The Impact of Restrictive Immigration Policy Counts on Violent Crime Rates: Evidence from U.S. States (2005–2012)

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Abstract

The impact of restrictive immigration policies on crime rates remains a topic of significant debate in both academic research and public policy discussions. Over recent decades, U.S. states have adopted increasingly divergent approaches to immigration, with some enacting stringent laws aimed at limiting undocumented immigrants' access to public resources and services. Notable examples include Arizona's SB 1070, which expanded law enforcement authority to verify immigration status, and Alabama's HB 56, which imposed restrictions on undocumented immigrants enrolling in public schools and accessing public services [Legislature, 2010, 2011]. Despite these developments, the relationship between such policies and public safety—particularly violent crime—remains poorly understood [Light and Miller, 2018, Wadsworth, 2010].

This study seeks to bridge this gap by employing a fixed-effects regression model to analyze state-level data on restrictive immigration policies, crime reports, and demographic factors across U.S. states from 2005 to 2012. By isolating time-invariant state-specific factors, this approach provides robust estimates of the annual impact of these policies on violent crime rates. The findings reveal nuanced dynamics, highlighting both the potential unintended consequences of restrictive policies and their differential effects across states. This analysis contributes empirical evidence to the ongoing discourse on immigration, offering valuable insights into the complex interplay between policy, demographic factors, and public safety outcomes.

1 Introduction and Background

Immigration policies have long been a central topic of political and public discourse in the United States. In recent years, as immigration laws have become increasingly restrictive, their socio-economic and public safety implications—particularly the relationship between the number of restrictive immigration laws and violent crime rates—have drawn significant attention [Center, 2019, Office, 2018]. While substantial research has explored the economic effects of immigration policies, such as Card [1990] and Borjas [2003] on labor markets, the relationship between the number of restrictive immigration laws and violent crime rates remains less understood. Specifically, whether the quantity of such laws significantly impacts crime rates has not been systematically analyzed. By examining the relationship between the number of restrictive immigration laws and violent crime rates, this study seeks to address this gap in the literature. The existing research on immigration and crime provides a complex and varied picture. For instance, Butcher and Piehl [1998] found that immigrant populations did not significantly increase crime rates, challenging the stereotype that immigration leads to higher crime levels. In contrast, more recent studies suggest that restrictive immigration laws may exacerbate crime by reducing economic opportunities for immigrants. For example, Bohn et al. [2014] found that restrictive laws could destabilize immigrant communities, leading to adverse socio-economic consequences that may indirectly contribute to crime. Similarly, Light and Miller [2018] observed that cities

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with larger immigrant populations often exhibited lower crime rates, further complicating the narrative and highlighting the importance of policy context in shaping outcomes. In recent years, the political landscape surrounding immigration has grown increasingly polarized. Some political leaders have framed immigration as a national security and public safety issue, advocating for stricter immigration laws [News, 2019, Times, 2020]. This narrative has amplified debates about the relationship between immigration and crime, though the evidence remains mixed. While some argue that restrictive laws may unintentionally fuel criminal activity by limiting economic opportunities for immigrants, others assert that such measures are essential for ensuring public safety. These contrasting perspectives underscore the need for empirical research to better understand how the quantity of restrictive immigration laws affects crime rates, particularly violent crime. This study examines the impact of the number of restrictive immigration laws on violent crime rates across U.S. states from 2005 to 2012. Using state-level data on crime reports, demographic characteristics, and policy measures, this research addresses the core question: Does the number of restrictive immigration laws have a positive or negative impact on violent crime rates? A fixed-effects regression model is employed to account for unobserved state-level heterogeneity, providing robust estimates of the policy impacts over time. Although previous studies, such as Wadsworth [2010] and Mastrobuoni and Pinotti [2015], have explored various dimensions of immigration policy and crime, they have not fully accounted for the direct impact of the number of restrictive laws or regional differences in enforcement. Moreover, much of the existing literature focuses either on the economic effects of immigration policies or on crime, without sufficiently examining the intersection of immigration laws and public safety. By analyzing the relationship between the number of restrictive immigration laws and violent crime rates, this study addresses this critical gap and emphasizes the role of regional political, social, and economic contexts. Unlike previous research, this study incorporates not only the direct effects of the number of restrictive immigration laws but also key socio-economic covariates such as unemployment and poverty rates. Additionally, it investigates how these laws operate differently across varying political environments, such as Democratic versus Republican states. By providing empirical evidence on how restrictive immigration laws shape crime outcomes, this study contributes to a nuanced understanding of the interplay between governance, socio-economic conditions, and public safety, offering valuable insights for policymakers aiming to balance these priorities effectively.

2 Descriptive Statistics

This section provides an overview of the dataset and presents descriptive statistics relevant to the analysis of restrictive immigration policies and violent crime rates. The data is drawn from the Correlates of State Policy Project, which compiles over 3,000 variables spanning U.S. state policies, social and economic indicators, and political factors. For this study, variables related to violent crime rates, immigration policies, socio-economic conditions, and demographic characteristics have been selected for analysis, covering all 50 U.S. states from 2005 to 2012.

2.1 Overview of Key Variables

This analysis focuses on three main groups of variables:

Restrictive Immigration Laws: The annual count of laws restricting immigration in each state, including measures like enhanced enforcement authority, limited access to public services, and employment verification requirements.

Violent Crime Rates: The annual number of violent crimes per 100,000 residents, covering offenses such as homicide, rape, robbery, and aggravated assault.

Other Variables: Key socio-economic and demographic controls, including unemployment, poverty, income inequality (Gini coefficient), racial composition, median age, and education

expenditure, are included to isolate the impact of restrictive immigration laws.

These variables provide a comprehensive basis for analyzing the relationship between immigration policies and violent crime rates across states.

