The Impact of Time Delays on Criminal Sentencing:

A Multi-Method Analysis of Cook County Cases from the COVID Era

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Summary

This study examines the impact of time delays on criminal sentencing severity using Cook County data from 2020–2024. Results across OLS regression, clustering, and Random Forest analysis confirm that longer delays are associated with harsher punishments, with significant influences from demographics, crime types during the COVID-19 period.

Research Objective

Fundamental principles of penal justice emphasize that morally similar cases should receive consistent punishments, regardless of external factors. However, recent research by Kundro et al. (2023) revealed that time delays between crime and arrest significantly influence punishment severity. Their study combined controlled experiments with 6,029 participants, survey-based sampling, and archival analysis of sentencing data (160,772 civilian cases and police misconduct records), establishing that longer delays were associated with harsher punishments due to intensified perceptions of unfairness.

Our research builds on and extends this work by re-analyzing real-world judicial decisions using criminal case data from Cook County (2020–2024)—a period marked by systemic disruptions caused by the COVID-19 pandemic. According to the Washington Post report(2021) and Azab et al. (2023), "The question remains: is COVID solely to blame for the crisis which has overtaken the court system long after COVID makes the court shut down?" This observation emphasizes the need to examine fundamental inefficiencies within judicial processes that were magnified during the pandemic.

While Kundro et al.'s approach successfully demonstrated the moral and perceptual implications of time delays, our study focuses on how these delays interact with actual sentencing patterns though distinct methodologies. This study extends existing literature by bridging moral perceptions with judicial dynamics, offering actionable insights into systemic inefficiencies and sentencing disparities. We aim to achieve the following objectives:

- Validate and quantify the relationship between time delays and punishment severity in contemporary court decisions
- Uncover natural patterns in sentencing outcomes through advanced clustering techniques, particularly focusing on how different case types respond to delays
- Identify and rank the relative importance of factors influencing sentencing severity, including temporal, demographic, and case-specific variables

Data Source

Our study utilizes data from the Cook County State Attorney's Office database, following the original literature, analyzing criminal cases from January 2020 to October 2024. This timeframe is particularly significant as it spans three distinct phases—Pre-COVID, Peak-COVID, and Post-COVID—enabling analysis of how unprecedented systemic disruptions affected judicial decision-making.

From an initial dataset of 303,963 records, we obtained 41,986 cases after filtering for study period. While approximately 78.3% of these cases involved immediate arrests, our analysis specifically focuses on the remaining 9,111 cases that experienced delays. This methodological choice differs from the original study, allowing us to more precisely examine how varying lengths of delay influence sentencing outcomes in cases where temporal gaps exist between crime and arrest. Table 1 presents the complete set of variables used in our analysis.

Table 1: Dataset Features Description

Variable Name	**Description**
Original Features	
Incident begin date	Date when the criminal incident occurred
Arrest date	Date when the defendant was arrested
Commitment term	Numerical value of sentence length
Commitment unit	Unit of measurement for sentence (e.g., months, years)
Commitment type	Type of sentence imposed (e.g., incarceration, probation)
Case length	Duration from case initiation to resolution in days
Age at incident	Defendant's age when crime occurred
Race	Defendant's racial identification
Gender	Defendant's gender identification
Updated offense category	Original detailed crime category
Sentence Judge	Identifier for presiding judge, serving as fixed court effect
Charge count	Number of charges filed in the case
Derived Features	
Delay in days	Time difference between the incident date and arrest date, representing the length of delays
Standardized sentence months	All sentences converted into months to ensure consistency in punishment duration analysis
Crime group	Mapped offense categories into six groups: Violent, Property, Drug-Related, Sexual and Exploitation, Public Order and Regulatory, and Miscellaneous Crimes
COVID period	Categorical variable marking three pandemic phases: Pre-COVID (Jan 2020 – Mar 2020), Peak-COVID (Apr 2020 – Dec 2021), and Post-COVID (Jan 2022 – Oct 2024)
Case complexity	Interaction term between case length (in days) and charge count, representing administrative and legal complexity
Severity level	Scale 1–3 based on commitment type severity: incarceration, probation, and supervision or lighter sentences
Weighted punishment (*Target feature*)	Composite measurement: Sentence Months × Severity Level (1–3), capturing both duration and severity of punishment

Techniques Applied

To examine the relationship between time delays and punishment severity, we applied three complementary techniques: OLS regression, Bi-Secting K-Means clustering, and a Random Forest model. Each method provides unique insights into sentencing patterns, from quantifying relationships to uncovering hidden structures and identifying influential factors.

