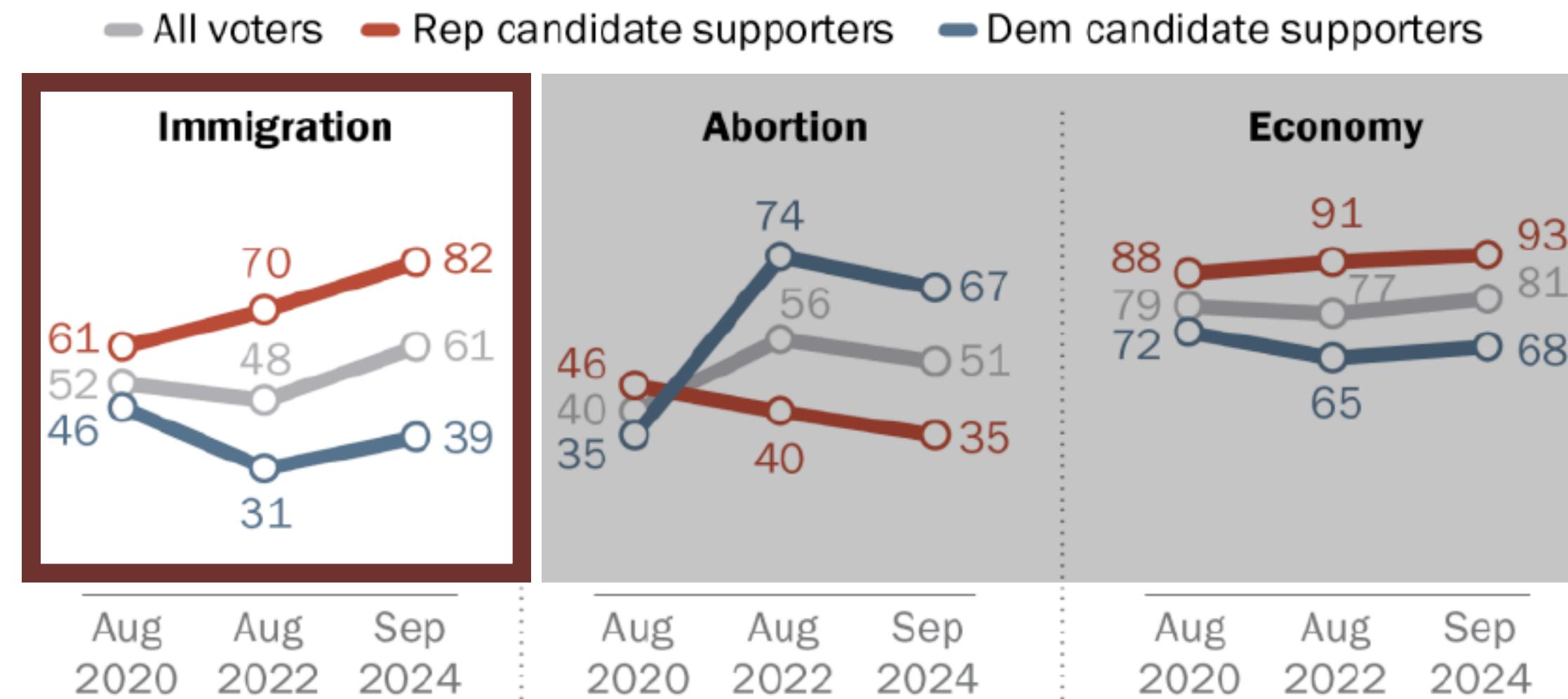


The Pardee Atlas Journal of Global Affairs

Immigration has become increasingly a top-of-mind issue for voters, standing among the top ones

Immigration has increased in importance among Republican voters; abortion surged in importance for Democrats in 2022, remains high today

*% of registered voters who say each issue is **very important** to their vote in that year's election*



Note: Based on registered voters. In 2020 and 2024, candidate supporters are for the presidential election. In 2022, candidate supporters are for the congressional election.
Source: Survey of U.S. adults conducted Aug. 26-Sept. 2, 2024.



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The border crisis is ‘about as bad as I’ve ever seen it’: Border patrol chief

ABC News’ Matt Rivers reports on the latest in the border surge on “This Week.”

September 24, 2023

Illegal immigrants with 'terrorism ties' will continue to exploit border, Homeland Security report warns

By Louis Casiano

Published October 03, 2024

≡ [CNN Politics](#) [Trump](#) [Facts First](#) [CNN Polls](#) [2025 Elections](#) [Redistricting Tracker](#)

Everyone can now agree – the US has a border crisis



Analysis by [Stephen Collinson](#), CNN

⌚ 7 min read · Published 12:03 AM EST, Fri December 16, 2022

B B C

US migrant crisis shifts from Texas to California border

20 April 2024

Sumi Somaskanda & Naomi Choy Smith

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Research Question

Do macroeconomic
conditions affect
public sentiment
about immigration?
A case study with NY
economic data

Literary Review

David Card (1990)

Immigration has little negative effect on wages.

The Mariel Boatlift (1980) compare Miami's workforce (a sudden 7% growth) to similar cities show no significant drop in wages or rise in unemployment.

Suggesting that local labor markets can flexibly absorb new workers.

George Borjas (2003, 2017)

Immigration significantly lowers wages.

National "skill-cell" evidence shows a 10% labor-supply increase cuts wages for that group by about 3–4%.

A Mariel reappraisal focusing on low-skilled Miami workers finds wage losses of 10–30%.

Literary Review

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Suggesting that local labor markets can flexibly absorb new workers.

George Borjas (2003, 2015)

Sadly, criticized by Clemens, M. A., & Hunt, J. (2019) after immigrating, correcting the errors. Immigration's impact remains small low-skilled wages.

A Mariel reappraisal focusing on low-skilled Miami workers finds wage losses of 10–30%.

Literary Review

Islam (2007)

$$\log(U_t-p) = 75.84 - 0.046t - 0.17\log(M_t-p) + 15.75\log(Y_t-p) + 23.76\log(W_t-p)$$

Immigration has no significant impact on unemployment rates in Canada.

**Bruce-Tagoe
(2022)**

$$UNEM_{it}/WAGE_{it} = \beta_0 + \beta_1 COLL_{it} + \beta_2 IMM_{it} + \beta_3 INF_{it} + \beta_4 RGDP_{it} + \mu_{it}$$

Immigration growth does not significantly affect U.S. unemployment or wage growth.

Chen (2020)

$$Y_{it} * = \beta \cdot Treatment_i \times Post_t + x_{it}' \beta_x + \alpha_i + \gamma_t + \epsilon_{it}$$

Economic insecurity from unemployment drives left-wing populism, while cultural anxiety from immigration influx fuels right-wing populism.

2021–2024? Biden-era immigration wave

Current Population Survey (CPS)

7.6 million “new immigrants” accounting for about 78% of net U.S. employment growth between 2019 and 2024

Younger and highly attached to the labor market

Monthly, nationally representative household survey of about 60,000 households, and the primary source of official U.S. labor-force statistics

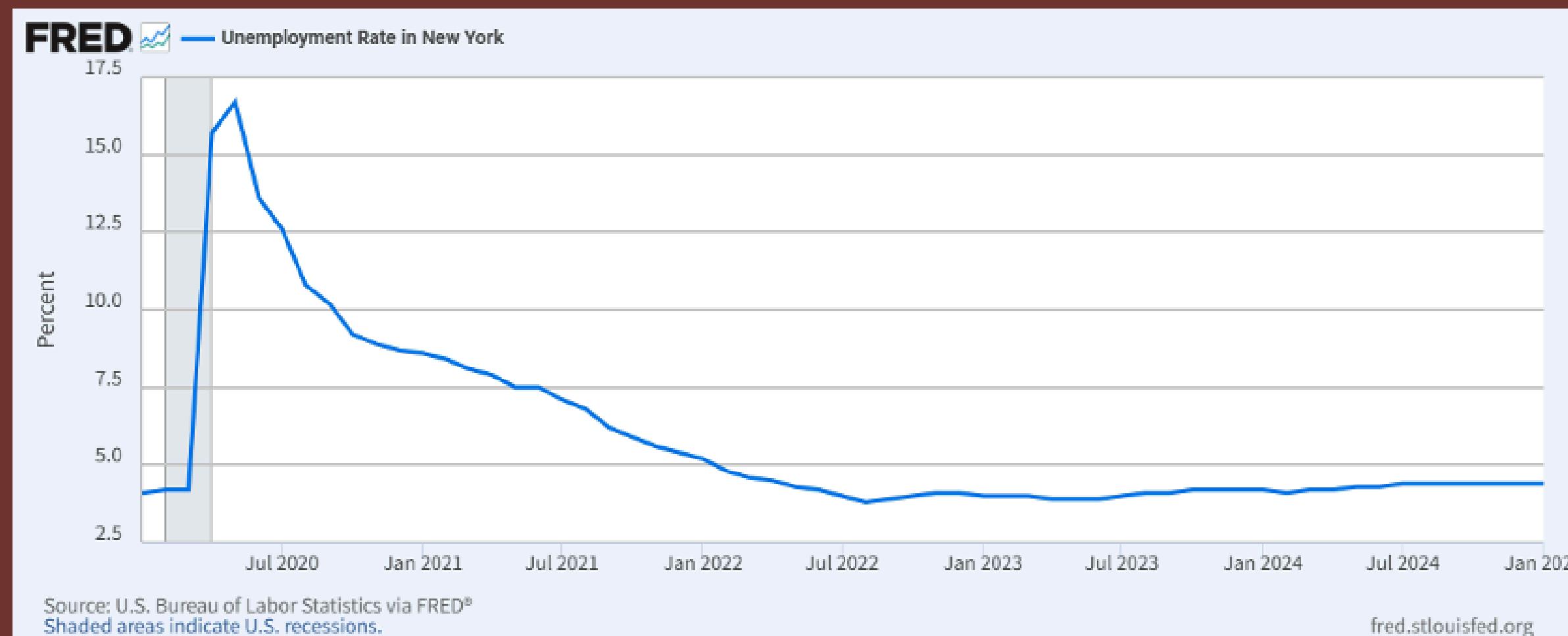
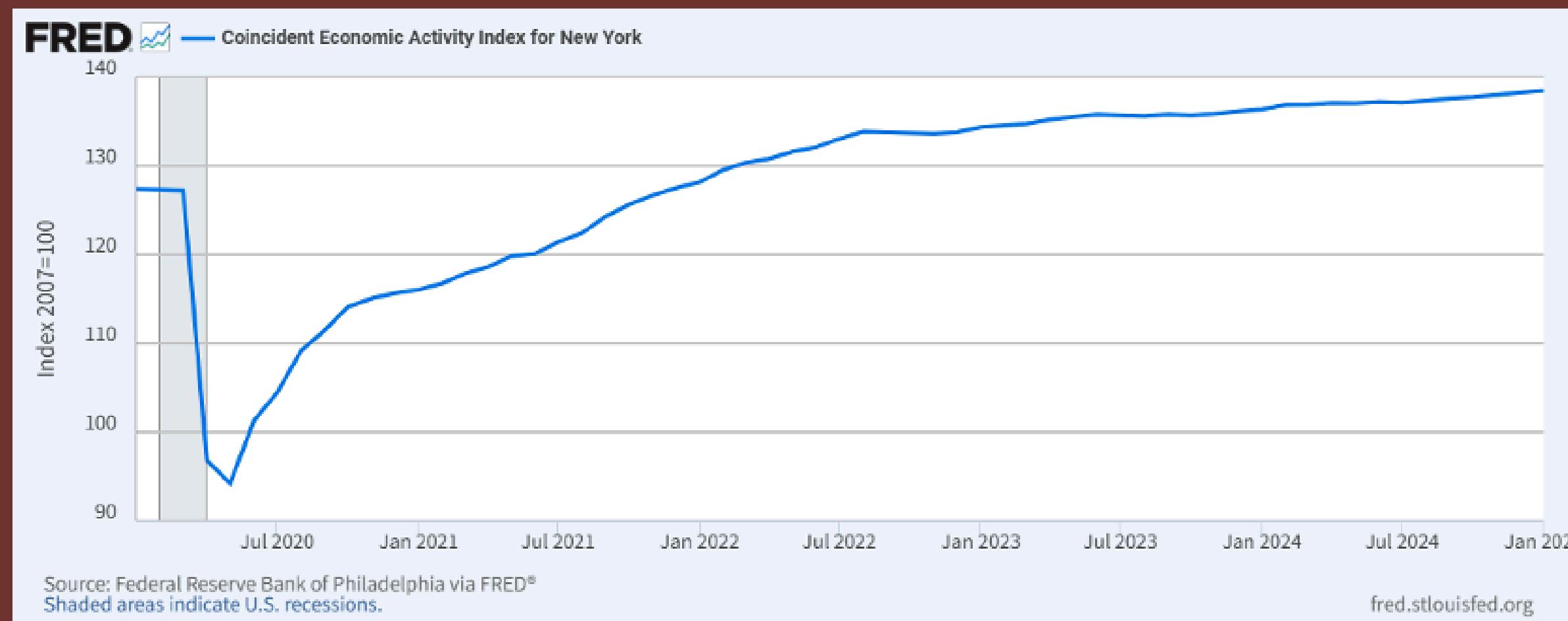
Consistent data with rich demographic, nativity and citizenship information.