2.2 Descriptive Statistics for Selected Variables

Table 1 provides an overview of the descriptive statistics for key variables in the dataset, summarizing their distributions across all states from 2005 to 2012. These variables capture critical aspects of the research, including crime rates, policy restrictiveness, unemployment, and demographic compositions.

Table 1: Descriptive Statistics for Key Variables (2005-2012)

Statistic	vcrimerate	immig_laws_restrict	unemployment	nonwhite
Observations	408	408	408	408
Year Range	2005–2012	2005–2012	2005–2012	2005–2012
Mean	407.06	1.61	6.49	0.2549
SD	208.47	2.41	2.35	0.1399
Min	111.00	0	2.60	0.0184
Max	1508.40	15	13.70	0.7681
Median	354.25	1	6.10	0.2303

2.3 Descriptive Statistics for Selected States

Table 2 focuses on a subset of five selected states: Arizona, Georgia, Utah, Delaware, and Connecticut. The selection highlights contrasts in policy restrictiveness, with Arizona, Georgia, and Utah enacting the highest average number of restrictive immigration laws, while Delaware and Connecticut represent the states with the lowest averages.

Table 2: Descriptive Statistics for Selected States (2005-2012)

State	Avg Immig Laws Restrict	SD Immig Laws Restrict	Avg Violent Crime Rate	SD Violent Crime Rate	Avg Unemployment	SD Unemployment	Avg Gini Coef	SD Gini Coef
Arizona	8.38	3.66	452.12	35.67	7.14	2.70	0.61	0.01
Georgia	5.00	3.30	387.45	29.12	7.56	2.63	0.63	0.01
Utah	4.25	4.06	324.56	31.67	5.06	2.02	0.59	0.01
Delaware	0.25	0.46	298.33	28.56	5.92	2.14	0.56	0.01
Connecticut	0.12	0.35	310.77	27.89	6.69	2.04	0.65	0.03

2.4 Number of Restrictive Immigration Laws

Figure 1 illustrates the number of restrictive immigration laws passed each year across the selected states. Arizona, a state well-known for its restrictive immigration stance, experienced a sharp increase in the number of restrictive laws enacted between 2009 and 2010. This surge in restrictive policies was largely in response to heightened public and political concerns regarding undocumented immigration. Conversely, Delaware and Connecticut had minimal restrictive laws during this period, reflecting a more lenient approach to immigration issues. The differences in legislative activity provide a critical backdrop for understanding how policy approaches vary significantly across the United States and the potential impact of these policies on social dynamics, including crime rates.

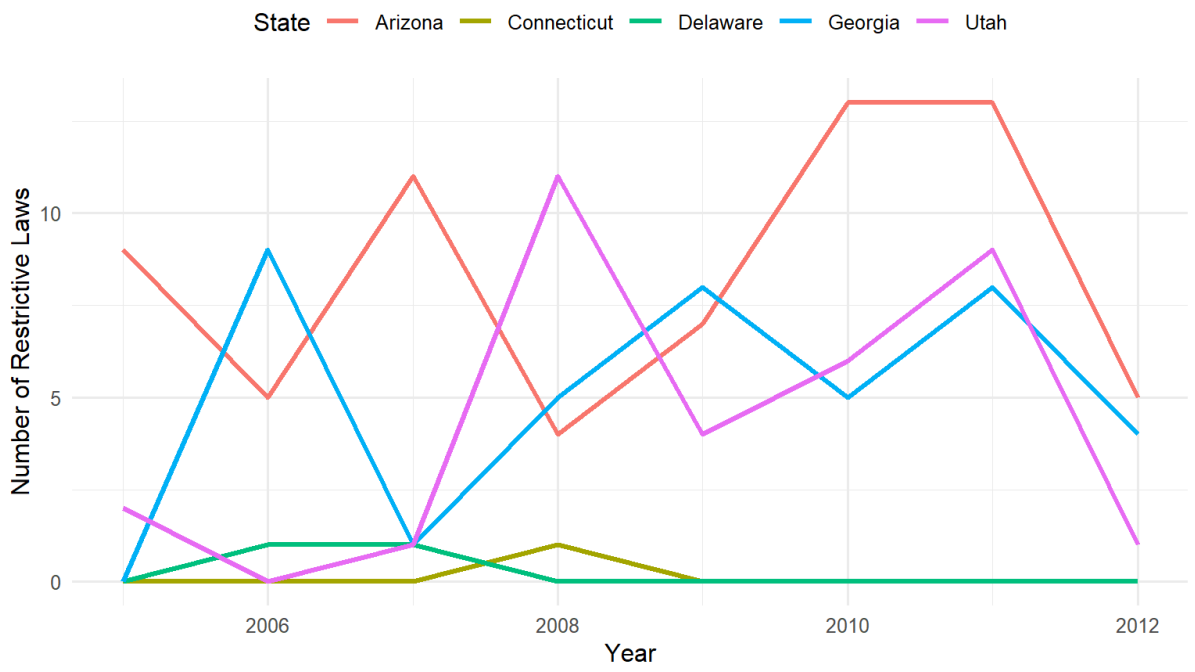

Figure 1: Trends in Violent Crime Rates and Predicted Outcomes (2005-2012)

2.5 Violent Crime Rate Trends

Figure 2 presents the trends in violent crime rates over time for the selected states. Arizona consistently reports higher violent crime rates compared to the other states, which aligns with the state's aggressive stance on restrictive immigration policies. The correlation between higher violent crime rates and more restrictive immigration policies raises questions about the effectiveness of such policies in promoting public safety. Utah and Delaware, with fewer restrictive laws, tend to have lower violent crime rates, suggesting that other socio-economic factors, such as lower unemployment and better social cohesion, might contribute to maintaining lower crime rates in these states. These observations highlight the complexity of relationships between immigration policy, economic conditions, and crime outcomes.