OLS Regression Model The prepetitive OLS regression was used to examines whether the previously established relationship still holds true and quantify the linear relationship between time delays and severity of punishment while controlling for confounding factors. The model incorporated interaction terms and fixed effects to account for systemic differences across courts and time periods.

Model performance was evaluated through multiple validation metrics. The R-squared value of 0.3595 indicates moderate explanatory power, with approximately 36% of variance in punishment severity explained by our predictors. We used information criteria (AIC = 26,437.68, BIC = 27,863.71) to assess the trade-off between model fit and complexity. The relatively high values reflect the model's substantial complexity, suggesting potential opportunities for feature selection refinement. While the linear assumption may not fully capture the complexity of real-world sentencing decisions, the results provided a solid starting point for further exploration.

Bi-Secting K-Means Clustering To identify latent patterns in sentencing outcomes, we employed Bi-Secting K-Means clustering, a hierarchical approach that iteratively splits clusters. Compared to traditional K-Means, this method improves the cohesiveness and separation of groups, making it particularly effective for handling datasets with irregular cluster shapes and varying cluster sizes. Additionally, it retains the simplicity and computational efficiency of standard K-Means while introducing greater refinement through localized optimization during each split.

Cluster validation was performed using silhouette plots (Figure 1), where stability was observed around k=4, indicating an optimal solution without overfitting. Further increases in k (up to 7) showed no significant improvement in quality. An elbow plot corroborated this finding, with diminishing reductions in WCSS (Within-Cluster Sum of Squares) beyond k=4. We further validated the clustering solution through parallel coordinate plots, which provided visual confirmation of cluster separation and helped identify the key features driving cluster formation.

Random Forest Model The Random Forest model was selected for its ability to handle non-linear relationships, rank feature importance, and manage high-dimensional data without requiring feature scaling. This ensemble machine learning method is particularly effective in identifying the most critical predictors driving sentencing outcomes. Model implementation involved comprehensive hyperparameter tuning through grid search with 5-fold cross-validation across parameter combinations, ensuring an optimal balance between bias and variance. The model's reliability was evaluated through multiple metrics including accuracy, precision, and recall scores, providing a robust assessment of predictive performance.