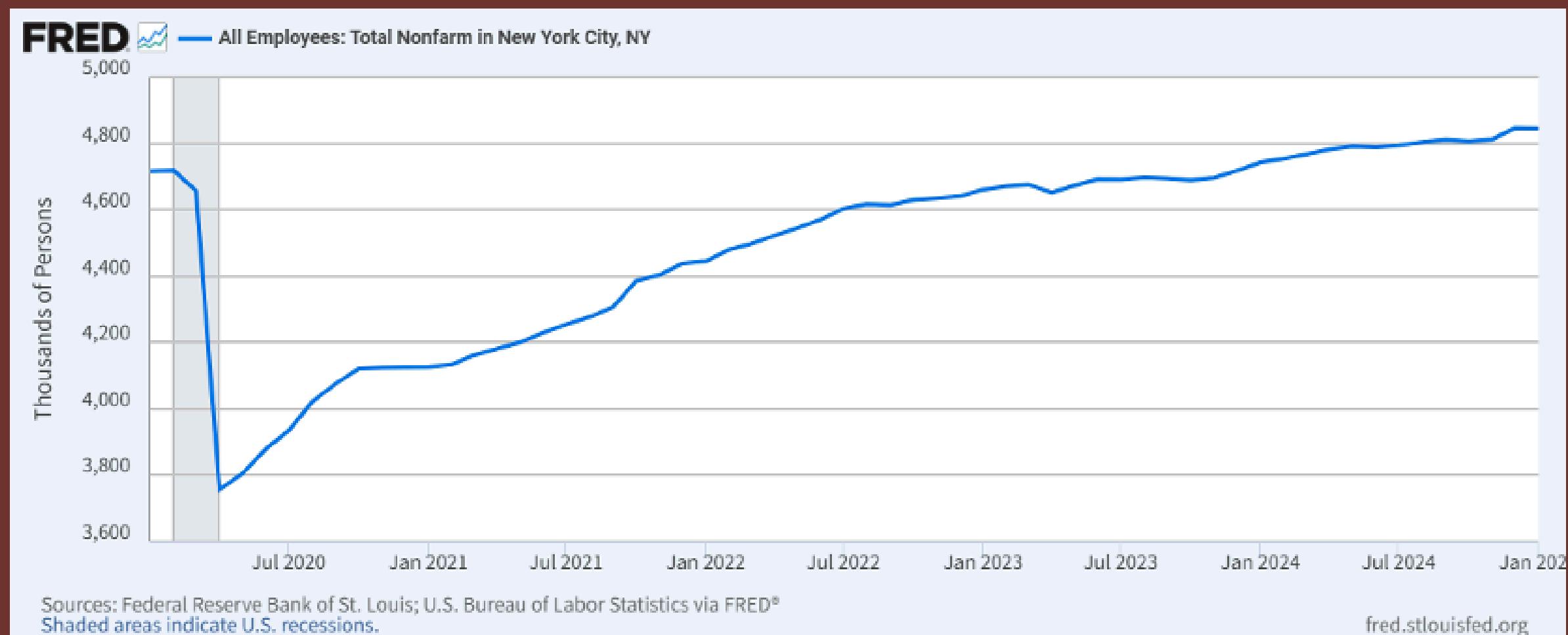
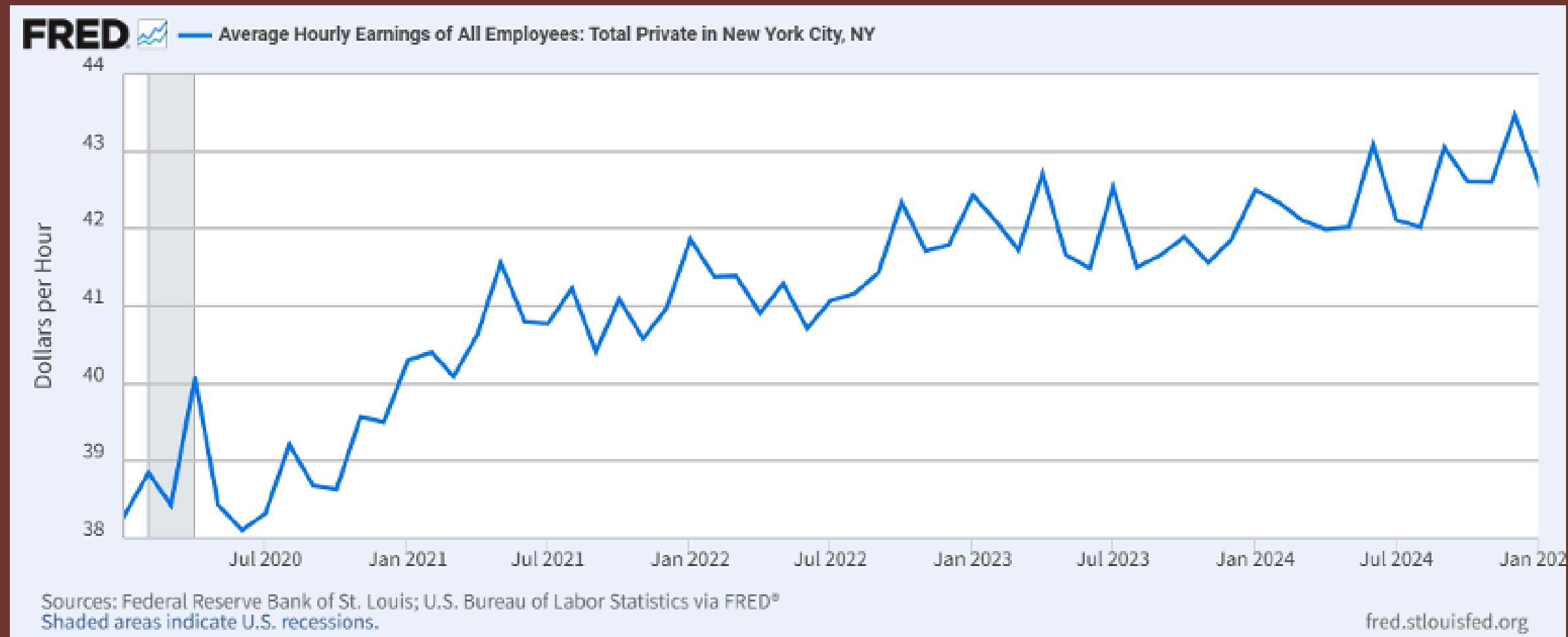
Economic Data

- **Key Monthly Variables (NY)**
 - **Immigration:** p_{immi}
 - share of non-citizens (CPS); monthly proxy for immigration pressure / (potential) undocumented immigrants.
 - **Labor-market outcomes:**
 - NYUR (unemployment rate)
 - \ln_{wage} (log average hourly wage)
 - \ln_{empl} (log total nonfarm employees)

