

Waiting for Trial: A Case Study of Detention Times Prior to Sentencing

Lillian Clark

12/7/2021

1. Introduction

1.1 Context

In 2019, 23.3% of incarcerated people in the United States were legally innocent – they had not been tried on their charges in a court of law [1]. The Prison Policy Initiative found that the number of people in jail pretrial has nearly quadrupled since the 1980s [2]. Pretrial detention is severely destabilizing for incarcerated individuals and their families. Even a few days in jail can cause people to lose their jobs, their homes, or custody of their children. Studies have shown that people who are detained pretrial are more likely to be convicted and more likely to receive harsher sentences than those who go free [3]. Pretrial detention is also associated with significantly higher recidivism rates [4].

Widespread use of money bail has led to the criminalization of poverty, where individuals who can afford to pay a bail bondsman’s fee or to tie up thousands of their own dollars in the court system for months or years can go free, and individuals without those funds sit in jail. This can force innocent individuals who can’t pay to claim guilt and accept a plea deal simply to get out of jail faster. In the U.S., there are also clear racial disparities among pretrial detainees. Young Black men are roughly 50% more likely to be detained than white individuals [5]. Some people are held in limbo by the criminal legal system for amounts of time comparable to what they would serve if they were convicted. In 2017, The New York Times profiled Kharon Davis, a man who spent at least ten years in county jail awaiting trial. They wrote, “Though he has not been found guilty, Mr. Davis has already served half of the minimum sentence for murder” [6].

Not everyone held in jail is awaiting trial – there are also individuals with relatively minor convictions, such as parole violations or misdemeanors, who serve their full sentences there, usually for less than a year. The proportion of pretrial detainees in jail populations has increased from 53% in 1970 to 64% in 2015 [4]. Some data on pretrial detention is available for web scraping from local jails but there are significant problems with transparency, inaccuracies and data entry issues in this data [7]. Availability also varies widely by local jurisdiction. These problems make it difficult to determine which jail inhabitants have been convicted and which have not. It also makes studying pretrial detention and inequities harder.

The Bureau of Justice Statistics (BJS) 2016 Survey of Prison Inmates contains data from 364 prisons across the United States. BJS surveyed prisoners 18 and older, and 24,848 incarcerated individuals participated, 81% of which were held in state prisons and the other 19% in federal prisons [8]. This data is available from ICPSR, the Inter-university Consortium for Political and Social Research, at the University of Michigan. Part of the survey asked respondents how long they had been detained in jail. Jail time is not a perfect proxy for length of pretrial detention, but we have reason to believe it is a good one. Given the way the legal system is supposed to work, those serving sentences for minor convictions in jails should not have been included – only prison inmates were surveyed – and split jail-prison sentences are not typical. Generally, individuals in prison, if they were detained pretrial, did so in jails, and were transferred to prisons after sentencing. As with any survey, this one is subject to error: jail time is self-reported and not verified from a second source. This data is restricted to individuals in prison, so will exclude those with dismissed or not guilty charges who were also held pretrial. Despite these limitations, national data on pretrial incarceration of this scale is hard to come by. Analysis of the BJS survey provides an important window into the punishment people face in America before they are even tried: the wait for justice.