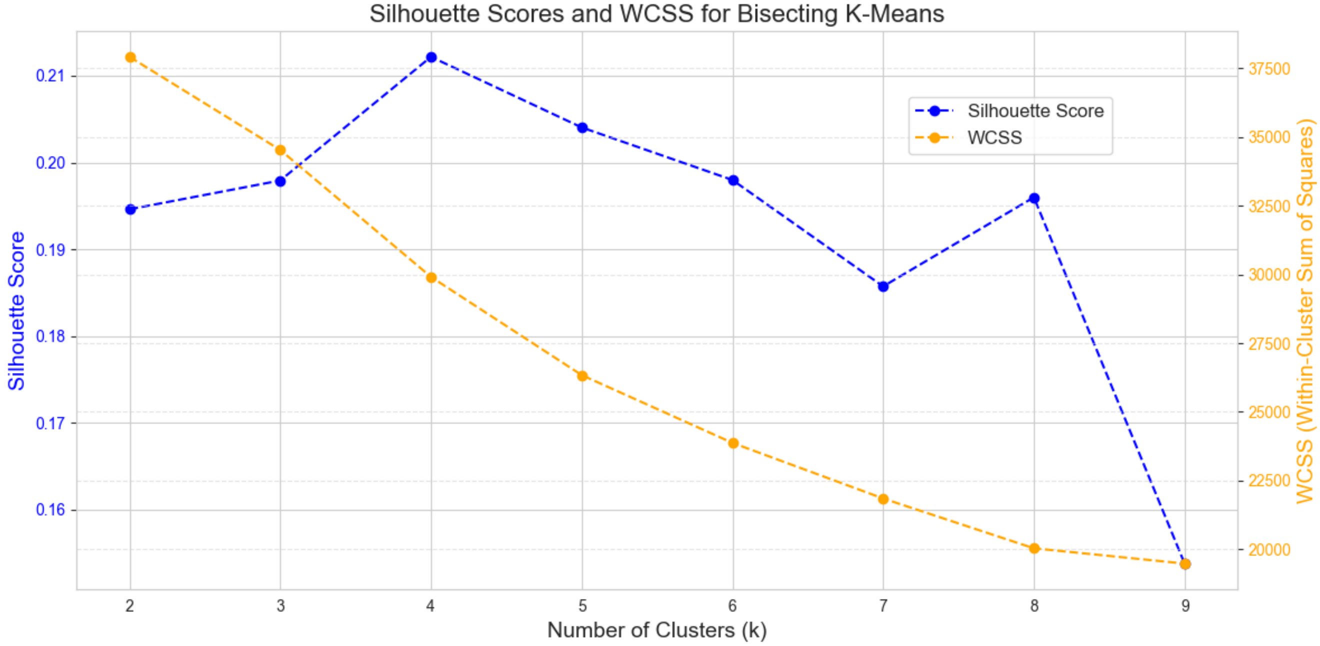

Figure 1: Silhouette Scores and WCSS for Bisecting K-Means

Findings

OLS Regression Model The OLS regression analysis validated the relationship between time delays and punishment severity, while controlling for key variables. **Longer delays** were significantly associated with harsher punishments, though the effect size was modest (0.0196 units). Additionally, demographic factors such as **male gender** and **increasing age** significantly influenced sentencing outcomes. Although race (black) was not statistically significant at the 5% level, it remains marginally relevant with a near-threshold p-value, warranting further exploration. The **COVID-19 period** also showed a significant impact, with harsher sentences observed, likely reflecting systemic disruptions, such as delays in court operations or changes in legal procedures during this phase.

Table 2: OLS Regression Results

Variable	**Coefficient**	**Std.Error**	**t-statistic**	P > |t|
Intercept	0.2578	0.0190	13.589	0.0000
Delay in days	0.0196	0.0070	2.675	0.0070
Charge counts	-0.0462	0.0090	-4.926	0.0000
Length of cases	0.0007	0.0001	10.118	0.0000
Case complexity	0.0001	0.0000	4.265	0.0000
Age at incident	0.0030	0.0010	2.946	0.0030
COVID Period	0.1613	0.0550	2.945	0.0030
Race: Black	0.1885	0.1030	1.834	0.0670
Gender: Male	0.2485	0.0340	7.244	0.0000