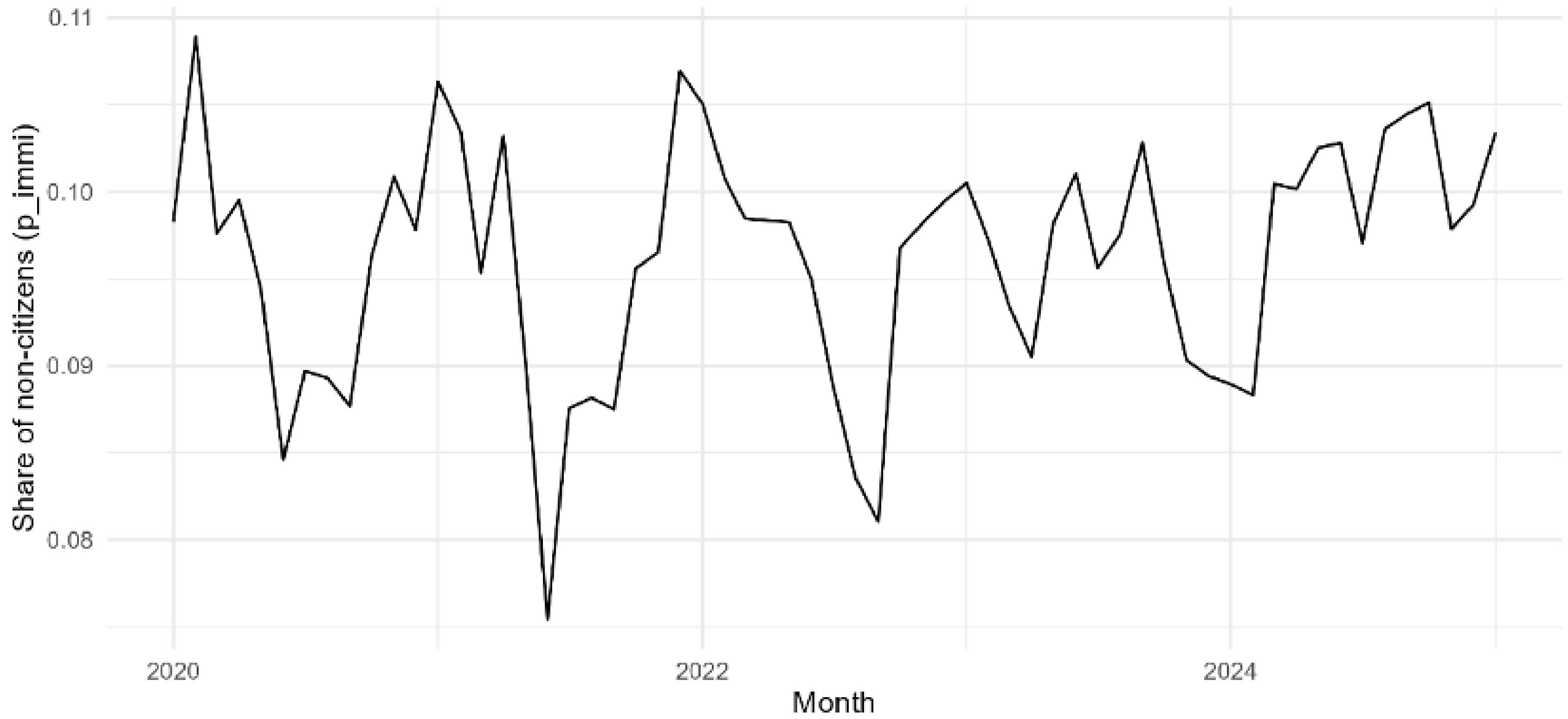
Economic Data

- Key Monthly Variables (NY)
- Macro control: NYPHCl
 - $\ln_{_}$ NYPHCl = log New York State Coincident Index; GDP-like monthly proxy for overall economic activity.
- Shock dummy: COVID
 - COVID = 1 during initial lockdown months,
 - 0 otherwise; captures extra pandemic shock





Non-citizen share (CPS) in New York, 2020–2025



Economic Data

- Key Models
- Model: Unemployment
 - $NYUR_t = \alpha + \beta \cdot p_{immi,t} + \gamma \cdot \ln(NYPHCl_t) + \delta \cdot COVID_t + \varepsilon_t$
- Model: Wages
 - $\ln(wage_t) = \alpha + \beta \cdot p_{immi,t} + \gamma \cdot \ln(NYPHCl_t) + \theta \cdot NYUR_t + \delta \cdot COVID_t + \varepsilon_t$
- Model: Employment Size
 - $\ln(empl_t) = \alpha + \beta \cdot p_{immi,t} + \gamma \cdot \ln(NYPHCl_t) + \delta \cdot COVID_t + \varepsilon_t$

Takeaways for Later Attitude Analysis

Dependent variable	Coef. on p_immi (p-value)	Coef. on ln_NYPHCI (p-value)	Coef. on NYUR (p-value)	Coef. on COVID (p-value)	Adj. R ²
NYUR (UNEM rate)	7.17 (0.535)	-27.95* (p < 0.001)	-	+1.91* (p < 0.001)	0.96
ln_wage (log wage)	0.03 (0.867)	+1.56* (p < 0.001)	+0.039* (p < 0.001)	+0.0017 (0.838)	0.94
ln_employee (log empl)	0.45 (0.053)	+0.60* (p < 0.001)	-	+0.0063 (0.483)	0.95

Takeaways for Later Attitude Analysis

- **p_immi** : no robust negative effect on unemployment or wages, and weak positive link to employment.
- **ln_NYPHCl** are the dominant driver of labour-market fluctuations in this period.

Data Gathering

- **YouTube API**

- Dataset #1: U.S. Congress members names + youtube channels
- Dataset #2: U.S. Congress members names + other important information such as chamber, party, state, etc.
 - 242 U.S. Reps. with Youtube Channels (122 Republicans, 120 Democrats)

Data Gathering

- **YouTube API**

- Youtube API request: all comment from all videos between Jan 2021–Jan 2025 (Biden's term in office)
 - 600k comments in total
 - Application: LDA Model
- Filtered by immigration comments using keywords
 - 17k comments concerning immigration (about 3%)
 - Application: RoBERTa Sentiment Model

Methodology

CardiffNLP Twitter RoBERTa Sentiment Model

- Transformer model trained on 124M+ Twitter posts for **positive / neutral / negative** classification
- Should account for sarcasm, slang, and online discourse, outperforming generic sentiment models: perfect for YouTube comments

Methodology

- **CardiffNLP Twitter RoBERTa Sentiment Model**

- Variables extracted for each observation:
 - `sent_label`: predicted category
 - `sent_score_raw`: predicted score (ranging from -1 to 1)
 - `is_negative`: 1 if label = negative, else 0

Methodology

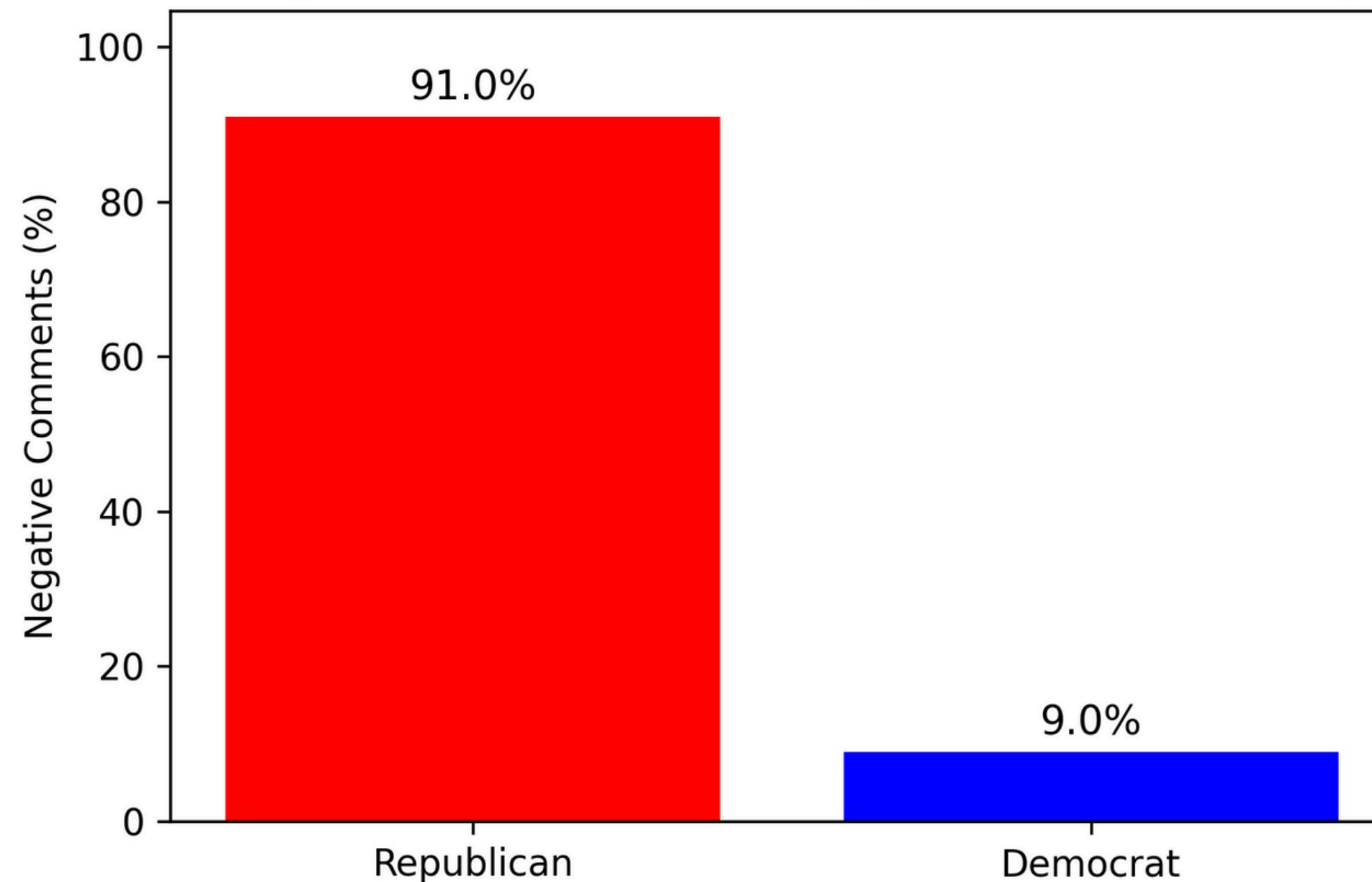
- **Unitary/multilingual-toxic-xlm-roberta**
 - Transformer model trained to detect hate, insults, threats and harassment
 - Produces a toxicity probability score (0-1):
 - 0 = no toxicity
 - 0.2–0.4 = mild/ambiguous
 - 0.5+ = clear hate/toxicity

