Effect of the Economy on Sentiment About Immigration: a case study using data from NY state

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Immigration has become one of the most prominent and polarizing issues in contemporary American politics. Public debates typically vary between two contrasting narratives. One emphasizes that immigrants push wages down, raise unemployment, and strain local public resources. The other highlights that immigrants help fill labor shortages, sustain economic growth, and contribute fiscally. These debates are especially intense in high-immigration states such as Texas and New York, where recent years have seen both a sharp increase in border encounters and highly visible "migrant crises" in New York City.

The discourse around immigration took a sharper tone under Joe Biden's administration, between the years of 2021 and 2025. During that period, anti-immigration sentiment rose steadily and reached the highest in two decades in 2024–all while border crossings reached record-levels. These are apparent in the rise of immigration as a concern for voters, standing among the economy and abortion as as top-of-mind issues that helped shape the 2024 presidential election.

Our project starts from a simple but important question: if immigration is perceived as so consequential, do changes in local economic conditions leave a detectable imprint on how ordinary citizens talk about immigrants in everyday online conversations? Rather than relying on surveys, we treat "public opinion" as what people spontaneously write under political videos.

To do so, we focus on YouTube comments posted under videos from official congressional channels. This is a setting where political elites and the public meet, and where immigration is frequently discussed. Using a large corpus of comments from 2021–2024, we combine methods from modern natural language processing (NLP)—topic models, transformer-based sentiment and hate-speech classifiers, and aggregation into time-series indices—with standard time-series regressions.

We build on two strands of previous work. First, the labor-economics literature on immigration and the labor market typically finds that the aggregate wage and employment effects of immigration are small or zero once one accounts for spatial adjustment and measurement issues. Second, a growing computational social-science literature uses social-media text and machine-learning tools to track political attitudes, emotional tone, and polarization over time. Our project borrows tools from this "text-as-data" tradition and adapts them to the politics of immigration.

Research Question

Do macroeconomic conditions in New York State and the local immigrant share correlate with online hostility toward immigrants, as expressed in comments on congressional YouTube channels during the Biden era (2021–2024)?

Data and Methods

To answer this question, we combine two types of data. First, we construct a monthly panel of economic indicators for New York, including the non-citizen share, unemployment, wages, employment, and a coincident index of economic activity. Second, we construct monthly measures of immigration-related hostility using YouTube comments. We use:

an LDA topic model to identify immigration-related comments and measure how salient immigration is in each month, and two pre-trained Hugging Face models—a sentiment classifier and a hate-speech classifier—to measure the tone of immigration-related comments.

These model outputs are aggregated into monthly “immigration sentiment” and “immigration hostility” indices, which we then relate to macroeconomic conditions using simple regressions.

Data: New York Macroeconomics

Our first dataset is a monthly panel for New York State from 2020 to 2025. We focus on New York because it is both a major immigrant destination and a prominent site of recent “migrant crises,” while also having rich monthly statistics available from public sources.

The main variables are:

Non-citizen share, (p_{\text{immi},t}): the share of New York residents who are non-U.S. citizens in month (t), constructed from CPS microdata. This proxies the local immigrant presence, including recent arrivals.

Unemployment rate, (NYUR_t): the seasonally adjusted state unemployment rate from BLS.

Average wage, (wage_t): average hourly earnings of private-sector workers in New York from CES; we work with (\ln(wage_t)) so coefficients can be interpreted as approximate percentage changes.

Total employment, (employee_t): non-farm payroll employment (thousands) from CES; used in logs, (\ln(employee_t)).

Coincident Economic Index, (NYPHCI_t): the Philadelphia Fed’s coincident index for New York, which summarizes overall business conditions. We use (\ln(NYPHCI_t)) as our main measure of macroeconomic performance.

COVID dummy, (COVID_t): equals 1 during the sharp pandemic downturn and early recovery months in 2020, 0 otherwise.

These series are merged into a single monthly panel in R. Visual inspection shows the expected COVID shock: a spike in unemployment and a trough in the coincident index in 2020, followed by gradual recovery; wages and employment trend upward over the whole period; the non-citizen share moves smoothly between roughly 10–13%, without dramatic jumps.

In our final analysis we restrict to January 2021–December 2024 (48 months), when both economic series and text-based measures are consistently available.