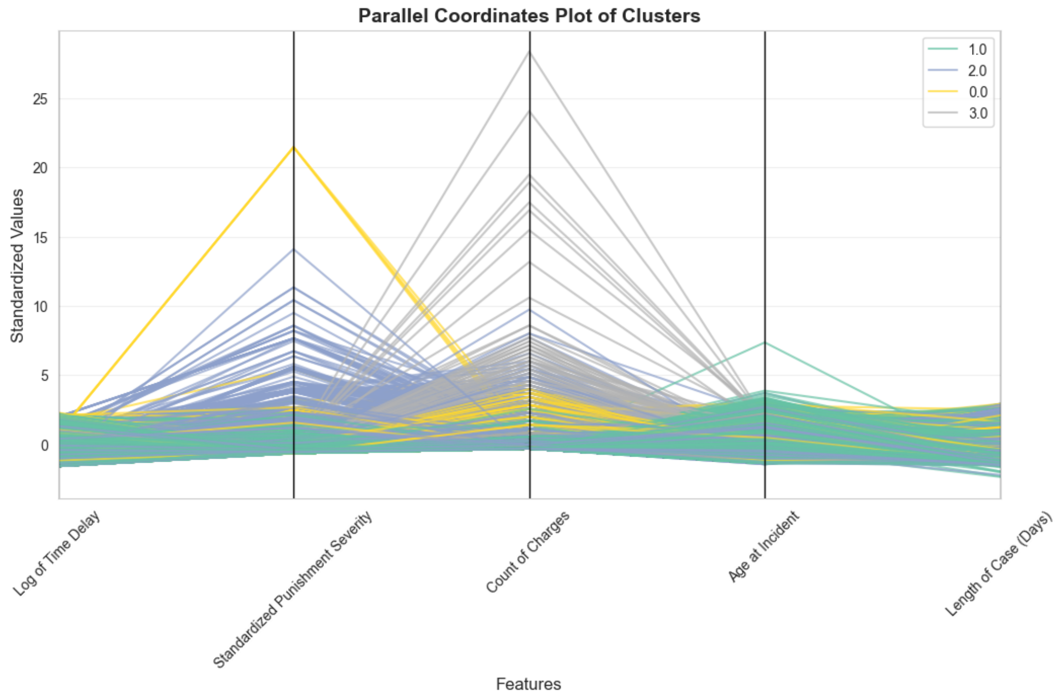

Figure 2: Parallel Coordinates Plots of Clusters

Crime type analysis revealed particularly severe sentencing for **violent** (e.g., aggravated robbery, homicide), **sexual exploitation offenses** (e.g., sex crimes, human trafficking), and certain **property-related** crimes (e.g., home invasion, vehicular hijacking). The model explains approximately 36% of the variance in sentencing outcomes, suggesting additional unobserved variables, such as judicial discretion or systemic differences, likely influence sentencing decisions.

Consistent with prior literature, the findings confirm that longer delays are associated with harsher punishments. However, the relatively small effect size highlights the need for further exploration of alternative model specifications, such as non-linear relationships, to better understand the dynamics.

Bi-Secting K-Means Clustering The clustering analysis revealed four distinct groups within sentencing outcomes, highlighting how time delays, case complexity, and crime types influence punishment severity:

- Cluster 0: High punishment severity for complex sexual or exploitation-related crimes, characterized by long delays and extended case resolution times (528 cases).
- Cluster 1: Low-severity cases involving property crimes, with shorter delays and lighter punishments (4,531 cases).
- Cluster 2: Serious cases involving violent crimes (e.g., aggravated robbery, homicide), with longer delays and higher punishment severity (2,594 cases).
- Cluster 3: A specific outlier group consisting of highly complex cases with extremely high charge counts per person, resulting in significant delays and harsh punishments (51 cases).

The parallel coordinates plot (Figure 2) highlights that Cluster 0 receives the harshest punishments, followed by Cluster 2, reflecting the severe sentencing of crimes, respectively. While Cluster 1 represents moderate and more frequent cases.

By focusing on Cluster 0 (sexual and exploitation crimes) and Cluster 2 (violent crimes), policymakers can prioritize reforms aimed at ensuring equitable and efficient sentencing for the most severe cases. In addition, the significant variability in charge counts and delays within Cluster 3 highlights the need to develop improved mechanisms for handling outlier cases effectively. The clustering results underscore that time delays and case complexity are critical factors driving sentencing outcomes. The findings emphasize the need for targeted judicial reforms, while addressing systemic inefficiencies in managing potential outlier scenarios.

Random Forest Model The model was fine-tuned using grid search with 5-fold cross-validation, testing 300 hyperparameter combinations across 1,500 fits. The best hyperparameters selected were: with bootstrap sampling, a maximum tree depth of 34, considering log2 of the total features at each split for the best feature selection, a minimum of 1 sample per leaf node, a minimum of 4 samples to split an internal node, and 151 decision trees. The optimized model achieved an overall accuracy of 71%, with balanced precision (0.70–0.73) and recall (0.70–0.71). While the balanced precision and recall indicate consistent performance across both classes, the overall accuracy is moderate at best, given the complexities of sentencing decisions and the data's high-dimensional nature. This suggests room for improvement in better capturing comprehensive patterns in sentencing outcomes.

The Random Forest model was used to evaluate the relative importance of features influencing punishment severity. According to the feature importance plot (Figure .3), the model identified the length of case in days, age at incident, and log of time delay as the top predictors of sentencing severity, followed by other significant factors.

- **Length of Case in Days** emerged as the strongest predictor of sentencing severity, reflecting the complexity and extended duration of severe cases.
- **Older defendants** were associated with harsher sentences.
- Not surprisingly, **time delay** reinforced the significance of delays in shaping sentencing outcomes.
- Additional variables that influenced sentencing severity include **charge count**, **gender**, **COVID period**, and **crime types**, consistent with patterns observed in the OLS regression analysis.

Limitations Our experiment is not as robust as the original study by Kundro et al. (2023), that based on six experiments combining controlled experimental data and archival analysis from multiple datasets. In contrast, our study focuses solely on Cook County criminal case data from 2020 to 2024, which might limit the generalizability of findings to national trends or other smaller jurisdictions. The original literature also incorporated survey-based moral perception studies, while we shifts the objective from public attitudes to systemic and case-specific factors by analyzing real-world judicial decisions. This divergence provides unique insights but also reinforces challenges in directly comparing results.