Methodology

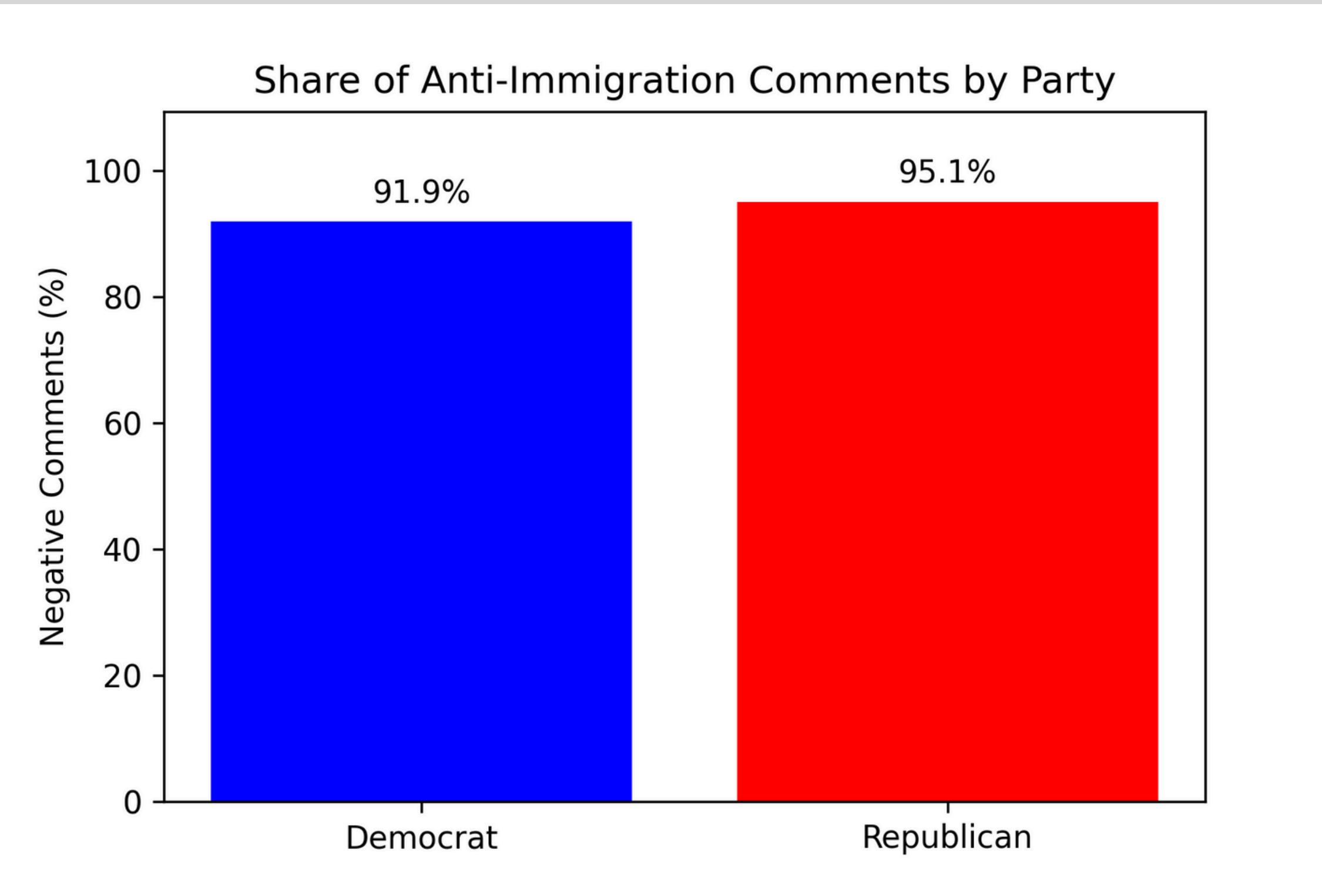
- **Unitary/multilingual-toxic-xlm-roberta**
 - We defined toxicity as **toxic** if **score > 0.5**
 - Variables extracted:
 - **hate_score**: intensity of toxic speech
 - **is_hate**: indicator for counting hate comments

Results

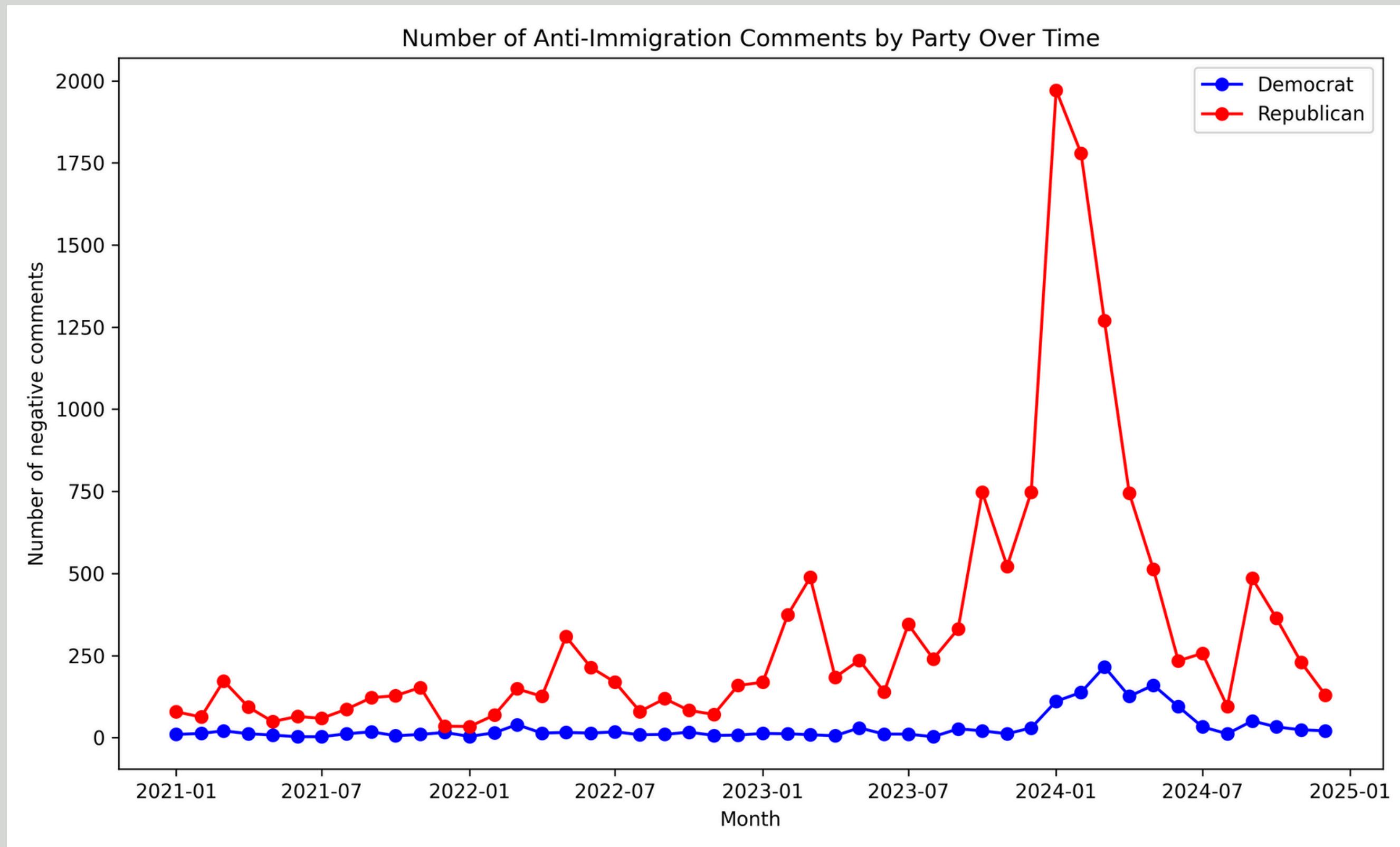
Anti-Immigration Sentiment On Congressional Channels by Party