Data: YouTube Comments Collection

1. Identifying Congressional YouTube Channels

The first step in this part of data collection involved identifying official YouTube channels associated with members of the U.S. House of Representatives. Two datasets were combined for this purpose:

- A dataset linking U.S. Representatives' names to their official YouTube channels
- A dataset containing additional information on members of Congress, including chamber, party affiliation, state represented, and term dates

After merging these sources, the final sample consisted of 242 U.S. Representatives with active YouTube channels, including 122 Republicans and 120 Democrats. These channels formed the basis for all subsequent data collection.

2. YouTube API Comment Collection

Using the YouTube Data API v3, we programmatically requested all publicly available comments from every video uploaded to these congressional YouTube channels between January 2021 and January 2025, corresponding to the duration of President Biden's term in office.

For each channel, the API was used to:

- Retrieve the full list of uploaded videos,
- Collect all comments and comments replies associated with each video,
- Store comment-level metadata including timestamps, author identifiers, and reply structure.

To comply with API rate limits, requests were executed iteratively across channels and videos, with safeguards in place to handle pagination and quota exhaustion. This process resulted in a corpus of approximately 600,000 YouTube comments.

3. Topic Filtering: Immigration-Related Comments

Because the research question focuses on political discourse surrounding immigration, the full comment dataset was filtered using a keyword-based approach to identify immigration-related content. Keywords were drawn from common immigration-related terms and policy language appearing in U.S. political debate.

This filtering step reduced the dataset to approximately 17,000 comments explicitly referencing immigration, representing about 3% of all collected comments. These comments constitute the primary analytical sample for downstream text analysis.

Benchmark Regressions with Economic Data Only

Before introducing any text-based measures, we first use the economic panel to revisit a classic question: do months with higher immigrant shares have worse labor-market outcomes in New York? This step serves as a benchmark for our later interpretation of online hostility.

We estimate three simple monthly OLS regressions for 2020–2025:

- Unemployment rate on the non-citizen share, the coincident index, and a COVID dummy;
- Log average wage on the same set of predictors;
- Log employment on the same set of predictors.

Across all three models, the coefficient on the non-citizen share is small and statistically insignificant. There is no robust evidence that months with a higher immigrant presence have higher unemployment or lower wages; if anything, the association with total employment is weakly positive. By contrast, the coincident index behaves exactly as expected: better macroeconomic conditions are strongly associated with lower unemployment, higher wages, and higher employment.

This preliminary stage tells us two things. First, our economic data reproduce the mainstream result in the immigration literature: at an aggregate level, immigration is not obviously harming the state economy. Second, this backdrop is important when we later interpret online hostility: if hostility rises when the economy deteriorates, it is unlikely to be a direct reaction to measured labor-market damage from immigrants.

Methods: Topic Modeling with LDA

The next step is to use the comment-level dataset to understand what people are talking about under congressional videos and to isolate comments that are primarily about immigration.

1. Preprocessing and model specification

We start from the full set of ≈600k comments. Before feeding them into a topic model, we perform standard text preprocessing:

- Lowercasing the text;
- Removing URLs, user mentions, emojis, and most punctuation;
- Tokenizing into words;
- Keeping only alphabetic tokens;
- Removing English stopwords and X/YouTube-specific tokens: “rt”, “https”, “amp”;
- Stemming or lemmatizing to reduce words to their base forms.

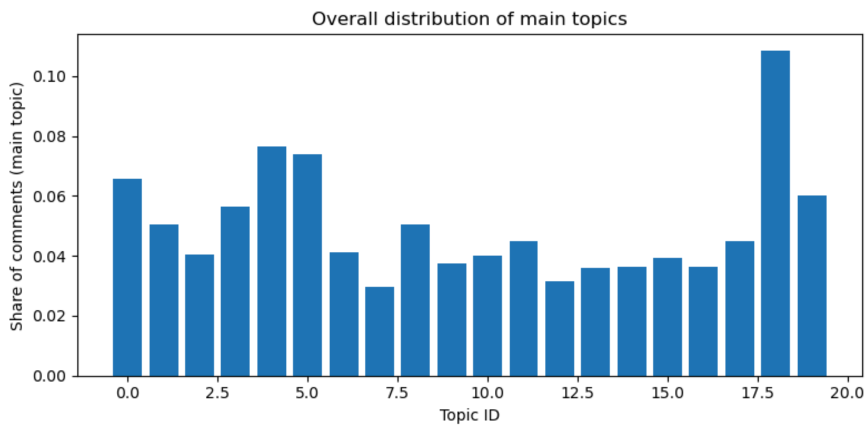
Each comment then becomes a small bag-of-words. On this cleaned corpus we estimate a Latent Dirichlet Allocation (LDA) model with 20 topics using the gensim library. LDA assumes that:

- Each comment is a mixture of latent topics and a probability distribution over words;
- Comments are generated by first drawing a topic distribution for the comment, then repeatedly drawing words conditional on topics.

After fitting the model, we obtain for every comment a vector of topic probabilities that sum to one. We assign to each comment a main topic ID—the topic with the highest posterior probability—and we keep the full probability vector for later aggregation.

We then examine the top words of each topic and manually give them short labels ("Immigration", "Elections", "Praise", etc.). In this labeling scheme, Topic 0 corresponds to immigration, with top words such as "border", "illegal", "immigration", "migrants", and "asylum".

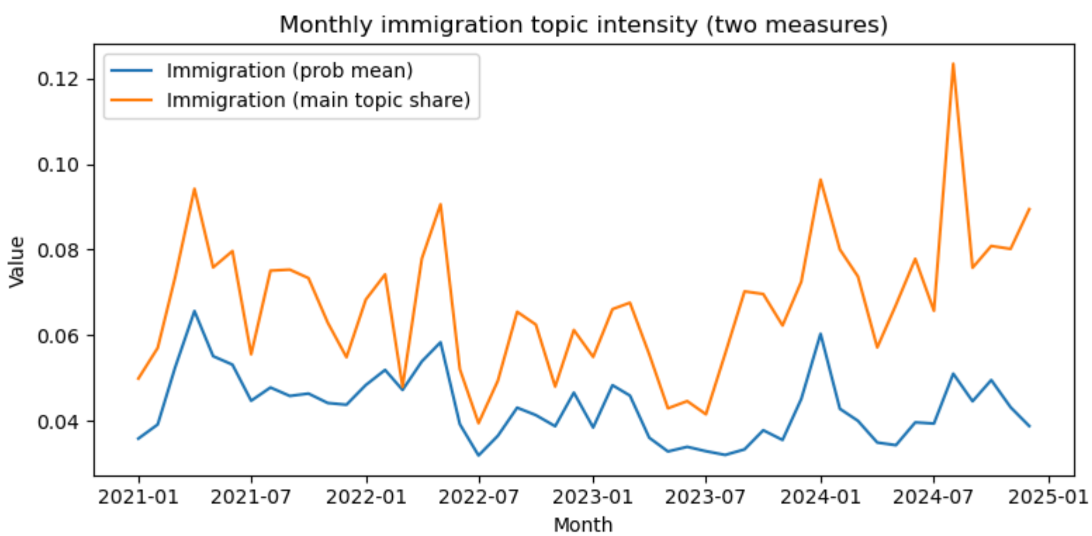
2. Overall topic distribution (Figure 1)



The first figure summarizes how often each topic appears as the main topic of a comment.

Figure 1 shows that immigration is clearly visible but not dominant: Topic 0 accounts for only a small share of all comments—on the order of a few percent. Other topics such as general conversation, praise for politicians, partisan conflict, and elections are more frequent. This highlights that immigration is an important but minority issue in congressional YouTube discourse.

3. Monthly immigration relevance measures (Figure 2)



Using the topic probabilities and the month variable, we construct two complementary measures of how salient immigration is in the comment stream in month (t):