A key limitation of is the restricted variability in time delays, as approximately 80% of cases are one-day arrests without delay. According to Cd Batson(2007), anger at unfair treatment has been called moral outrage. Kundro et al. emphasized that longer delays exacerbate punishment severity, driven by mechanisms such as moral outrage or deterrence. However, our findings indicate that the predominance of short delays constrained the ability to fully evaluate these mechanisms, suggesting the need for a more diverse dataset or personal survey-based studies to draw robust conclusions.

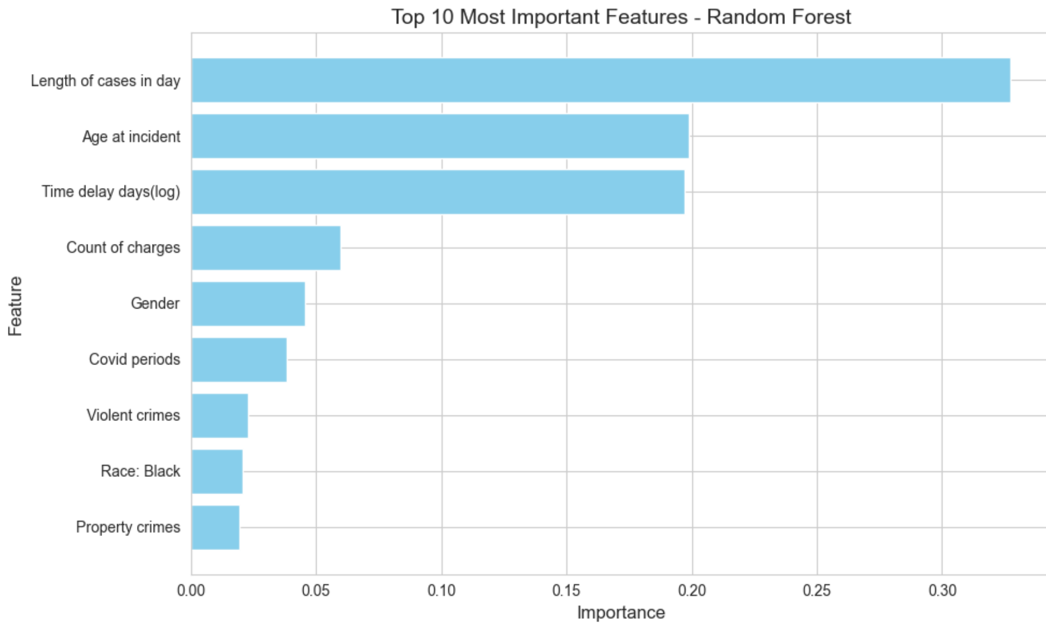

Figure 3: Importance features - Random Forest

Additionally, the dataset's high-dimensional nature, with numerous categorical variables, poses challenges for clustering analysis, as techniques like Bi-Secting K-Means that would perform better with lower-dimensional data. The characteristic of OLS regression further restricts the ability to capture potential non-linear relationships or complex interaction effects in practical judicial decisions. With over 200 predictors, some variables may contribute noise, diluting the Random Forest model's ability to generalize effectively. Dimensionality reduction techniques like PCA or regularization methods could address this issue.

While fixed judge effects are included in the model, judicial discretion may have played a greater role than anticipated, and further analysis using hierarchical models could better capture these influences. Moreover, while the COVID-19 period is incorporated as a feature, broader societal disruptions during this time introduced additional confounding factors that were not fully accounted for.

Overall Implications Despite these limitations, our study builds on Kundro et al. (2023) by extending their work to the analysis of real-world judicial decisions. Across all methodologies, the findings consistently demonstrate that time delays exacerbate punishment severity, while also revealing systemic inefficiencies in handling complex cases and demographic disparities (e.g., harsher punishments for male and older defendants). These results highlight the complexity of judicial processes, where essential and case-specific factors play significant roles in shaping outcomes.

Importantly, the study identifies critical disparities in sentencing outcomes based on demographics (e.g., gender, age, and race), reinforcing the need for judicial reforms to reduce bias and enhance court transparency, especially for more vulnerable groups. Additionally, by examining patterns during the COVID pandemic, this study offers a unique perspective on how systemic disruptions amplified delays and sentencing severity, highlighting the importance of building resilient judicial systems to handle future crises. The inclusion of COVID as a variable sheds light on how external shocks interact with inefficiencies, underscoring the necessity of adapting processes to maintain fairness during crises.

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