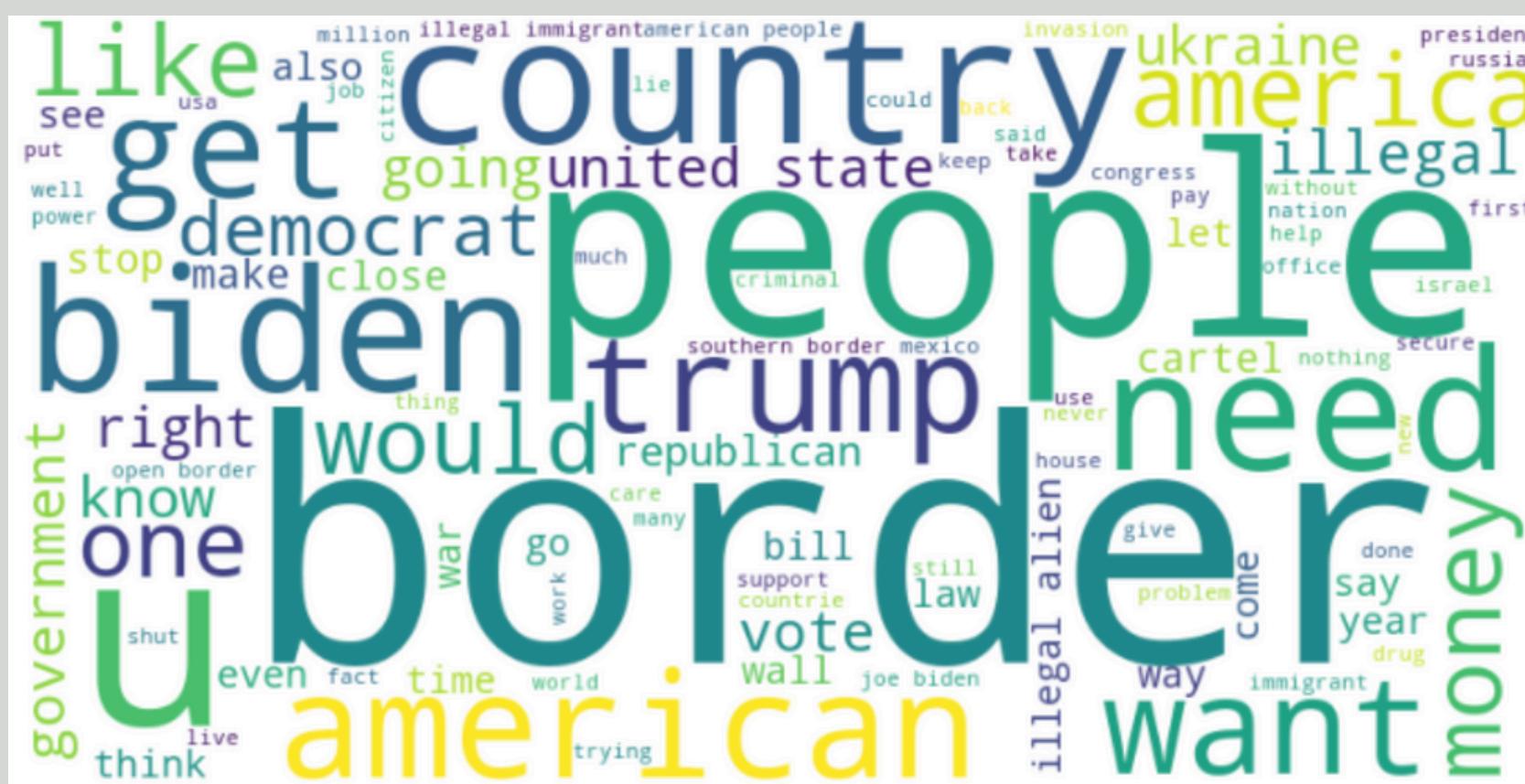
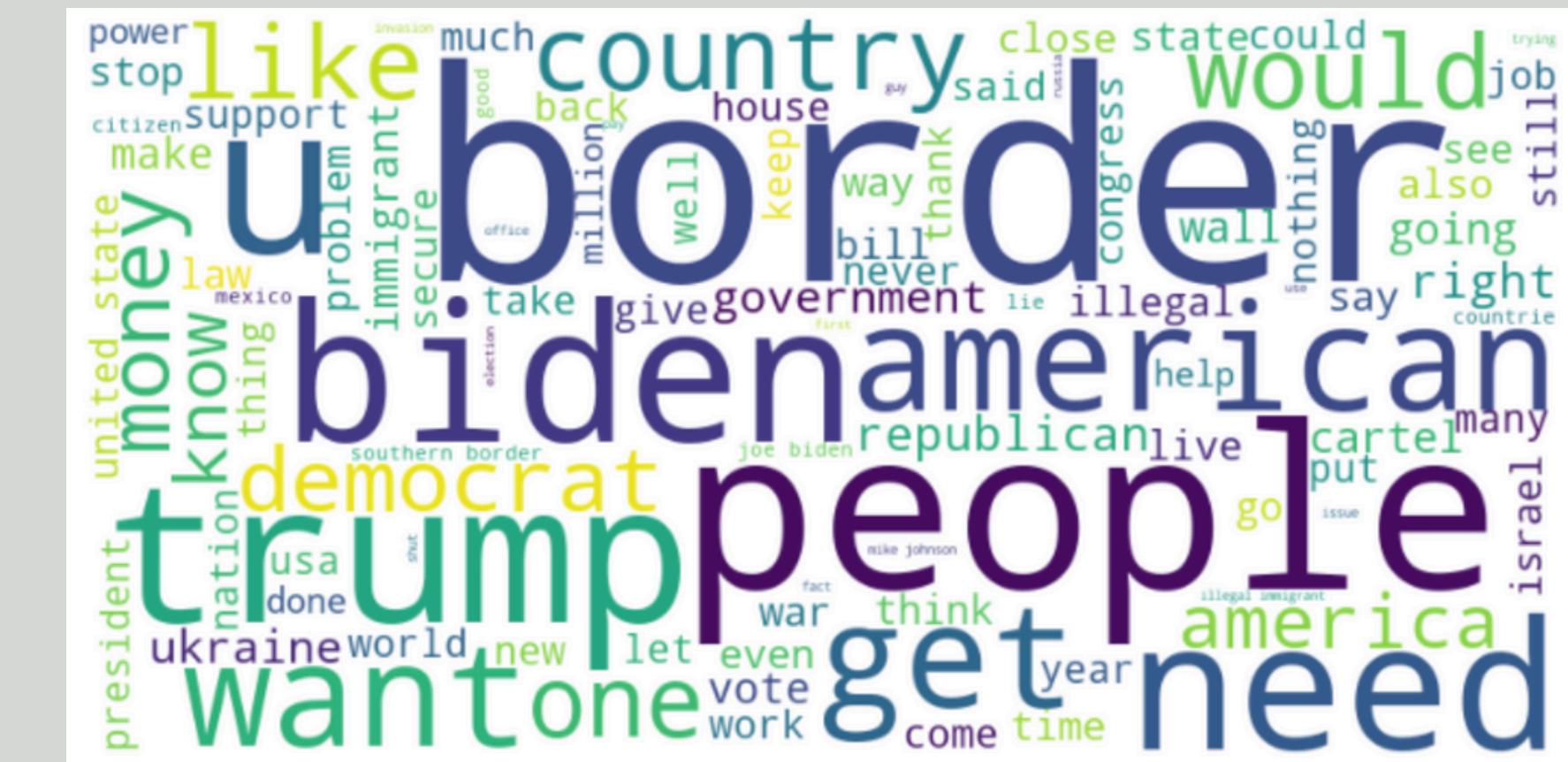
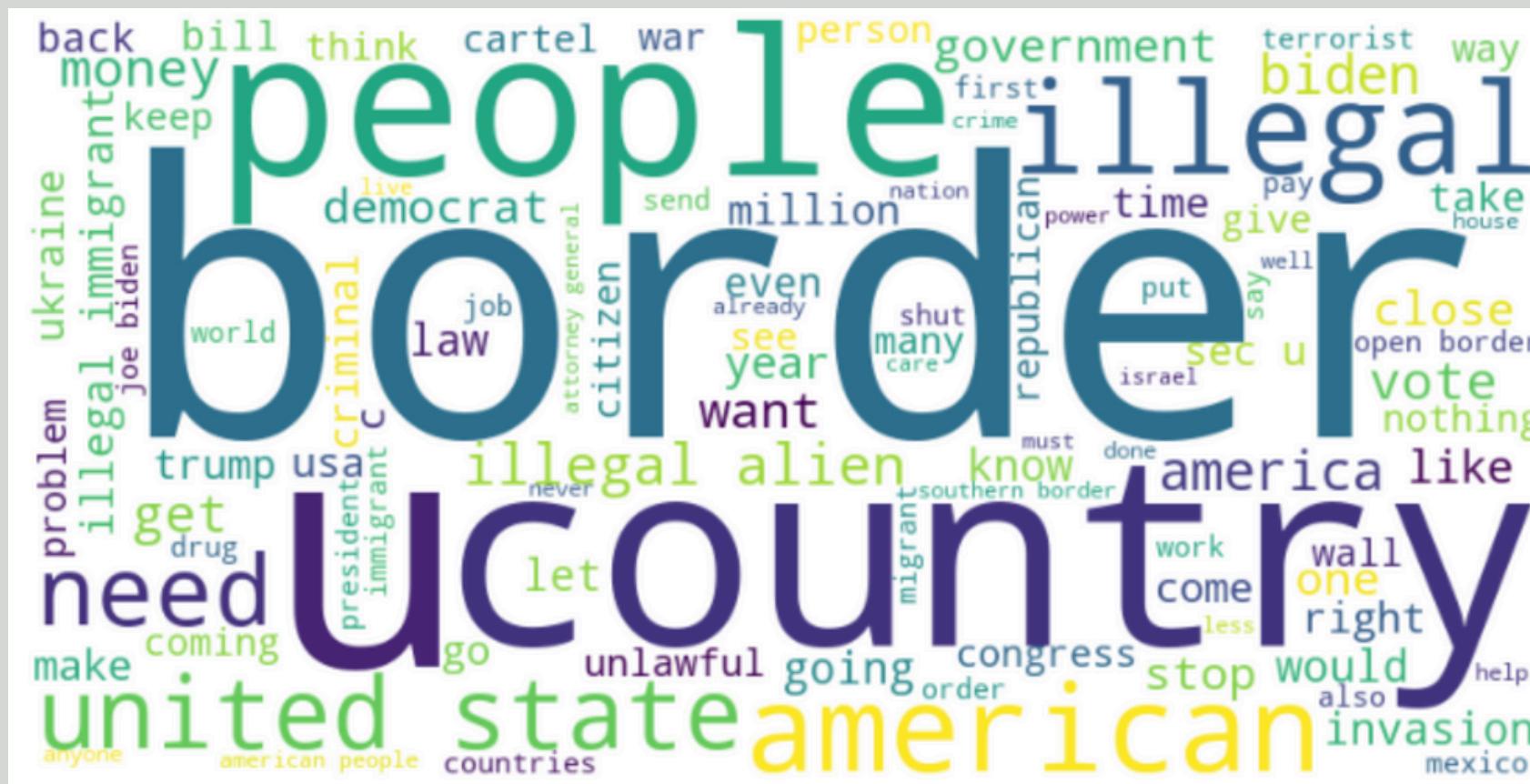


