Bayesian Hierarchical Modeling of Universal Background Check Laws and Firearm Mortality in the United States

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1 Introduction

Firearm-related mortality remains a critical public health crisis in the United States. In 2023 alone, 46,728 deaths were attributed to firearms, marking one of the highest annual totals recorded [Hop24]. In response, Universal Background Check (UBC) laws mandate background checks for all firearm sales even including private transactions, and have been widely proposed as a primary policy intervention to prevent firearm access by prohibited individuals. However, empirical evidence on the efficacy of UBC laws remains mixed. Existing studies report a wide range of estimated effects, from significant reductions in firearm homicide and suicide rates to statistically null impacts [Ran20]. These inconsistencies reflect substantial challenges with studying the effects of these policies, including heterogeneous state implementation, differences in enforcement, co-occurring firearm laws, and the difficulty of analyzing sparse, multi-level policy data.

To address these challenges, this study applies a Bayesian hierarchical modeling framework to two decades of state-level firearm mortality data. The Bayesian approach is well suited to this policy question because it incorporates uncertainty and prior information in a principled way. We first perform estimation of differences in firearm death rate in periods before and after UBC policies were implement. Then, we complement this analysis with a Bayesian difference-in-differences model to estimate the causal association between UBC adoption and changes in firearm mortality while accounting for unobserved, time-invariant state-level confounders.

Overall, our goal is to provide clearer, more statistically rigorous evidence to inform ongoing debates about the effectiveness of firearm background check policies.

2 Data

To evaluate the relationship between universal background checks and firearm-related mortality, we combined two complementary datasets: (1) state-level mortality data from the CDC's

WONDER Underlying Cause of Death database, and (2) state-level firearm policy data from the Tufts CTSI State Firearm Database.

2.1 Mortality Data: CDC WONDER Database

Annual state-level counts of firearm-related deaths (y_{jt}) and corresponding population estimates (N_{jt}) for each state j and year t were obtained from the CDC WONDER Underlying Cause of Death database [CDC WONDER]. Firearm deaths were identified using relevant ICD-10 cause-of-death codes. All CDC data use and disclosure policies were followed, including the suppression of small cell counts.

2.2 Policy Data: Tufts CTSI State Firearm Database

UBC enactment dates were obtained from the Tufts State Firearm Laws Database [Tufts CTSI]. A binary indicator $\text{universal}_{jt} = 1$ was created for state j in year t if a UBC law was in effect for the entire calendar year. The first such year for each state is denoted T_j^{UBC}.

2.3 Data Integration and Analytical Samples

- **Pre-UBC sample**: 170 state-year observations ($t < T_j^{\text{UBC}}$) from 10 states that enacted UBC (Sections 3–4).
- **Post-UBC sample**: 116 state-year observations ($t \geq T_j^{\text{UBC}}$) from 10 states with UBC laws (Sections 5–6).

Table 1 summarizes the analytical samples used in our Bayesian hierarchical models.

Table 1: Summary of Analytical Samples

Sample	States	State-Years	Period
Pre-UBC Analysis	10	170	1999–2019
Post-UBC Analysis	10	116	1999–2020

3 Methods

3.1 Analytical Framework

We estimate firearm mortality rates before and after Universal Background Check (UBC) adoption using two separate Bayesian hierarchical Poisson models. These models stabilize state-level estimates by borrowing strength across states and allow us to characterize changes in mortality patterns surrounding UBC implementation. All models are also fit in `Stan`.

3.2 Bayesian Hierarchical Poisson Models (Pre- and Post-UBC)

We estimate two separate hierarchical Poisson models for firearm mortality before and after the enactment of Universal Background Check (UBC) laws. For each state-year observation,

$$y_{jt} \mid \lambda_j \sim \text{Poisson}(N_{jt}\lambda_j), \qquad \alpha_j = \log \lambda_j,$$

so that

$$\log \mathbb{E}[y_{jt} \mid \alpha_j] = \log N_{jt} + \alpha_j.$$

State log-rates follow a Gaussian prior

$$\alpha_j \mid \mu_\alpha, \sigma_\alpha^2 \sim \text{Normal}(\mu_\alpha, \sigma_\alpha^2),$$

with weakly informative hyper-priors

$$\mu_\alpha \sim \text{Normal}(-10, 5^2), \quad \sigma_\alpha \sim \text{Normal}^+(0, 2^2).$$