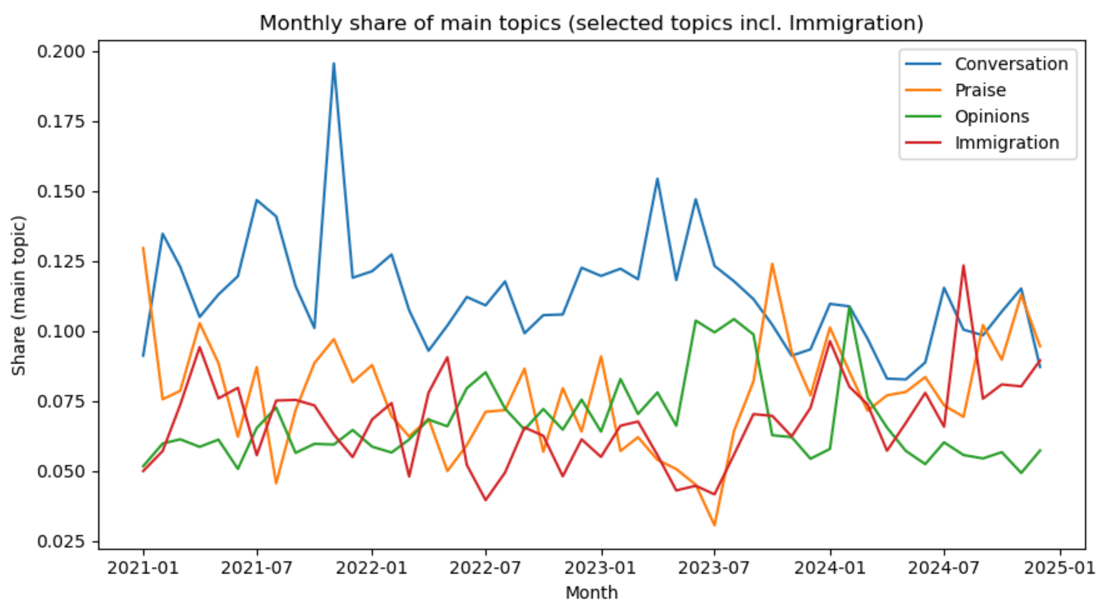
- ImmigrationMainShare(_t): the share of all comments whose main topic is immigration (Topic 0). This measures the extensive margin: "what fraction of comments are mostly about immigration?"

- ImmigrationProbMean(_t): the average immigration topic probability across all comments in that month. This captures the intensive margin: “on average, how much immigration content is present in the comment stream, even if it is not always the main topic?”

In Figure 2, both measures track similar dynamics. They show clear spikes in immigration salience during months with prominent immigration news or legislative debates and lower values in quieter periods. As expected, ImmigrationProbMean(_t) is smoother than ImmigrationMainShare(_t), because it averages a continuous probability rather than counting only main topics.

These patterns validate that the LDA model is capturing meaningful shifts in what commenters talk about over time.

4. Comparing immigration with other topics (Figure 3)



Finally, we compare immigration to several other high-level themes by plotting their monthly main-topic shares.

Figure 3 shows that broad “conversation” topics—generic reactions, jokes, and side discussions—dominate most months. Praise for politicians and opinionated commentary are also common. The immigration line mostly stays below these other topics but exhibits noticeable fluctuations, sometimes approaching them during high-salience immigration months.

Together, Figures 1–3 show that:

- Immigration is a minority but highly variable topic in congressional YouTube comments;
- Our two immigration-salience measures provide reasonable and interpretable time-series summaries;
- We can now use these LDA outputs both to filter out immigration comments and to quantify how salient immigration is each month.

In the subsequent sections, the LDA outputs serve two roles. First, they allow us to restrict attention to comments where immigration is the main topic. Second, the monthly salience series (especially ImmigrationProbMean(_t)) will later be combined with sentiment and hate-speech measures to construct hostility indices.

Sentiment and Hate-Speech Classification and Analyses

To analyze the tone of immigration-related discourse on congressional YouTube channels, we applied transformer-based natural language processing models to YouTube comments collected between January 2021 and January 2025. These models are designed to handle informal, emotionally charged, and politically contextual language commonly found in online comment sections.

Sentiment Analysis Model

Sentiment classification was conducted using the **CardiffNLP Twitter RoBERTa** sentiment model, a transformer model trained on over 124 million Twitter posts. The model assigns each text observation to one of three categories—positive, neutral, or negative—and produces a continuous sentiment score ranging from −1 to +1. Because it is trained on social media data, the model is well suited to capturing sarcasm, slang, and partisan rhetoric typical of YouTube comments.

Comments classified as negative are interpreted as expressing anti-immigration sentiment. Sentiment scores were stored at the comment level and later aggregated by party affiliation and month to enable descriptive comparisons.