Results

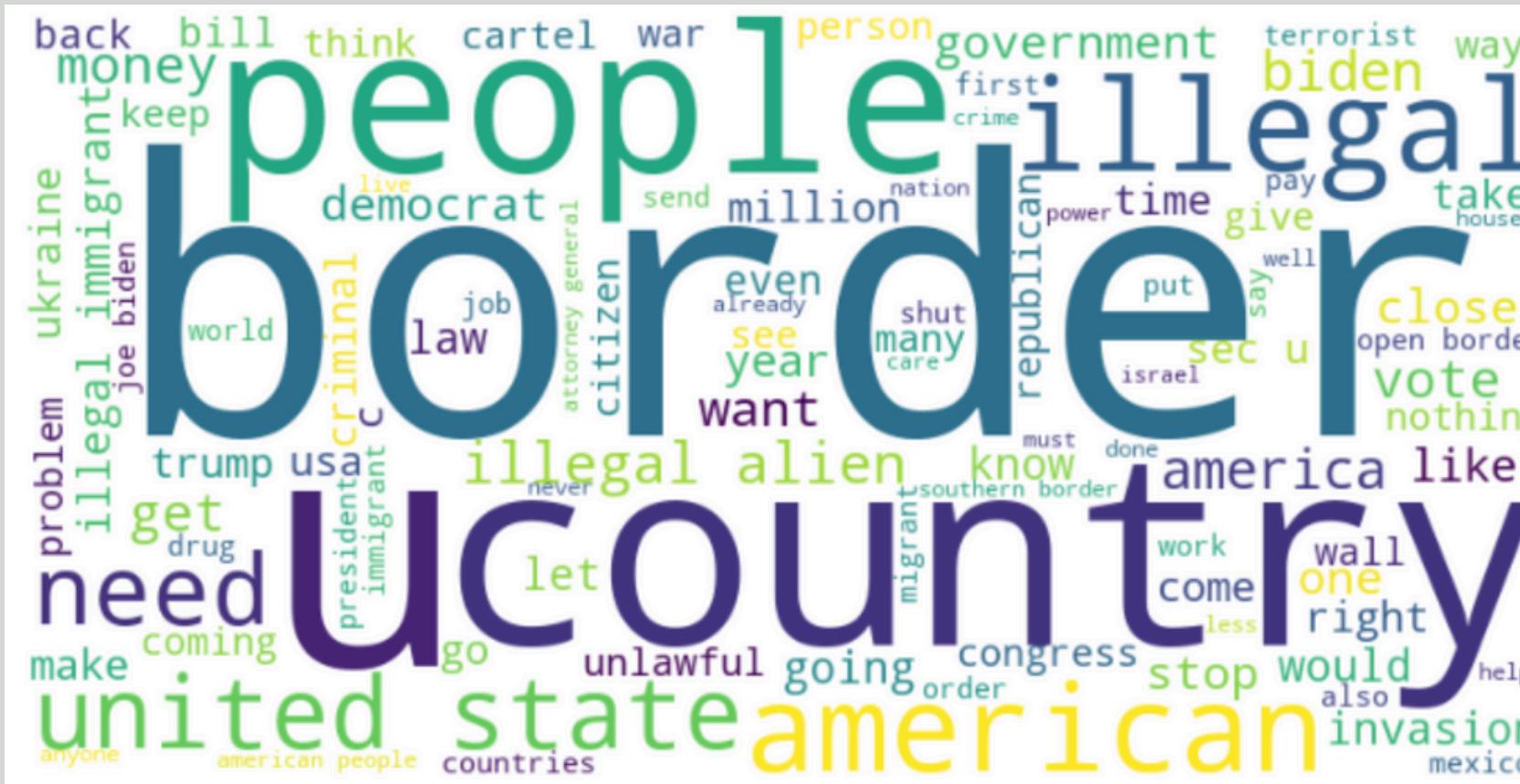


Results

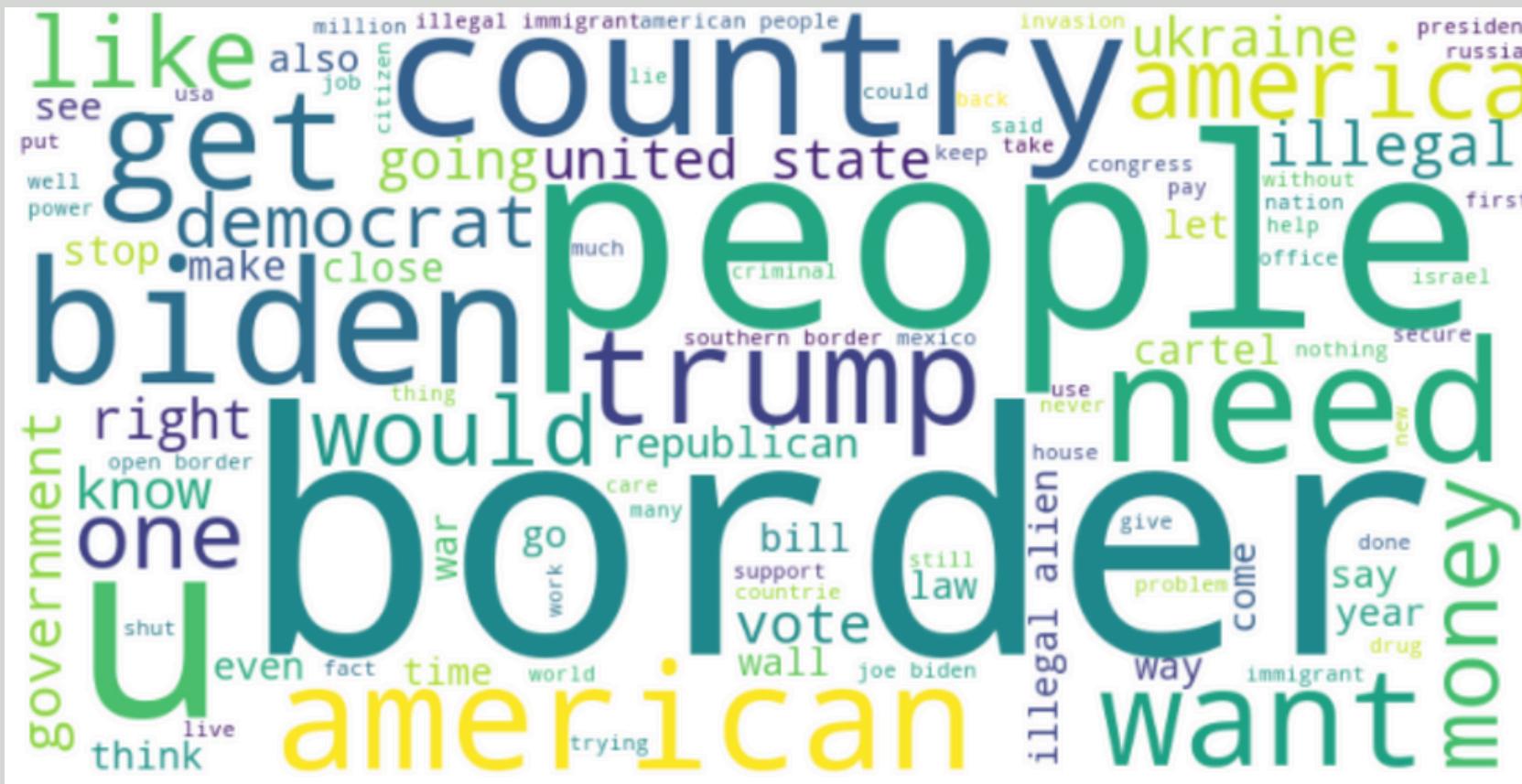




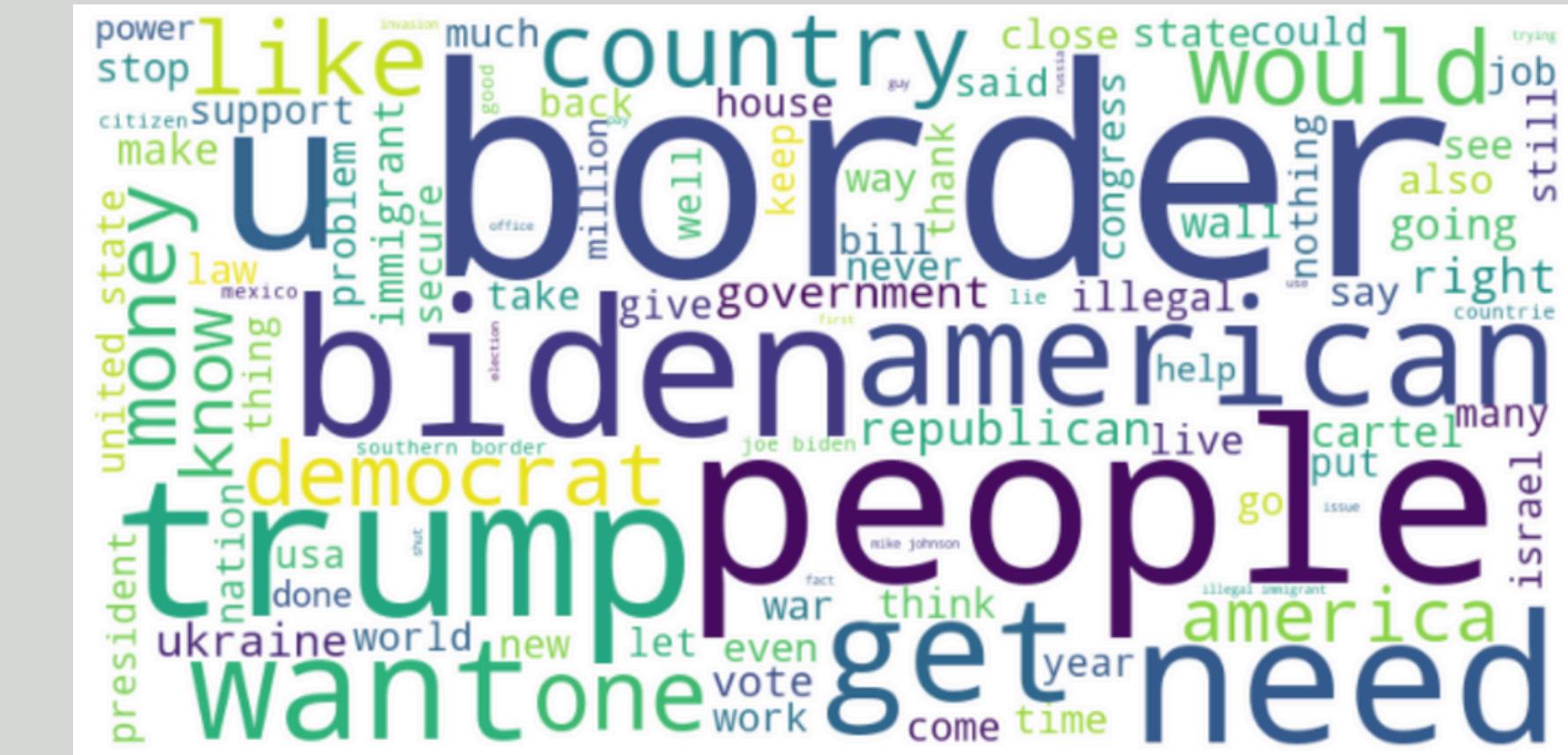
Hate comments



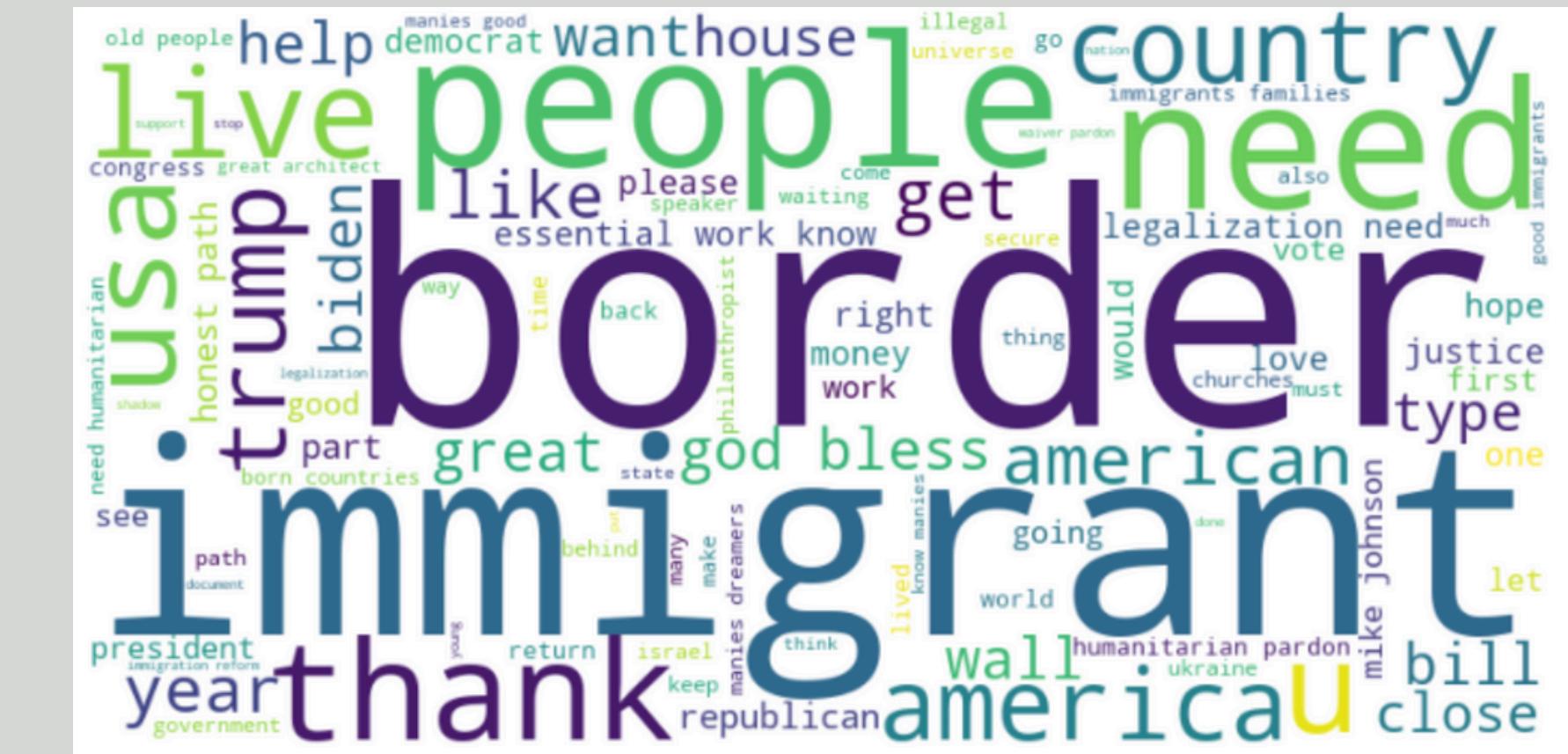
Negative sentiment



Non-hate comments



Positive/neutral sentiment



Methodology

- **LDA**

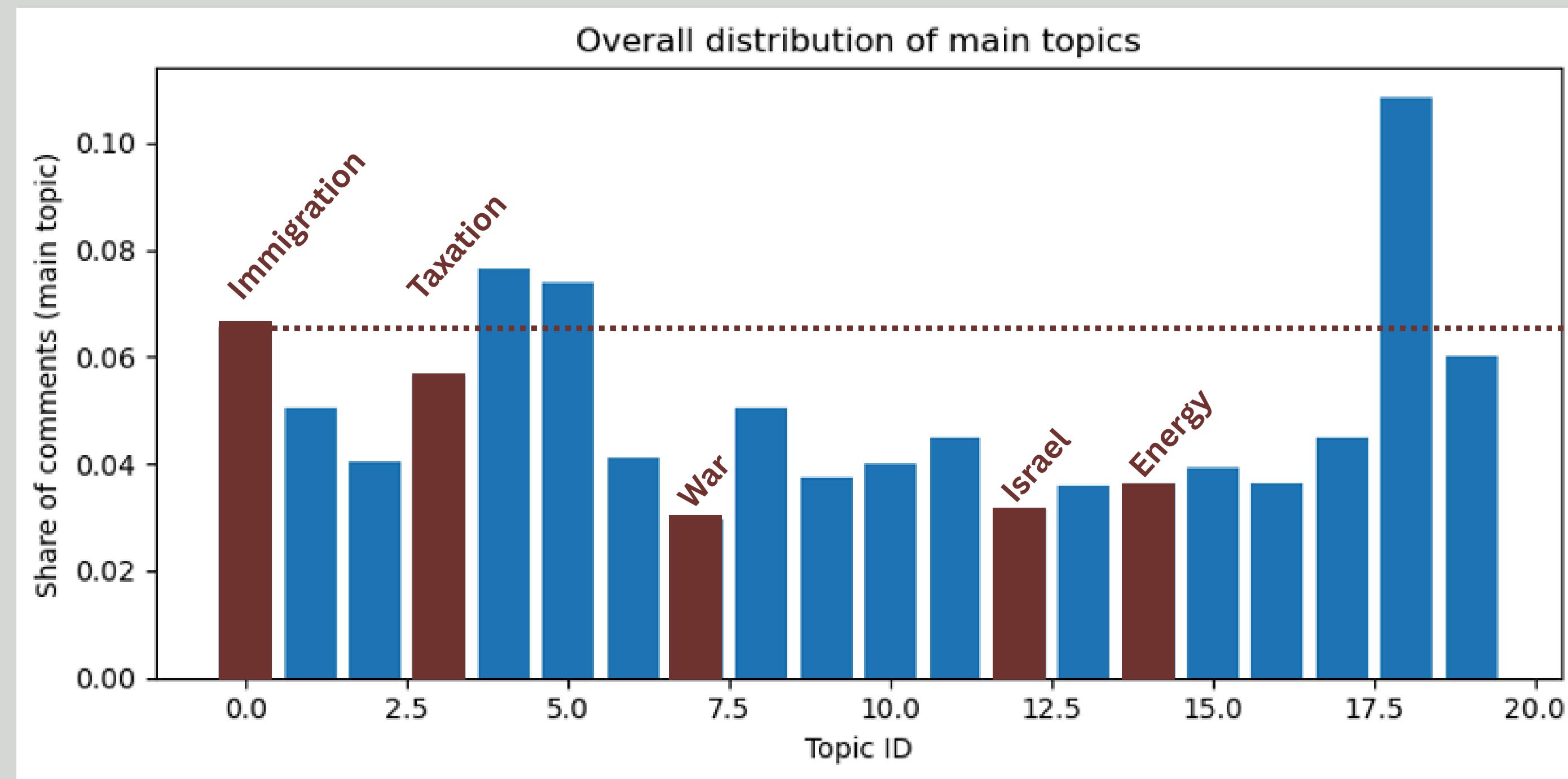
- Application: measures how many of the 600k comments are about immigration and compare it to other topics