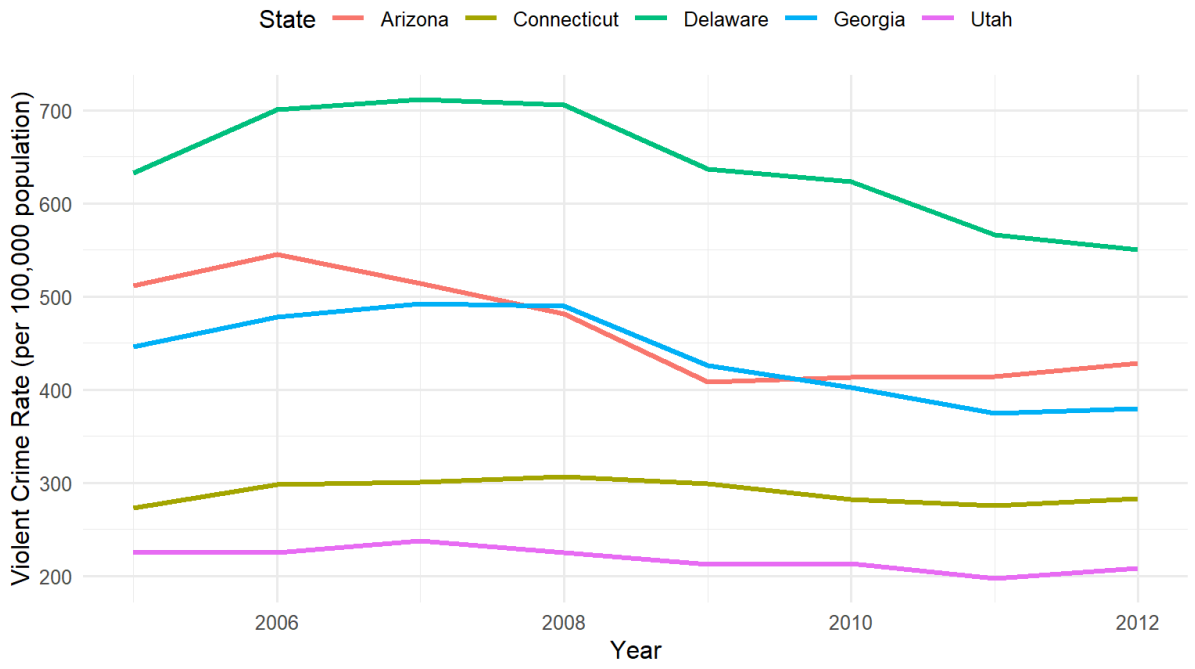

Figure 2: Violent Crime Rate Over Time in Selected States (2005-2012)

2.6 Key Socioeconomic Covariates: Unemployment and Income Inequality

Unemployment and income inequality, as measured by the Gini coefficient, represent two critical socioeconomic covariates that influence the relationship between restrictive immigration policies and state-level socioeconomic stability and public safety outcomes.

During the economic recession of 2008, states such as Georgia, Arizona, and Connecticut experienced significant increases in unemployment. Arizona, in particular, saw a sharp rise in unemployment, which aligns with the state's implementation of strict immigration policies during this period. In contrast, Utah maintained relatively low unemployment rates throughout the observation period, indicating a more stable economic environment despite nationwide economic challenges. These differences underscore the importance of accounting for labor market conditions when assessing the interplay between restrictive immigration policies and socioeconomic outcomes.

Income inequality, as reflected by the Gini coefficient, also varies considerably across states. Connecticut consistently exhibits the highest levels of income inequality, whereas Delaware reports the lowest Gini coefficient. Higher levels of income inequality, such as those observed in Connecticut, may exacerbate the adverse effects of restrictive immigration policies, as unequal income distribution can heighten social tensions and indirectly influence crime rates. These trends highlight the need to integrate income inequality with other socioeconomic variables to gain a comprehensive understanding of the impacts of immigration policies on public safety and economic conditions.

2.7 Summary

The descriptive statistics and trends presented in this section highlight significant variations in economic and policy-related factors across the selected states. States such as Arizona and Georgia, which have enacted numerous restrictive immigration policies, are characterized by relatively high unemployment rates, income inequality, and violent crime rates. On the other hand, states like Delaware and Connecticut, which have fewer restrictive immigration policies, exhibit lower unemployment rates, Gini coefficients, and violent crime rates. This descriptive

analysis provides an essential foundation for the subsequent exploration of the causal relationships between restrictive immigration policies and violent crime rates. By understanding these underlying socio-economic and policy differences, it becomes possible to more accurately assess the impacts of restrictive immigration legislation on public safety and social welfare across different states.

3 Model Setup and Explanation

This section presents the model employed to analyze the impact of restrictive immigration policies on violent crime rates across U.S. states from 2005 to 2012. The study uses a fixed effects regression model to control for unobserved heterogeneity among states. By focusing on within-state variation over time, this model allows for a more robust examination of how changes in restrictive immigration policies are associated with changes in violent crime rates, controlling for time-invariant characteristics of each state.

3.1 Model Specification

The fixed effects model is specified as follows:

$$
\begin{aligned}
y_{it} = \beta_0 + \beta_1 \text{immig\_laws\_restrict}_{it} & \quad (1)\\
+ \sum_{k=2}^{10} \beta_k X_{k,it} & \quad (2)\\
+ \sum_{m=11}^{14} \beta_m \left(X_{m_1,it} \times X_{m_2,it} \right) & \quad (3)\\
+ \gamma_t + \alpha_i + \epsilon_{it} & \quad (4)
\end{aligned}
$$

where y_{it} represents the violent crime rate in state i at time t, and α_i denotes the fixed effects specific to the state, capturing unobserved and time-invariant characteristics unique to each state. These include factors such as cultural differences, historical context, and institutional structures that can influence crime rates. By including α_i, the model effectively controls for such state-level differences, allowing a more precise assessment of the impact of the predictors.