Pre-UBC Model: fitted on data with $t < T_j^{\text{UBC}}$. Posterior summaries: $\mu_\alpha^{\text{post}} = -9.33$ (95% CrI: $-9.68, -8.97$), $\sigma_\alpha^{\text{post}} = 0.63$ $(0.41, 0.98)$, yielding $10^5 e^{\mu_\alpha^{\text{post}}} = 9.03$ $(6.23, 12.67)$ per 100,000.

Post-UBC Model: fitted on $t \geq T_j^{\text{UBC}}$. Posterior summaries: $\mu_\alpha = -9.32$ (95% CrI: $-9.61, -9.03$), $\sigma_\alpha = 0.45$ $(0.27, 0.77)$, implying a geometric mean mortality of $10^5 e^{\mu_\alpha} = 9.07$ $(6.71, 11.98)$ per 100,000.

Both models exhibit excellent convergence ($\hat{R} = 1.00$, ESS $> 7{,}000$). Results suggest stable overall mortality following UBC enactment, but with increased between-state heterogeneity in the post-policy period.

3.3 Difference In Difference Modeling

As we observed inconclusive results with some states showing increased rates of firearm fatalities following enaction of UBC policies, while others showed decreases, we decided to adopt a hierarchical Bayesian difference-in-difference (DiD) framework to better estimate the causal effect of UBC laws.

3.4 Core DiD Logic

The traditional DiD approach estimate policy effect by looking at differences in how the control and treated group change when the policy is implemented [Normington 2019]. For the purposes of our study we took a time period of 6 years before and after policies were implemented in treated states, and a time period of 6 years before and after the mean adoption year for untreated states The classical difference-in-differences (DiD) estimand is defined as:

$$\text{DiD Effect} = \left(\overline{Y}^{\text{post}}_{\text{treated}} - \overline{Y}^{\text{pre}}_{\text{treated}}\right) - \left(\overline{Y}^{\text{post}}_{\text{control}} - \overline{Y}^{\text{pre}}_{\text{control}}\right).$$

For our Bayesian approach, we estimate the causal effect of universal background checks (UBC) using a hierarchical Poisson regression model for firearm mortality across states and years. Our data consist of state-year observations of firearm deaths. The model accounts for potential confounding policies, including domestic violence restrictions, dealer regulations, and reporting requirements for lost or stolen firearms. By modeling state-level mortality hierarchically, we allow for partial pooling across states to improve estimates, particularly for states with sparse data, while capturing heterogeneity in baseline firearm mortality rates.

For each state-year observation we ultimately use a (log) Poisson for likelihood to model total firearm deaths:

$$y_{it} \mid \lambda_{it} \sim \text{Poisson}(N_{it}\lambda_{it}), \quad \log \lambda_{it} = \alpha_i + \gamma_t + \beta_{\text{DiD},i} D_{it} + \sum_{k=1}^{K} \beta_k X_{kit},$$

where y_{it} denotes firearm deaths, N_{it} population, D_{it} a UBC treatment indicator (0 or 1), and X_{kit} additional covariates.

Hierarchical Priors:

$$\beta_{\text{DiD},i} \mid \beta_{\text{DiD}}, \sigma^2_\beta \sim \text{Normal}(\beta_{\text{DiD}}, \sigma^2_\beta), \quad \alpha_i \mid \mu_\alpha, \sigma^2_\alpha \sim \text{Normal}(\mu_\alpha, \sigma^2_\alpha),$$

$$\gamma_t \sim \text{Normal}(0, \sigma^2_\gamma), \quad \beta_{\text{DiD}} \sim \text{Normal}(0, 5^2),\ \sigma_\beta, \sigma_\alpha, \sigma_\gamma \sim \text{Exponential}(1),\ \beta_k \sim \text{Normal}(0, 2^2).$$

Parameter Roles:

Symbol	Interpretation
λ_{it}	Expected count of firearm deaths in state i, year t
α_i	State intercept (baseline mortality)
γ_t	Year effect (shared temporal trend)
$\beta_{\text{DiD},i}$	State-specific UBC effect (treatment impact)
β_{DiD}	Mean UBC effect across states
β_k	Effect of covariate k (e.g., demographics, economics)
$\sigma_\alpha, \sigma_\beta, \sigma_\gamma$	Variability in intercepts, DiD effects, and year terms

Table 2: Summary of model parameters and interpretations.