- How: Automatically identifies main themes in all comments.
 - Each topic is a probability distribution over words
 - Each comment is a probability mixture of topics

Methodology

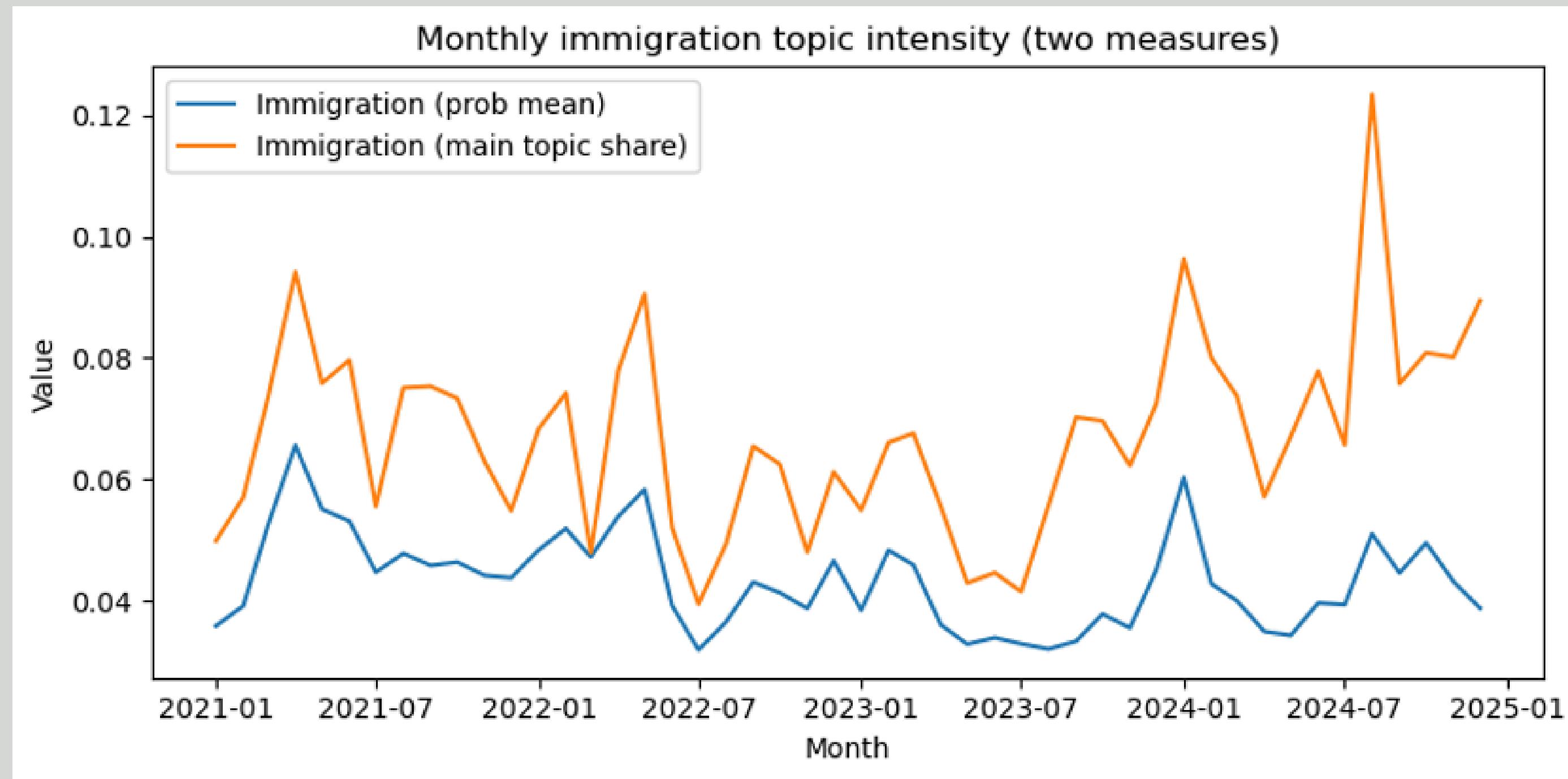
- **LDA**

- Steps:
 - Create a month variable.
 - Clean text: lowercase, tokenize, remove non-letters. and English stopwords
 - Filter words by relevance and frequency
 - Final vocabulary size = 7272 unique words
- Define: 20 topics