The term γ_t represents fixed time-specific effects, accounting for consistent temporal variations in all states. These variations might include national economic trends, changes in federal policies, or other macrolevel events that affect violent crime rates uniformly. Incorporating γ_t ensures that the model adjusts for these common temporal shocks, preventing potential bias in estimating the effects at the state level.

To estimate coefficients β, the fixed effects model employs a transformation within, which focuses on deviations from state-level means. This transformation eliminates the influence of α_i, allowing the model to analyze witin-state variation over time:

$$y_{it} - \overline{y}_i - \overline{y}_t + \overline{\overline{y}} = \tag{5}$$

$$\beta_1 \left(\text{immig\_laws\_restrict}_{it} - \overline{\text{immig\_laws\_restrict}}_i - \overline{\text{immig\_laws\_restrict}}_t + \overline{\overline{\text{immig\_laws\_restrict}}} \right) + \tag{6}$$

$$\beta_2 \left(X_{it} - \overline{X}_i - \overline{X}_t + \overline{\overline{X}} \right) + \tag{7}$$

$$\beta_3 \left((\text{interactions})_{it} - \overline{(\text{interactions})}_i - \overline{(\text{interactions})}_t + \overline{\overline{(\text{interactions})}} \right) + \tag{8}$$

$$(\epsilon_{it} - \overline{\epsilon}_i - \overline{\epsilon}_t + \overline{\overline{\epsilon}}) \tag{9}$$

This transformation ensures that the fixed effects (α_i) are removed from the equation, enabling the model to focus exclusively on how changes in the predictors within each state affect violent crime rates.

The simplification consolidates individual covariates (X_{it}) and interaction terms ($(\text{interactions})_{it}$), while still preserving the ability to evaluate both direct effects (e.g., $\text{immig\_laws\_restrict}_{it}$) and combined impacts (e.g., interaction terms), ensuring analytical clarity and interpretive rigor.

3.2 Explanation of Variables

- $\text{immig\_laws\_restrict}_{it}$: The number of restrictive immigration laws enacted in state i during year t. This variable is of primary interest, as it represents policy interventions aimed at controlling immigration. The coefficient β_1 measures the impact of these restrictive laws on violent crime rates.

- povrate_{it}: The poverty rate in state i during year t. This variable is included to control for the economic conditions that may affect crime rates, with β_2 representing its effect.

- unemployment_{it}: The unemployment rate in state i during year t. This variable measures labor market conditions, and β_3 captures the relationship between unemployment and violent crime.

- nonwhite_{it}: The proportion of the population in state i that is nonwhite. This demographic variable is included to account for the racial composition of each state, which may influence crime rates. The coefficient β_4 measures this effect.

- medianage_{it}: The median age of the population in state i. Age distribution is important for understanding crime rates, as younger populations are often associated with higher crime levels. The effect is captured by β_5.

- achgt_{it}: State and local revenues from current charges, in millions of dollars. This variable reflects the income generated by the state and local governments from various charges, which can affect the resources available for public services and, consequently, crime rates. The coefficient β_6 captures this relationship.

- $\text{exp\_education}_{it}$: Public expenditure on education per capita in state i. This variable represents the state's investment in education, which may indirectly affect crime rates by improving economic opportunities. The coefficient β_7 represents its effect.

- apolpi_{it}: Police, fire, regulatory spending as a percentage of income. This variable captures the spending priorities of state and local governments, which may influence both crime rates and policy enforcement. The effect of these expenditures is represented by β_8.

- gini_coef_{it}: The Gini coefficient, measuring income inequality in state i. Higher inequality might lead to higher crime rates, as represented by the coefficient β_9.

- guncontrol_opencarry$_{it}$: An indicator of whether open carry laws for firearms are in effect in state i. The coefficient β_{10} measures the effect of firearm policy on violent crime.

- w_guncontrol_bc_privatesales$_{it}$: Whether background checks for private gun sales are required. This variable helps capture the stringency of gun control measures, with β_{11} representing its impact on violent crime.

3.3 Interaction Terms

Including interaction terms allows the model to capture how the combined effects of key variables influence violent crime rates, providing a more nuanced understanding of their interrelationships. These specific interaction terms were selected based on their theoretical and policy relevance:

- **immig_laws_restrict**$_{it} \times$ **povrate**$_{it}$: This term examines whether the effect of restrictive immigration laws on violent crime is moderated by poverty levels. Poverty is often linked to higher crime rates due to limited economic opportunities and social stressors [Lochner and Moretti, 2004, Bourguignon, 2001]. By including this interaction, the model tests whether restrictive policies exacerbate these effects in high-poverty contexts, providing insight into whether such policies disproportionately affect disadvantaged communities.

- **immig_laws_restrict**$_{it} \times$ **unemployment**$_{it}$: Unemployment is another critical socio-economic factor associated with crime [Raphael and Winter-Ebmer, 2000, Levitt, 2004]. This interaction captures whether the relationship between restrictive immigration policies and violent crime depends on the labor market's health. Since unemployment can amplify economic competition and social tensions [Cohen and Felson, 1979], this term explores whether restrictive policies have a differential impact in states with higher unemployment rates.

- **povrate**$_{it} \times$ **unemployment**$_{it}$: Poverty and unemployment are closely related and often co-occur in economically distressed areas. This interaction term assesses their joint influence on violent crime rates, providing a deeper understanding of how these two factors together shape crime dynamics. Including this term allows the model to capture compounding effects that may not be evident when considering each variable separately [Wadsworth, 2010, Mustard, 2010].

These interaction terms were chosen because they address key socio-economic mechanisms that potentially mediate or amplify the impact of restrictive immigration policies on violent crime. Alternative interactions, such as those involving other variables like education spending or racial composition, were excluded to maintain a parsimonious model and focus on the most theoretically significant relationships. By limiting the scope to these terms, the model balances complexity and interpretability while capturing essential dynamics between policies, economic conditions, and crime rates.