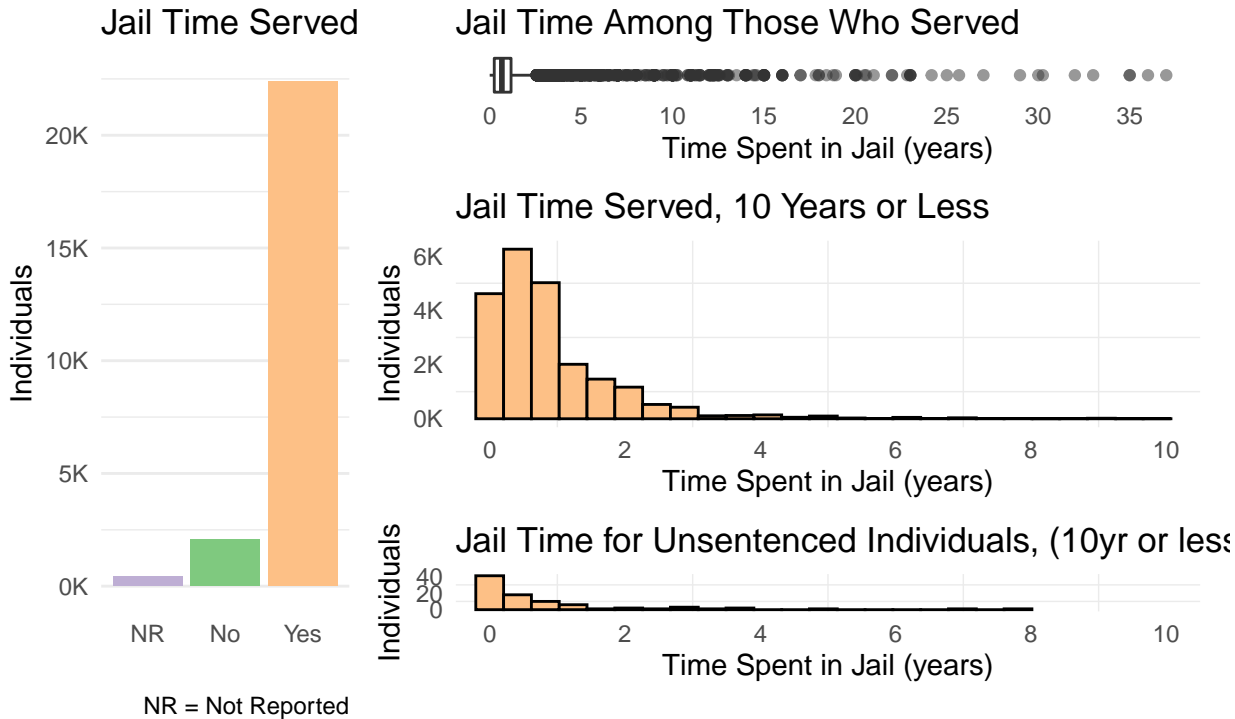
In this study, we will aim to answer **1) When controlling for aspects of the main offense they are prosecuted for and other policy-related covariates, do individuals incarcerated in United States prisons in different racial and ethnic groups wait longer before sentencing?** and **2) Does time detained pretrial have any relationship with characteristics, such as sex, race, age, and whether they were known by the detained individual, of the victims of violent crimes?**

Extended pretrial detention keeps both the detained accused and victim in limbo, waiting for resolution. Examining victim characteristics is essential because of the way racial bias and violence have historically been and continue to be codified in the criminal legal system, where white victims are more likely to get attention and justice than Black and brown victims. We see this in the disproportionate national media fervor over cases of white women who go missing or face violence while the cases of missing Black and Indigenous women are often ignored. Class can play into this as well, with lower-class white victims experiencing different levels of treatment and attention than upper-class white victims. Unfortunately, the BJS survey does not include information on victim income, so we lack the data necessary to add this consideration to analysis. Regardless, the disparities in treatment based on racial dynamics are complicated. It’s difficult to outline an ideal outcome. We can imagine scenarios in which less time spent pretrial might be worse for the defendant. As Bryan Stevenson documented in the case of Walter McMillian, innocent Black

men have historically been accused of violence against white women and swept through speedy and unfair trials on waves of white supremacist fervor [9]. Hasty prosecution and extensive pretrial detention are two very important ways justice is denied, but they manifest as opposite effects in our data. This analysis is limited in its ability to address all that complexity, keeping in mind the meanings of such varied outcomes for both victims and defendants alike. However, we will attempt to shed some light on whether there are differences based on the characteristics of the detained accused and of the victim and what the magnitudes of those differences are.