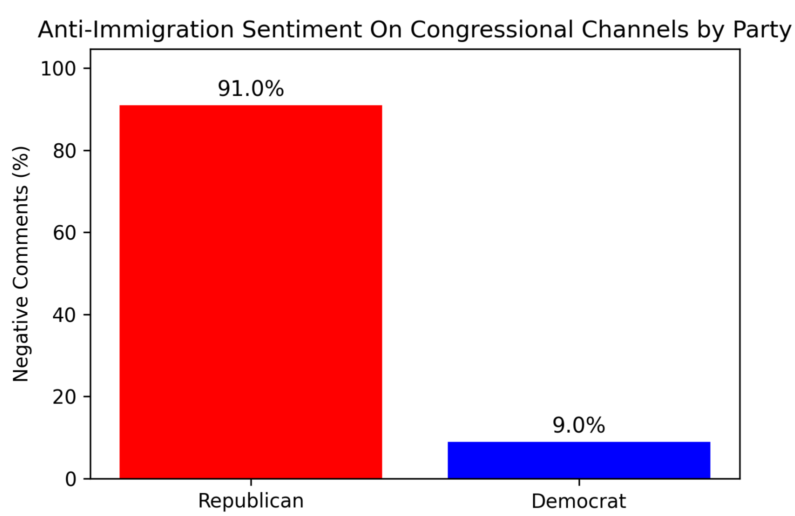
Hate and Toxicity Classification

To capture explicitly hostile language, we applied the **unitary/multilingual-toxic-xlm-roberta model**. This transformer-based classifier detects hate speech, insults, threats, and harassment, producing a toxicity probability score between 0 and 1.

Comments with a toxicity score greater than 0.5 were classified as hateful. This allows the analysis to distinguish between generally negative sentiment and explicitly toxic speech.

Model Outputs and Illustrative Results

Anti-Immigration Sentiment by Party (Figure 4)

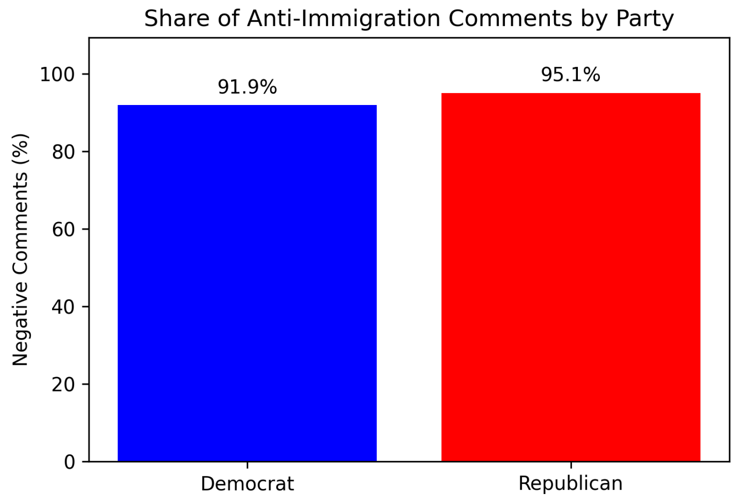


This figure uses model-classified sentiment to compare the total volume of anti-immigration comments across party-affiliated congressional YouTube channels.

Republican-affiliated channels account for the majority of negative immigration sentiment in absolute terms.

The figure illustrates how sentiment labels can be aggregated at the party level.

Share of Anti-Immigration Comments Within Party Channels (Figure 5)

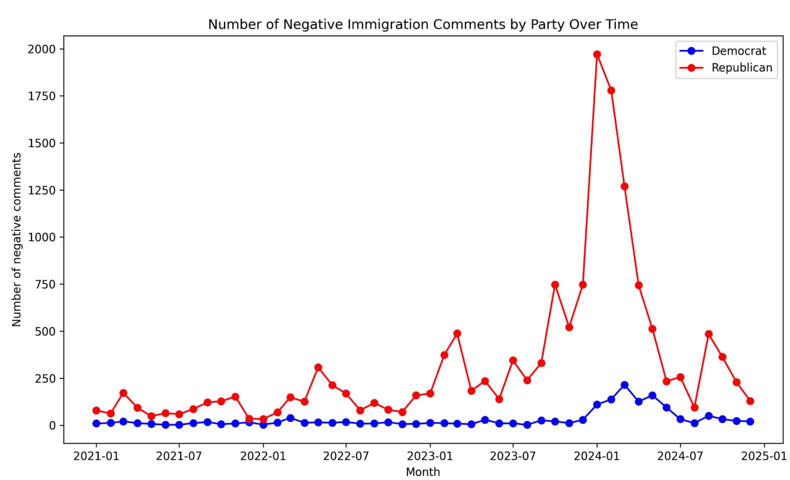


This figure shows the share of immigration-related comments that are classified as negative within each party's channels.