4 Results

4.1 Nationwide Regression Results

4.1.1 Overview of the Models

This section compares four regression models that analyze the impact of restrictive immigration laws on violent crime rates across U.S. states. Each model varies in complexity and the inclusion of covariates and interaction terms, enabling a robust examination of the hypothesized relationships.

- **OLS Model (OLS)**: The baseline model estimates the relationship without accounting for unobserved heterogeneity across states. While straightforward, this approach may be vulnerable to omitted variable bias if unobserved factors influence both restrictive immigration laws and crime rates.
- **Fixed-Effects Model 1 (FE1)**: This comprehensive model includes all main covariates and interaction terms, controlling for time-invariant state-specific heterogeneity. FE1 provides the most detailed understanding of the relationship between restrictive immigration laws and violent crime rates.
- **Fixed-Effects Model 2 (FE2)**: A balanced model incorporating a broader set of covariates but excluding interaction terms. FE3 tests the robustness of results under varying specifications while controlling for unobserved state-level heterogeneity.
- **Fixed-Effects Model 3 (FE3)**: A simplified model focusing on key covariates, including unemployment, the proportion of the nonwhite population, and gun control policies. FE2 excludes interaction terms to simplify interpretation while testing whether primary variables explain the observed trends.

The differences between these models reflect varying levels of complexity, ranging from the simplicity of OLS to the detailed control of fixed effects models, ensuring robust insights into the studied relationships.

4.1.2 Regression Results Summary

Table 3 summarizes the regression results. Coefficients and p-values for main variables are provided, with "Yes" or "No" indicating whether additional variables or interaction terms are included in each model.

Table 3: Regression Results with Main Effects, Other, and Interactions

Variable	OLS	FE1	FE2	FE3
(Intercept)	-326.737 (0.428)	No	No	No
immig_laws_restrict	9.943 (0.576)	0.347 (0.930)	0.490 (0.581)	0.624 (0.486)
unemployment	12.713 (0.496)	7.671 (0.078)	-8.424*** (0.000)	-9.789*** (0.000)
nonwhite	304.784*** (0.000)	110.837** (0.001)	119.426** (0.001)	112.564*** (0.000)
gini_coef	440.239 (0.158)	-186.871* (0.051)	-53.822 (0.551)	-39.130 (0.667)
guncontrol_opencarry	-167.706*** (0.000)	2.779 (0.847)	7.243 (0.622)	4.611 (0.756)
achgt	-0.001 (0.275)	-0.008*** (0.000)	-0.010*** (0.000)	-0.009*** (0.000)
Other	Yes	Yes	Yes	No
Interactions	Yes	Yes	No	No

4.1.3 Other Variables and Interaction Terms

The "Other" covariates include poverty rates, median age, educational expenditure, political affiliation, and background check policies for private gun sales. Interaction terms in FE1, such as *immig_laws_restrict:povrate*, assess whether poverty or unemployment moderates the effect of restrictive immigration laws on violent crime rates. However, none of these interaction terms achieve statistical significance, indicating limited evidence for such moderating effects.

4.1.4 Interpretation of Main Variables

This section examines the main variables included in the models, focusing on their estimated effects and potential mechanisms driving their relationships with violent crime rates.

- **Restrictive Immigration Laws (immig_laws_restrict):** Across all models, the coefficient for restrictive immigration laws is positive but statistically insignificant, with the OLS estimate at 9.943 ($p = 0.576$) and the FE1 estimate at 0.347 ($p = 0.930$). These results suggest that while stricter immigration policies might correlate with higher violent crime rates, the evidence does not support a robust causal relationship. One explanation could be that restrictive immigration laws exacerbate social tensions or reduce community trust in law enforcement, indirectly influencing crime rates [Light and Miller, 2016]. However, limited policy variation or unmeasured state-specific factors may attenuate the observed effects.

- **Other Covariates:** The analysis of additional covariates across the models reveals varying levels of significance:

  - **Unemployment (unemployment):** A significant negative relationship with violent crime is observed in FE2 (-8.424, $p < 0.001$) and FE3 (-9.789, $p < 0.001$), but no significant effect is found in OLS or FE1;
  - **Nonwhite Population Proportion (nonwhite):** A strong positive association with violent crime is evident across all models, e.g., 110.837 ($p = 0.001$) in FE1;
  - **Income Inequality (gini_coef):** Marginal significance is observed in FE1 (-186.871, $p = 0.051$), while no significance is found in other models;
  - **Gun Control Policies (guncontrol_opencarry):** A significant negative association is identified in OLS (-167.706, $p < 0.001$), but this relationship does not persist in fixed-effects models;
  - **State and Local Revenues (achgt):** A significant negative association is consistently observed in all fixed-effects models, e.g., -0.008 ($p < 0.001$) in FE1, though it is not significant in OLS.

  These findings align with research suggesting that investments in public services, such as education, help mitigate criminal behavior by enhancing economic opportunities and reducing inequality [Lochner and Moretti, 2004]. Moreover, revenues allocated to community programs and public safety initiatives may address underlying social determinants of crime [Bourguignon, 2001].

4.1.5 Focus on Restrictive Immigration Laws

The consistently positive but statistically insignificant relationship between restrictive immigration laws and violent crime rates across models underscores the complexity of this relationship. These findings suggest that restrictive immigration policies alone are insufficient to explain variations in violent crime. Future research should incorporate additional mediating factors, such as community-level social cohesion and economic integration programs, to better understand the nuanced dynamics of immigration policies and public safety.

4.2 Comparing States with High and Low Numbers of Restrictive Immigration Laws

To explore the relationship between restrictive immigration policies and violent crime rates, states were divided into two groups: those with high numbers of restrictive immigration laws and those with low numbers. The classification was based on the average annual number of restrictive immigration laws enacted per state between 2005 and 2012. States with averages greater than the first quartile (Q1) were categorized as "high," while those with averages below the third quartile (Q3) were categorized as "low."