4 Results

4.1 State-Level Posterior Mortality Estimates

Table 3 presents the posterior mean mortality rates per 100,000 population with 95% credible intervals for each state in the pre- and post-UBC periods, based on the hierarchical models described above.

Table 3: State-Level Posterior Estimates of Firearm Mortality (per 100,000) for States Enacting UBC Policies

2*State	Pre-UBC		Post-UBC	
	Mean	**95% CrI**	**Mean**	**95% CrI**
Colorado	13.28	(12.9, 13.6)	10.65	(10.4, 10.9)
Delaware	10.53	(9.8, 11.2)	8.10	(7.6, 8.6)
Nevada	16.03	(15.3, 16.7)	14.80	(14.5, 15.2)
New Jersey	4.47	(4.2, 4.7)	4.84	(4.7, 5.0)
New Mexico	20.71	(19.3, 22.1)	14.90	(14.6, 15.3)
New York	4.26	(4.16, 4.36)	5.10	(5.0, 5.2)
Oregon	12.14	(11.7, 12.5)	10.40	(10.1, 10.7)
Vermont	10.48	(9.0, 11.9)	7.51	(7.0, 8.0)
Virginia	13.28	(12.5, 14.0)	10.80	(10.6, 10.9)
Washington	10.06	(9.7, 10.3)	8.68	(8.5, 8.9)

4.2 Empirical Variation in Mortality Rates

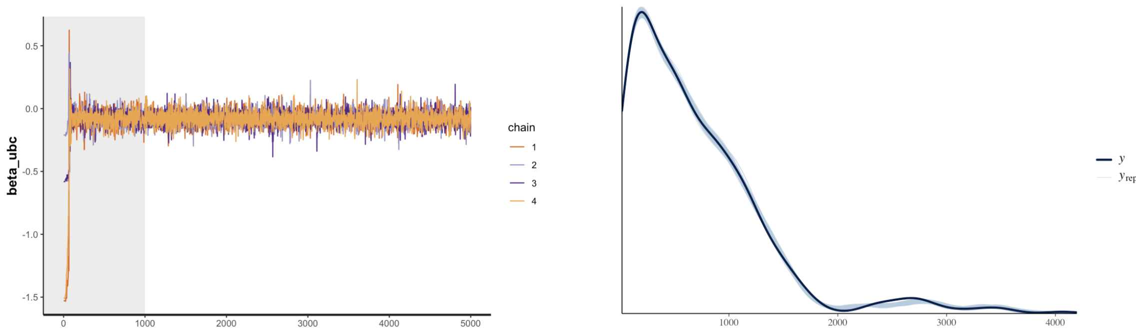
Table 4 summarizes the empirical distribution of state-level log mortality rates ($\log \hat{\lambda}_j$) in the pre- and post-UBC periods. The standard deviation increased from 0.39 to 0.56, indicating greater between-state heterogeneity in firearm mortality following UBC implementation.

Table 4: Summary Statistics of Empirical Log-Rates ($\log \hat{\lambda}_j$) Across States.

Model	mean($\log \hat{\lambda}_j$)	sd($\log \hat{\lambda}_j$)
Pre-UBC	-9.33	0.56
Post-UBC	-9.32	0.39

4.3 Results From DiD

We ran 4 chains for 5000 iterations and observed that all chains mixed efficiently and converged quickly. Our posterior predictive checks reveal that our model does a good job of fitting the data