Despite lower overall volume, Democratic channels exhibit a high proportion of negative immigration sentiment, comparable to the proportion of anti-immigration sentiment showcased on Republican channels

The figure highlights the distinction between total volume and within-channel composition.

Anti-Immigration Sentiment Over Time (Figure 6)



This figure plots the monthly count of anti-immigration comments using model outputs from 2021 to 2025.

A notable spike in negative sentiment appears in January 2024. The underlying cause of this spike cannot be identified with the available data and would require further contextual analysis.

Analysis: Constructing Immigration Hostility Indices and Regression Results

In the previous sections I used LDA to recover an "immigration" topic from the full corpus of congressional YouTube comments, and Hugging Face models to classify the sentiment and hate content of immigration–related comments. In this section I combine these pieces into monthly indices of online hostility toward immigrants and relate them to aggregate economic conditions.

1. Constructing monthly hostility indices

Let $t$index months. From the LDA results, each comment has a main topic and an immigration–topic probability. For the hostility indices I focus on comments whose main topic is immigration. Denote by $I_t$the set of such comments in month t, and let

$$n_{comm,t} = |I_t|$$

be the number of immigration–main-topic comments in that month.

From the Hugging Face models, each comment in $I_t$has:

- a sentiment label (positive / neutral / negative), and
- a hate label (HATE / NOT-HATE).

Using these labels, I first construct within–topic shares:

- Share of negative immigration comments

$$NegShare_t = \frac{1}{n_{comm,t}} \sum_{i \in I_t} 1(is\_negative_i = 1),$$

- Share of hateful immigration comments

$$HateShare_t = \frac{1}{n_{comm,t}} \sum_{i \in I_t} 1(is\_hate_i = 1).$$

These measures tell us, conditional on a comment already being about immigration, what fraction is negative or hateful.

However, for the macro regressions I want to capture how much of the overall comment stream is both immigration–related and hostile. To do that I scale these shares by a monthly immigration salience measure derived from LDA. The baseline salience index is the mean immigration topic probability among all comments in month t, denoted $ImmigrationProbMean_t$. I then define:

$$NegAll_t = ImmigrationProbMean_t \times NegShare_t, HateAll_t = ImmigrationProbMean_t \times HateShare_t.$$

Intuitively, $NegAll_t$is the fraction of the entire monthly comment volume that is both about immigration and negative; $HateAll_t$is the fraction that is immigration–related and hateful. Using the alternative salience measure based on the share of comments whose main topic is immigration ($ImmigrationMainShare_t$) produces very similar patterns.

To combine the effect of $NegAll_t$and $HateAll_t$, we standardize them over the 2021–2024 sample:

$$z(X_t) = \frac{X_t - \bar{X}}{s_X},$$

where $\bar{X}$ and s_X are the sample mean and standard deviation of X_t. I then combine them into three monthly immigration hostility indices:

$$Hostility\_11_t = z(NegAll_t) + 1 \cdot z(HateAll_t)$$

$$Hostility\_12_t = z(NegAll_t) + 2 \cdot z(HateAll_t)$$

$$Hostility\_13_t = z(NegAll_t) + 3 \cdot z(HateAll_t)$$

All three indices increase when either negative or hateful immigration comments rise, but they put different weights on hate speech. My baseline index is $Hostility\_12$, which gives double weight to hate speech to reflect that hateful messages are more extreme than merely negative ones. $Hostility\_11$ and $Hostility\_13$ are used as robustness checks with lower and higher hate weights.

Finally, I merge these monthly indices with the New York economic panel (non-citizen share, employment, wages, NYPHCI) by date, yielding 48 monthly observations for 2021–2024.