4.2.1 Descriptive Statistics for 2005 and 2012

Table 4 presents the descriptive statistics for violent crime rates (`vcrimerate`) and restrictive immigration laws (`immig_laws_restrict`) in 2005 and 2012 for the two groups. These statistics provide a snapshot of differences in violent crime rates and immigration laws between the high and low groups.

Table 4: Descriptive Statistics for 2005 and 2012: High vs. Low Restrictive Immigration Laws

Statistic	Low	High
2005		
vcrimerate		
Mean	329.67	511.23
SD	168.38	164.50
Count	12	13
immig_laws_restrict		
Mean	0.25	1.00
SD	0.45	2.48
Count	12	13

Statistic	Low	High
2012		
vcrimerate		
Mean	313.09	418.55
SD	139.78	125.72
Count	12	13
immig_laws_restrict		
Mean	0.33	2.08
SD	0.65	1.66
Count	12	13

4.2.2 Observations

- **Violent Crime Rates (`vcrimerate`):** - In both 2005 and 2012, states classified as "high" reported higher average violent crime rates than "low" states. In 2005, the average violent crime rate for high states was 511.23 incidents per 100,000 people, compared to 329.67 for low states. Similarly, in 2012, high states had an average of 418.55 compared to 313.09 for low states. - The standard deviation of violent crime rates was similar between the two groups in both years, indicating comparable levels of variability.

- **Restrictive Immigration Laws (`immig_laws_restrict`):** - As expected, the average number of restrictive immigration laws was higher in the high group. In 2005, high states enacted an average of 1.00 restrictive law, compared to 0.25 in low states. By 2012, high states averaged 2.08 laws compared to 0.33 in low states. - The variability in restrictive immigration laws was more pronounced in the high group, reflecting greater diversity in legislative activity.

4.2.3 Analysis of Predicted vs. Actual Violent Crime Rates by Group

Figure 3 presents the predicted and actual violent crime rates for states classified as having "high" and "low" numbers of restrictive immigration laws from 2005 to 2012. Predictions were generated using the FE1 model, which incorporates fixed effects to control for time-invariant state-level heterogeneity. The analysis reveals that there is no clear evidence to suggest that restrictive immigration laws contribute to reducing violent crime rates.

Temporal Trends in Actual Crime Rates: The actual violent crime rates for both groups show a gradual decline over the observed period. States with high numbers of restrictive immigration laws consistently exhibit higher violent crime rates compared to those in the low group. For instance, in 2005, the actual violent crime rate for the high group exceeded 500 incidents per 100,000 population, while the low group reported rates closer to 350. By 2012, both groups experienced reductions in violent crime rates, with the high group stabilizing around 400 incidents and the low group falling below 350. These patterns align with broader national trends of declining violent crime during this period, likely driven by improved policing strategies, economic recovery, or other macro-level factors unrelated to immigration laws.

Performance of the Predictive Model: The predicted crime rates, represented by dashed lines, closely align with the actual rates for both groups, capturing the overall downward trend in crime rates. However, the predictions do not indicate that high numbers of restrictive immigration laws are associated with lower violent crime rates. Notably, the high group—despite enacting significantly more restrictive immigration laws—maintains higher violent crime rates than the low group throughout the observation period. This consistency suggests that other factors, such as socioeconomic conditions, unemployment, and demographic composition, play a more significant role in shaping violent crime trends.

Implications of the Findings: The persistent gap in violent crime rates between high and low groups challenges the notion that restrictive immigration policies effectively reduce crime. The FE1 model's predictions, while accurate in capturing general trends, indicate that the additional laws in high states did not lead to a comparative decrease in violent crime. On the contrary, the high group consistently reported higher crime rates, which may reflect broader structural or social issues that restrictive immigration laws fail to address.

Conclusion: Figure 3 highlights the ineffectiveness of restrictive immigration laws in reducing violent crime rates. While both groups experienced declines in crime over time, this trend appears driven by broader national factors rather than state-level policy differences. These results underscore the importance of considering alternative explanations and interventions to address violent crime effectively.

4.3 Comparative Analysis: Democrat vs. Republican Governed States

4.3.1 Introduction

This section provides a detailed comparative analysis of violent crime rate trends across states governed by Democratic and Republican parties from 2005 to 2012. The analysis leverages both predicted and actual violent crime rates, as shown in Figure 4, to explore the relationship between governance styles and crime dynamics. This study emphasizes that restrictive immigration laws, a focal point of state-level policymaking, show limited evidence of reducing violent crime rates.