1.2 Data Description

Figure 1: Distribution of Jail Time



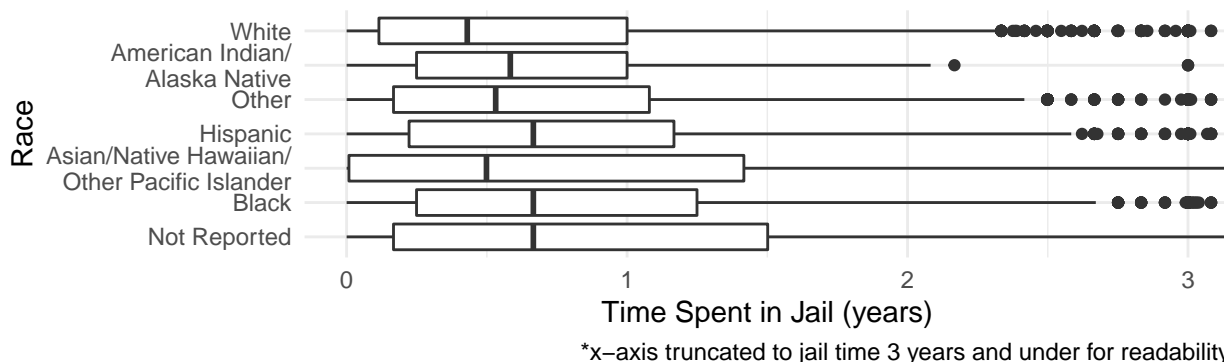
In the data, 90.0% of individuals reported serving jail time, 8.3% reported serving no jail time, and 1.7% did not respond to the related survey question. 457 individuals have missing data for length of jail time, and while we will consider those with missing values in a preliminary analysis, they will be excluded from our primary and secondary survival analyses. The maximum jail time reported in the data was 37 years, though the majority of individuals served 3 years or less. In 2017, The New York Times wrote that Kharon Davis’s 10-year wait pretrial was “among the most protracted” they could find [6]. Thus, this years will serve as our best estimate for expected maximum jail time, and we will filter the data before analysis to remove observations with jail time greater than ten years. After exclusion of missing jail times, this removes 116 observations or 0.5% of the dataset. Also, three individuals who did not report their military status and ten individuals who did not report their sentencing status were excluded from analysis. We believe that a failure to report certain values may be meaningful, so for all variables other than length of jail time, missingness is encoded as the factor level “Not Reported” to preserve this information through analysis.

Additionally, incarcerated individuals were asked whether they had been sentenced, and a small number (133 individuals, or 0.55% of the data after the above filtering) reported that they had not yet been sentenced. Thus, their pretrial detention times are right-censored. The majority of these unsentenced individuals were arrested in more years closer to the survey dates, between 2013 and 2016.

We are interested in controlling for a number of covariates when examining discrepancies in pretrial detention. These can be split into three groups: **policy-related** covariates (arrest year, authority detained by, and state of detention facility), **charge-related** covariates (primary offense and primary offense type, legal status at arrest, possession of firearm at offense, under the influence of alcohol at offense, and under the influence of drugs at offense), and **demographic-related** covariates (age at arrest, race, sex, citizenship, veteran status, education level, and whether homeless in 12 months prior to offense). Policy-related covariates matter because of changes in pretrial detention policy over time (such as during the “tough on crime” era in the 1980s and early 1990s) and across states and jurisdictions. The charge-related covariates represent all the offense-related information available in the BJS data, information which would have been available to the district attorneys and judges overseeing these cases and