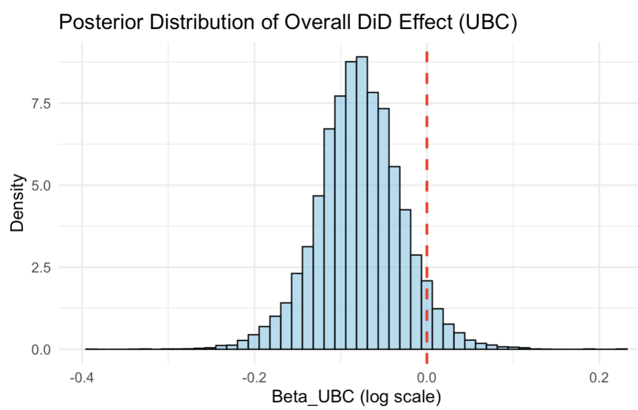


Trace plot for DiD model

Posterior predictive check

Figure 1: Left: Trace plot for DiD model. Right: Posterior predictive check.

Our Bayesian hierarchical DiD model estimates the overall effect of UBC laws on firearm deaths with a posterior mean of -0.078 and a 95% credible interval of $[-0.179, 0.020]$. This suggests a modest reduction in firearm deaths associated with UBCs, though the credible interval includes zero, reflecting uncertainty about the precise direction of the effect.

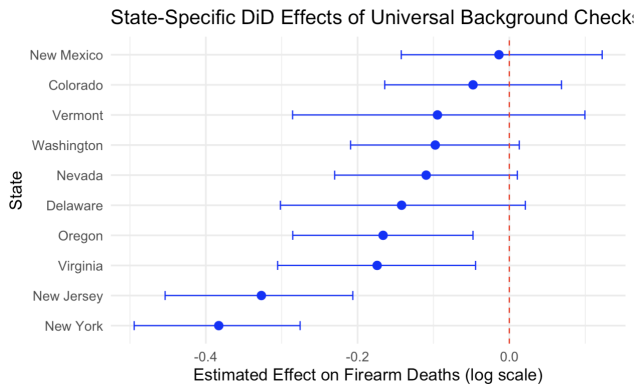


Parameter	Mean	SD	95% CI
Beta_DiD	-0.078	0.049	[-0.179, 0.020]

Summary of posterior estimates.

Figure 2: Bayesian DiD analysis: Posterior distribution (top) and summary table (bottom).

When we separate out these effects by state, we observe that all means fall below 0, indicating that, on average, UBC laws are associated with reductions in firearm mortality across every state in our sample. However, the magnitude of these reductions varies substantially, and several states (e.g., New Mexico and Colorado) have 95% credible intervals that include 0, suggesting that the evidence for a clear effect not strong in those locations. In contrast, states such as New Jersey and New York show larger reductions with credible intervals fully below 0, providing stronger evidence that UBC policies meaningfully decreased firearm mortality here. Due to the wide range of many of these intervals, it is likely that as more data are collected in future years, our estimates will become more precise, reducing uncertainty and allowing for clearer identification of the states in which UBC policies have the greatest impact.



State	States Mean	95% CrI	State	States Mean	95% CrI
New Mexico	-0.0137	[-0.1425, 0.1223]	Colorado	-0.0479	[-0.1642, 0.0687]
Vermont	-0.0948	[-0.2857, 0.0996]	Washington	-0.0977	[-0.2092, 0.0131]
Nevada	-0.1096	[-0.2302, 0.0105]	Delaware	-0.1420	[-0.3017, 0.0211]
Oregon	-0.1664	[-0.2855, -0.0479]	Virginia	-0.1743	[-0.3054, -0.0445]
New Jersey	-0.3268	[-0.4537, -0.2063]	New York	-0.3830	[-0.4944, -0.2758]

Figure 3: Bayesian DiD analysis Seperated By State

5 Discussion

5.1 Summary of Key Findings

This study used Bayesian hierarchical Poisson models and a Bayesian difference-in-differences (DiD) framework to evaluate the association between Universal Background Check (UBC) laws and state-level firearm mortality. Our primary findings contain three aspects: Firstly, hierarchical models revealed substantial and persistent heterogeneity in baseline mortality rates across states. Secondly, the global Bayesian DiD estimate indicated a modest reduction in firearm mortality associated with UBC adoption (posterior mean $\delta = -0.078$), though the 95% credible interval slightly overlapped zero ($[-0.179, 0.020]$). Lastly, state-specific DiD effects displayed considerable variation, ranging from negligible to strongly negative, underscoring the context-dependent nature of the policy's impact.