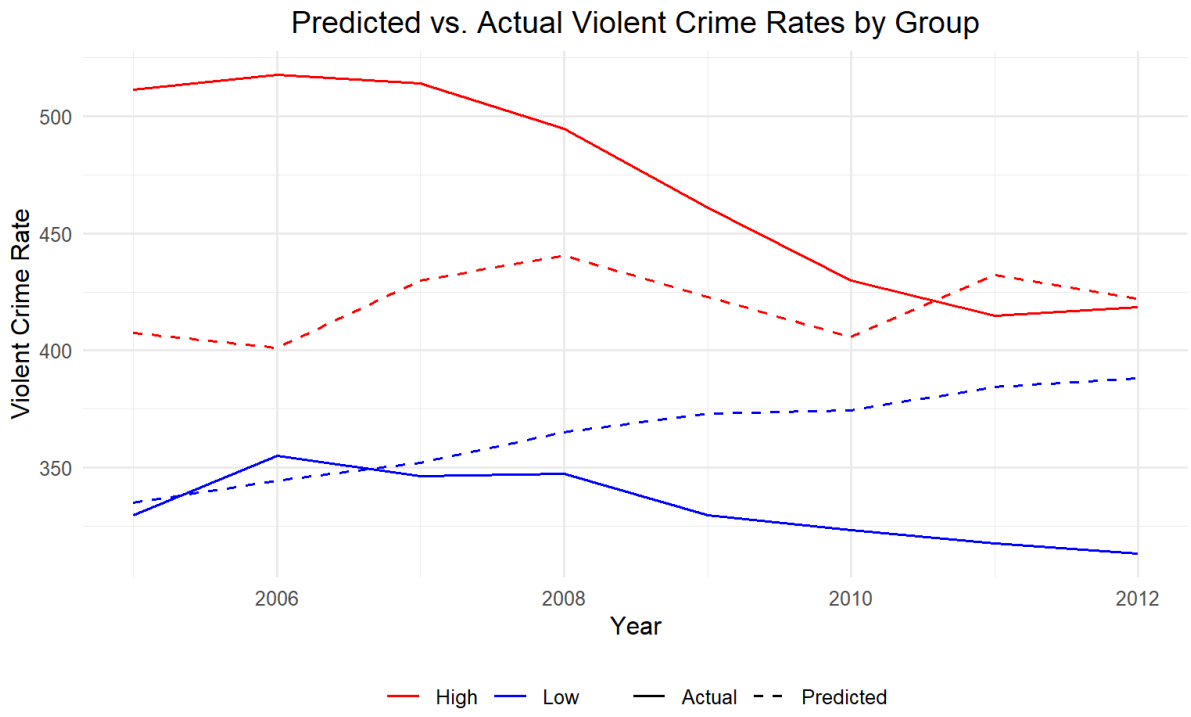

Figure 3: Predicted vs. Actual Violent Crime Rates by Group (FE1 Model)

4.3.2 Key Observations from the Trends

- **Limited Effectiveness of Restrictive Immigration Laws:** Across both Democratic and Republican states, restrictive immigration laws show no consistent evidence of reducing violent crime rates. States governed by Republicans, which enact more such laws, continue to exhibit higher violent crime rates than Democratic states. This suggests that socioeconomic and structural factors outweigh the impact of these laws on crime reduction.

- **Consistent Party-Based Differences:** Democratic-governed states consistently report lower violent crime rates than Republican-governed states. For instance, in 2005, actual violent crime rates in Democratic states averaged around 400 incidents per 100,000 population, while Republican states exceeded 450. This trend persists across the observed period, highlighting fundamental differences in governance approaches and policy priorities.

- **Alignment Between Predicted and Actual Trends:** The predictive model performs robustly, capturing the general downward trend in crime rates for both party groups. However, slight deviations are observed, particularly in Republican states during the mid-period (2006–2008), where actual rates temporarily exceed predicted values. This suggests that unobserved factors, such as local economic conditions or enforcement practices, may influence these trends.

- **Temporal Trends:** Both groups exhibit a gradual decline in violent crime rates over time. However, the decline is steeper in Republican states, potentially reflecting the immediate impact of aggressive law enforcement policies. Despite this, Republican states still maintain higher overall crime rates, underscoring the limitations of punitive approaches in addressing structural issues like poverty and inequality.

- **Policy Implications:** The persistent gap between the two groups, despite similar national trends, indicates that state-level policies and governance styles play a significant

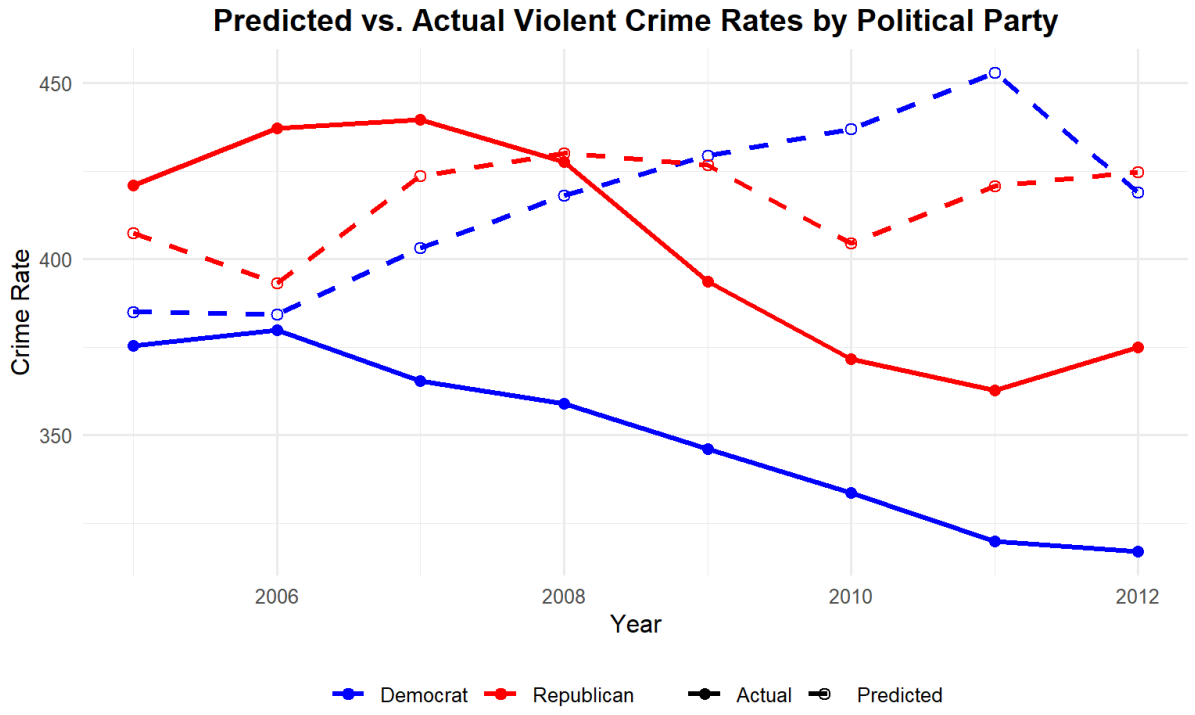

Figure 4: Predicted and Actual Violent Crime Rate Trends by Political Party (2005-2012)

role in shaping crime dynamics. Democratic states' emphasis on social investments and preventive measures likely contributes to their comparatively lower crime rates.