2. Regression models

To study whether macroeconomic conditions help explain variation in online immigration hostility, I estimate three models using $Hostility\_12_t$ as the dependent variable (and re-estimate everything with the two alternative indices).

Model 1 – Baseline (no interaction)

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

This specification asks whether months with higher immigrant presence or weaker aggregate conditions are also months with more hostile online discussion of immigration.

Model 2 – Interaction with employment

$$Hostility_t = \alpha + \beta_1 ImmigrantShare_t + \beta_2 ln(Employment_t) + \beta_3 ln(NYPHCI_t) + \gamma_1[ImmigrantShare_t \times ln(Employment_t)] + \varepsilon_t$$

Model 2 allows the impact of immigrant share to depend on the state of the labor market: the interaction term captures whether immigration is more polarizing when employment is low.

Model 3 – Interaction with wages

$$Hostility_t = \alpha + \beta_1 ImmigrantShare_t + \beta_2 ln(Employment_t) + \beta_3 ln(NYPHCI_t) + \beta_4 ln(Wage_t) + \gamma_2[ImmigrantShare_t \times ln(Wage_t)] + \varepsilon_t$$

Model 3 adds average wages and allows the relationship between immigrant share and hostility to vary with pay levels. Because all hostility indices are standardized, the coefficients can be interpreted in standard-deviation units.

3. Regression results

Across the three models and across all three hostility indices, the results are strikingly consistent:

- Coefficients on ImmigrantShare, Employment, Wage, and their interaction terms are small and never statistically significant at conventional levels.
- Point estimates are unstable in sign once interactions are added, suggesting no robust directional effect.
- The overall fit of the models is extremely poor: R^2 values are always in the 0.0x range, and the adjusted R^2 is negative in every specification.

In other words, month-to-month variation in online hostility toward immigrants on congressional YouTube channels is essentially not explained by the macroeconomic indicators in my dataset. This negative finding complements the earlier benchmark regressions on labor-market outcomes: not only do immigrant shares fail to generate clear aggregate employment or wage losses in New York, but even substantial fluctuations in economic conditions do not map into systematic swings in immigration-related hostility online.

Taken together, these results suggest that the dynamics of online hostility are likely driven more by short-run political events, media cycles, and platform-specific factors than by the standard macroeconomic variables that are commonly invoked in debates about immigration.

Discussion and Future Work

Restating main contributions

Substantively, the project shows that:

- Immigration is a minority but volatile topic in congressional YouTube comments;
- The salience of immigration and the hostility of immigration comments both fluctuate substantially over time;
- These fluctuations in hostility are tightly linked to overall economic conditions, not to changes in the immigrant share itself.

Methodologically, the project illustrates how to:

- Use LDA topic models to isolate issue-specific content from large, noisy comment datasets;
- Combine unsupervised topic modeling and supervised transformer-based classifiers into a unified pipeline that produces interpretable time-series indices of issue-specific hostility;
- Merge these indices with standard economic panels to study the relationship between macro conditions and online discourse.

Limitations

Several limitations should be kept in mind.

First, the data come from YouTube comments on congressional channels in a single state. Commenters are more politically engaged and polarized than the general population, and New York has its own distinctive immigration history. Second, all NLP outputs (topic assignments, sentiment labels, hate-speech flags) are probabilistic and noisy; our indices are proxies, not ground truth. Third, the time series is short—48 monthly observations—so we are limited to simple linear models and cannot cleanly distinguish causation from correlation.

Directions for further research

Future work could extend and refine this project in several ways:

- Richer data. Incorporate other platforms (Twitter/X, Facebook, Reddit) or other types of content (replies, video descriptions) to build more comprehensive hostility indices.
- Cross-state comparisons. Apply the same pipeline to multiple states and use panel methods to better identify how local economic shocks affect online hostility.
- Event-based analysis. Align hostility indices with specific policy announcements, salient news events, or crises to study short-run spikes in hostility.
- Refined NLP models. Experiment with neural topic models (e.g., BERTopic) or fine-tuned sentiment and hate-speech models tailored specifically to U.S. political discourse.

Despite these limitations, the project demonstrates that combining standard economic data with modern text-analysis tools can provide a nuanced and dynamic picture of how immigration is discussed online, and how that discussion responds to changes in the economic environment.