5.2 Interpretation of Results

The state-level estimates from the hierarchical models offer a nuanced picture of the U.S. firearm mortality landscape. As shown in Table 3, New Jersey and New York consistently showed the lowest mortality rates in our sample, both under 5 deaths per 100,000 in the post-UBC period. These states often have concurrently stringent firearm legislation bundles and distinct demographic profiles, suggesting that UBC laws may be most effective or are implemented within a broader context of gun violence prevention. In contrast, Nevada and New Mexico exhibited substantially elevated rates in both periods, with New Mexico displaying the highest post-UBC rate (20.71 per 100,000). This elevated uncertainty for some states (reflected in wider credible intervals) may be attributed to smaller population sizes or greater yearly volatility in death counts, while the high point estimates highlight that UBC laws alone may not be sufficient to address firearm mortality in all regional contexts.

The hierarchical post-policy model also indicates greater dispersion in state intercepts, as reflected in the larger posterior estimate of $\sigma_{\alpha}^{\text{post}}$ relative to σ_{α}. This widening spread implies increasing divergence in state-level firearm mortality after UBC implementation, potentially signaling differential responses to the policy across states.

The central causal estimate comes from the Bayesian DiD model, which provides an average treatment effect of approximately -0.078, with a 95 percent credible interval of [-0.179, 0.020], this effect represents the mean change in firearm mortality attributable to UBC adoption after adjusting for common time trends and unobserved, time-invariant state characteristics. Largely, this suggests that although there is some evidence in support of these policies, more data will be necessary to draw any concrete conclusions.

5.3 Implications for Policy and Research

Our findings suggest that Universal Background Check laws are associated with modest reductions in firearm mortality, but their effectiveness is clearly context-dependent, varying across states with different baseline risks and policy environments. UBCs should therefore be viewed as one element within a broader, multifaceted gun-violence prevention strategy rather than a stand-alone solution. Methodologically, the study highlights the value of Bayesian hierarchical models in policy evaluation: by pooling information across states, these models produce stable estimates even in data-sparse settings and explicitly quantify uncertainty through posterior distributions. Embedding a difference-in-differences design within this Bayesian framework further strengthens causal interpretation by adjusting for unobserved, time-invariant state characteristics and common temporal trends.

5.4 Limitations

This analysis has several limitations. Although the Bayesian DiD model adjusts for time-invariant state characteristics, it cannot fully account for time-varying confounders that may coincide with UBC adoption, such as economic shifts or other policy changes. Our use of total firearm mortality also masks important differences across subtypes: suicide, homicide, and accidental deaths, which may respond differently to background check laws. In addition, the precision of state-level estimates varies with population size, resulting in wider credible intervals for smaller states. Finally, because the analysis is conducted at the state level, it cannot capture within-state heterogeneity or policy spillover across borders, both of which may influence observed outcomes.

5.5 Conclusion and Future Directions

Our Bayesian analysis indicates that Universal Background Check laws are associated with a modest but meaningful reduction in state-level firearm mortality for some states, though the magnitude of this association varies substantially across states. Future work might involve breaking down outcomes by type of death to identify the types of gun violence solved by these policies, examine more deeply how UBCs interact with other firearm policies, and incorporate more detailed geographic data to capture within-state variation and possibly consider factors such as socioeconomic conditions. As debates over firearm regulation persist, Bayesian approaches provide a valuable framework for generating transparent, probabilistic evidence that can more effectively guide policy decisions.

References

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6 Statement of Contribution

Our group collaborated through a shared, consensus-based approach, with all major decisions discussed collectively. While we did not designate a formal leader, each member assumed responsibility for specific project components. Together, we cleaned and assembled the full combined dataset. Each member independently fit a separate model: Pu did the pre-UBC period, Xu did the post-UBC period, and Baker did the difference-in-differences analysis. This allowed parallel progress and balanced workload distribution. We jointly conducted model diagnostics, interpretation, and final writing. Throughout the project, we maintained consistent communication via group chat and held weekly in-person meetings to coordinate and review progress.