4.3.3 Interpretation of Results

- **Democratic Governance and Stable Crime Reduction:** Democratic states demonstrate stable and predictable reductions in violent crime rates, driven by policies that address root causes of crime, such as investments in education, healthcare, and socioeconomic equity. These findings align with research emphasizing the long-term benefits of preventive approaches [Lochner and Moretti, 2004, Bourguignon, 2001].

- **Republican Governance and Aggressive Enforcement:** Republican states achieve sharper declines in crime rates, likely due to aggressive enforcement policies. However, their persistently higher crime rates suggest that these measures may address symptoms rather than root causes. The reliance on punitive approaches, such as mandatory sentencing and increased incarceration, raises concerns about long-term sustainability and social equity [Alexander, 2010].

- **Socioeconomic Variables as Key Drivers:** Structural factors, including poverty, unemployment, and income inequality, play a significant role in shaping crime trends. Republican states, with generally weaker social safety nets, face challenges in mitigating these factors effectively. In contrast, Democratic states' focus on social programs likely buffers the impact of these variables, contributing to more stable crime reductions.

4.3.4 Broader Implications

- **Integrating Prevention and Enforcement:** The findings underscore the need for balanced policy approaches. Democratic states highlight the importance of preventive

measures, while Republican states demonstrate the immediate impact of enforcement. A hybrid approach that combines these strategies could yield sustainable crime reductions.

- **Future Research Directions:** The deviations between predicted and actual crime rates, particularly in Republican states, highlight the need for further research. Incorporating additional variables, such as community engagement and cultural attitudes, could enhance the model's explanatory power and provide deeper insights into the dynamics of crime reduction.

4.3.5 Conclusion

This analysis reveals that governance styles significantly influence violent crime trends. Democratic states consistently achieve lower crime rates through preventive policies and social investments, while Republican states rely on aggressive enforcement to achieve short-term gains. These findings emphasize the importance of tailoring crime reduction strategies to address both structural issues and immediate challenges. Future research should explore the interplay between political leadership, socioeconomic conditions, and crime outcomes to inform evidence-based policymaking.

5 Conclusion

This study examines the impact of restrictive immigration policies on violent crime rates across U.S. states from 2005 to 2012, employing a fixed-effects regression model to control for state-specific unobserved heterogeneity. By incorporating socio-economic, demographic, and policy-related variables, the analysis provides nuanced insights into the relationships between restrictive immigration policies, regional dynamics, and governance styles.

The findings reveal several critical trends and implications:

- **Restrictive Immigration Policies and Crime**: Across all models, the relationship between restrictive immigration policies and violent crime rates is statistically insignificant. While such policies are often implemented with the intention of enhancing public safety, the results suggest they may not have a uniform or direct effect on violent crime. Instead, these policies may exacerbate socio-economic disparities or reduce community trust in law enforcement, indirectly influencing crime dynamics.

- **Effectiveness of Restrictive Immigration Laws**: States with higher numbers of restrictive immigration laws consistently exhibited elevated violent crime rates compared to states with fewer such laws. Despite a gradual decline in violent crime rates across all states from 2005 to 2012—likely influenced by national trends such as economic recovery and improved policing—restrictive immigration laws alone did not appear to contribute significantly to crime reduction. These findings underscore the importance of addressing deeper socioeconomic challenges, including poverty and unemployment, to achieve meaningful and sustainable reductions in crime rates.

- **Governance Styles and Crime Outcomes**: States governed by the Democratic Party exhibit consistently lower violent crime rates, reflecting an emphasis on social investment and preventive measures such as education and healthcare. Republican-governed states achieve sharper reductions in crime rates, primarily through aggressive enforcement strategies, although these approaches may carry long-term societal costs, such as increased incarceration rates and social inequalities.

- **Socio-Economic Determinants**: Variables such as poverty, unemployment, income inequality, and racial composition significantly influence violent crime rates. The interactions between restrictive immigration policies and socio-economic conditions, such as

poverty and unemployment, highlight the need for policies that address underlying structural issues rather than focusing solely on punitive measures.

5.1 Policy Implications

The findings underscore the importance of adopting balanced and region-specific crime prevention strategies. While aggressive enforcement policies may yield rapid reductions in crime, sustainable outcomes require investments in education, healthcare, and community-building initiatives. Policies should also account for regional differences, tailoring interventions to the unique socio-economic and demographic characteristics of each state.

5.2 Directions for Future Research

The study highlights several avenues for future research:

- **Unobserved Heterogeneity**: Future studies should explore additional unobserved factors, such as cultural attitudes, community trust, and localized economic shocks, that may influence the relationship between immigration policies and crime.
- **Longitudinal Analyses**: Extending the time frame beyond 2012 would allow researchers to examine the long-term effects of restrictive immigration policies, particularly in the context of changing political and economic landscapes.
- **Micro-Level Data**: Incorporating community- or city-level data would enable a more granular analysis of the localized impacts of restrictive immigration policies, providing deeper insights into the mechanisms driving crime trends.
- **Policy Implementation and Timing**: Examining the timing and specific features of restrictive immigration policies could shed light on the causal pathways through which these policies influence crime rates.
- **Interactions with Broader Policies**: Future research could investigate how restrictive immigration policies interact with other policy domains, such as housing, labor markets, and public health, to influence crime and socio-economic outcomes.

This study contributes to the ongoing discourse on immigration and public safety by providing empirical evidence on the nuanced effects of restrictive immigration policies. By emphasizing the importance of regional and political contexts, it offers a foundation for designing more effective, equitable, and sustainable policy interventions.

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