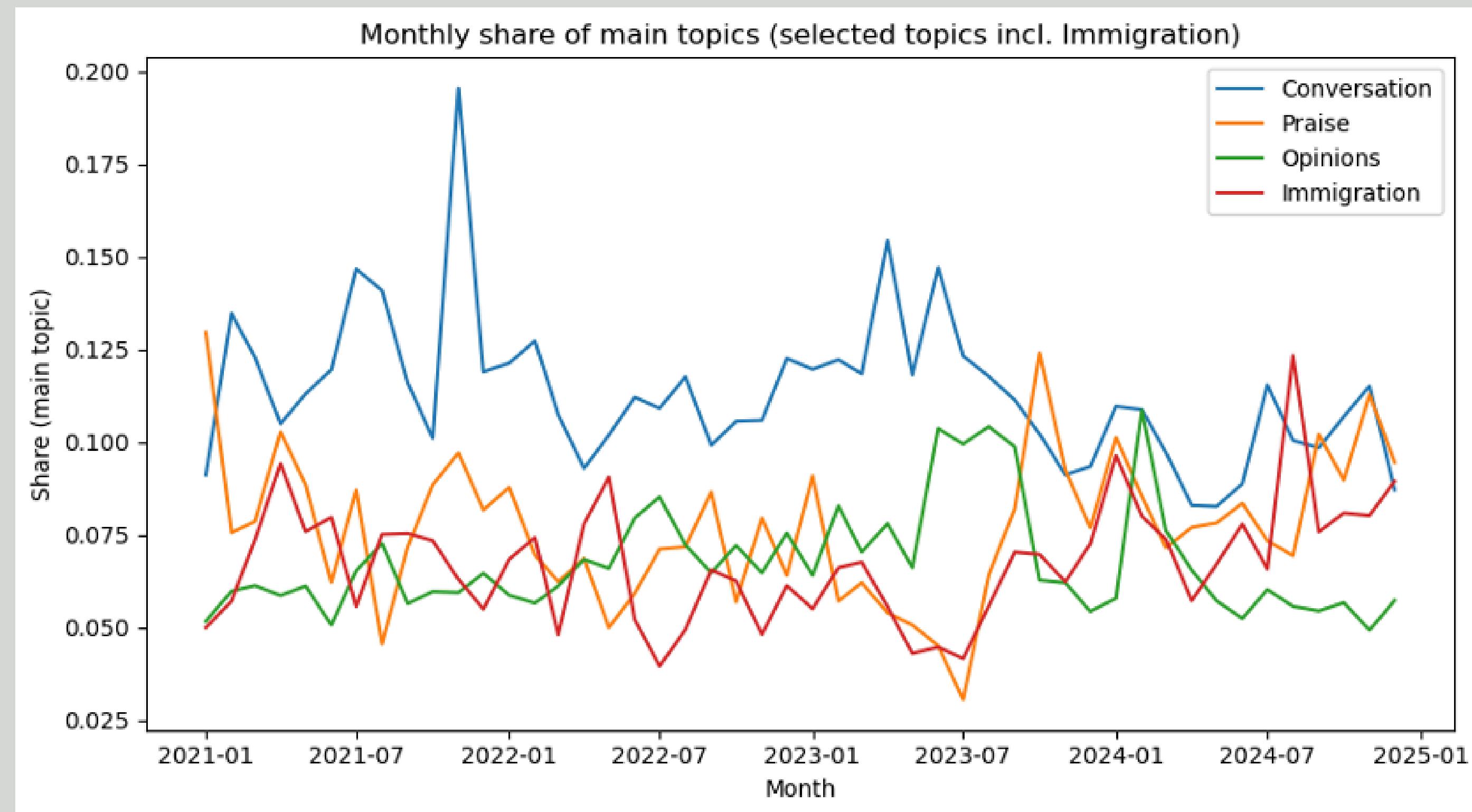
LDA results: 20 topics



LDA results



LDA results: 20 topics



Regression Results

- Steps to built the “Immigration Hostility Index”
 - Build monthly measures among immigration comments
 - $\text{NegShare}(_t)$ = share of immigration comments that are negative.
 - $\text{HateShare}(_t)$ = share of immigration comments that are hate speech.

Regression Results

- Steps to built the “Immigration Hostility Index”
 - Combine with issue salience: we convert the conditional shares into shares of all comments:
 - $\text{NegAll}(_t) = \text{ImmigrationMeanShare}(_t) \times \text{NegShare}(_t)$
 - $\text{HateAll}(_t) = \text{ImmigrationMeanShare}(_t) \times \text{HateShare}(_t)$

Regression Results

- Composite Immigration Hostility Index (formula)
 - Standardize the two monthly series

$$z_t^{\text{Neg}} = \frac{\text{NegAll}_t - \bar{\text{NegAll}}}{\text{sd}(\text{NegAll})}, z_t^{\text{Hate}} = \frac{\text{HateAll}_t - \bar{\text{HateAll}}}{\text{sd}(\text{HateAll})}$$

Regression Results

- Composite Immigration Hostility Index (formula)
 - Define three versions with different weights

$$\text{Index}_t^{(1:1)} = \frac{1 \cdot z_t^{\text{Neg}} + 1 \cdot z_t^{\text{Hate}}}{1 + 1}$$

$$\text{Index}_t^{(1:2)} = \frac{1 \cdot z_t^{\text{Neg}} + 2 \cdot z_t^{\text{Hate}}}{1 + 2}$$

$$\text{Index}_t^{(1:3)} = \frac{1 \cdot z_t^{\text{Neg}} + 3 \cdot z_t^{\text{Hate}}}{1 + 3}$$

- $\text{Index}^{(1:2)}$ is our **main Immigration Hostility Index** (hate speech gets double weight)
- $\text{Index}^{(1:1)}$ and $\text{Index}^{(1:3)}$ are used as robustness checks to show that results do not depend on one specific weighting scheme.

Regression Results

- Models

- Model 1 – Baseline (no interaction)

$$Hostility_t = \alpha + \beta_1 ImmigrantShare_t + \beta_2 \ln(Employment_t) + \beta_3 \ln(NYPHCI_t) + \varepsilon_t$$

- Model 2 – Interaction with employment

$$\begin{aligned} Hostility_t = & \alpha + \beta_1 ImmigrantShare_t + \beta_2 \ln(Employment_t) + \beta_3 \ln(NYPHCI_t) \\ & + \gamma_1 [ImmigrantShare_t \times \ln(Employment_t)] + \varepsilon_t \end{aligned}$$

- Model 3 – Interaction with wages

$$\begin{aligned} Hostility_t = & \alpha + \beta_1 ImmigrantShare_t + \beta_2 \ln(Employment_t) + \beta_3 \ln(NYPHCI_t) \\ & + \beta_4 \ln(Wage_t) + \gamma_2 [ImmigrantShare_t \times \ln(Wage_t)] + \varepsilon_t \end{aligned}$$

Regression Results: Model 1

Model	Non-citizen share (p_immi_c)	Employment (ln_emp_c)	Wage (ln_wage_c)	Economic conditions (ln_nyphci_c)	Immig × Employment	Immig × Wage	R ²
(1) Baseline	-0.39 (p = 0.99)	10.69 (p = 0.74)	–	-8.75 (p = 0.68)	–	–	0.01
(2) Immig × Employment	12.91 (p = 0.60)	0.15 (p = 1.00)	–	-2.17 (p = 0.92)	667.57 (p = 0.23)	–	0.04
(3) Immig × Wage	11.35 (p = 0.65)	-53.04 (p = 0.35)	19.35 (p = 0.23)	23.34 (p = 0.45)	–	724.68 (p = 0.30)	0.07

Regression Results: Model 2

Model	Non-citizen share (p_immi_c)	Employment (ln_emp_c)	Wage (ln_wage_c)	Economic conditions (ln_nyphci_c)	Immig × Employment	Immig × Wage	R ²
(1) Baseline	-0.26 (p = 0.99)	12.46 (p = 0.70)	-	-9.49 (p = 0.66)	-	-	0.01
(2) Immig × Employment	14.08 (p = 0.57)	1.09 (p = 0.97)	-	-2.40 (p = 0.91)	719.92 (p = 0.20)	-	0.05
(3) Immig × Wage	13.24 (p = 0.59)	-54.92 (p = 0.33)	20.15 (p = 0.21)	24.55 (p = 0.43)	-	833.70 (p = 0.24)	0.07

Regression Results: Model 2

Model	Non-citizen share (p_immi_c)	Employment (ln_emp_c)	Wage (ln_wage_c)	Economic conditions (ln_nyphci_c)	Immig × Employment	Immig × Wage	R ²
(1) Baseline	-0.19 (p = 0.99)	13.35 (p = 0.68)	-	-9.87 (p = 0.65)	-	-	0.01
(2) Immig × Employment	14.66 (p = 0.56)	1.56 (p = 0.96)	-	-2.51 (p = 0.91)	746.10 (p = 0.19)	-	0.05
(3) Immig × Wage	14.19 (p = 0.57)	-55.86 (p = 0.33)	20.54 (p = 0.21)	25.16 (p = 0.43)	-	888.21 (p = 0.21)	0.07

Limitations

Limited
Sample Size

Divergence in
Geography

Advanced Machine
Learning Model

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THANK YOU

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DS 1 | Dec. 2025
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