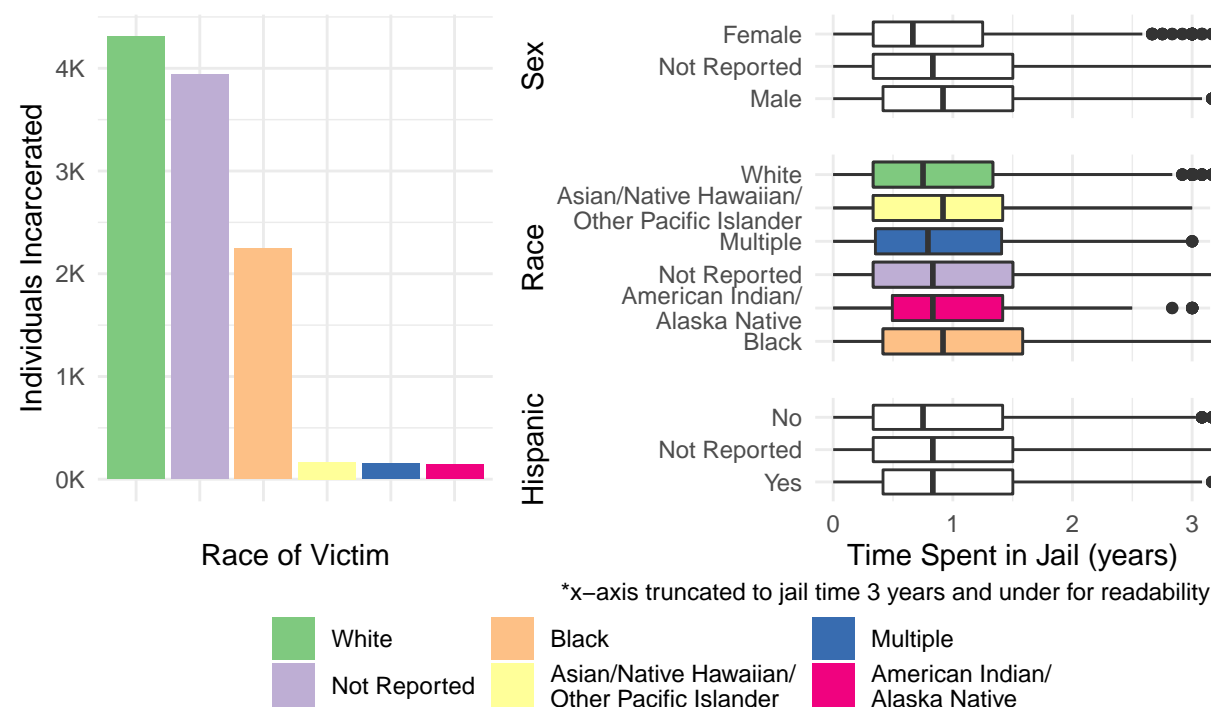
making decisions about bond and detention. And demographic-related covariates allow us to look for discrepancies in treatment between groups of people.

Figure 2: Distribution of Jail Time by Race of Incarcerated Individual



Before controlling for covariates, mean jail time seems lowest for white incarcerated individuals and highest for Black individuals and those who did not report their race. The discrepancies between groups in Figure 2 may not appear large. However, in a world where just days or weeks in jail can make a difference in the resources and support networks available to incarcerated individuals, small discrepancies matter.

Figure 3: Distribution of Jail Time for “Violent” Offenses by Victim Characteristics



Data for our secondary analysis contains only individuals serving time for a primary offense labeled ‘violent.’ Victim information for those convicted of drug and property crimes, offenses which are often victimless or which lack easily identifiable victims, is largely missing. However, 64% of those with a violent primary offense did report victim race. The proportion of missingness by offense type in victim sex and Hispanic ethnicity were similar. In Figure 3, we observe that individuals convicted of crimes against male victims appear to have a longer mean detention period pretrial. Black and Indigenous victims see the highest mean pretrial detention for the accused; white and multiracial victims the lowest. Hispanic victims also appear to see higher mean jail time than non-Hispanic victims.

1.3 Hypothesis

Due to the research cited above and preliminary data visualization, we hypothesize that Black, Indigenous and Latinx incarcerated people serve longer jail times. Also, despite the punishing and justice-denying effects of extended pretrial incarceration for those facing charges, due to the imbalance of community attention and outrage surrounding

(especially female) white victims versus victims of color, we hypothesize that violent crimes committed against white victims will be associated with shorter detention times pretrial compared to Black and Indigenous victims.

2. Methodology

2.1 Preliminary Analysis: Any Jail Time Served

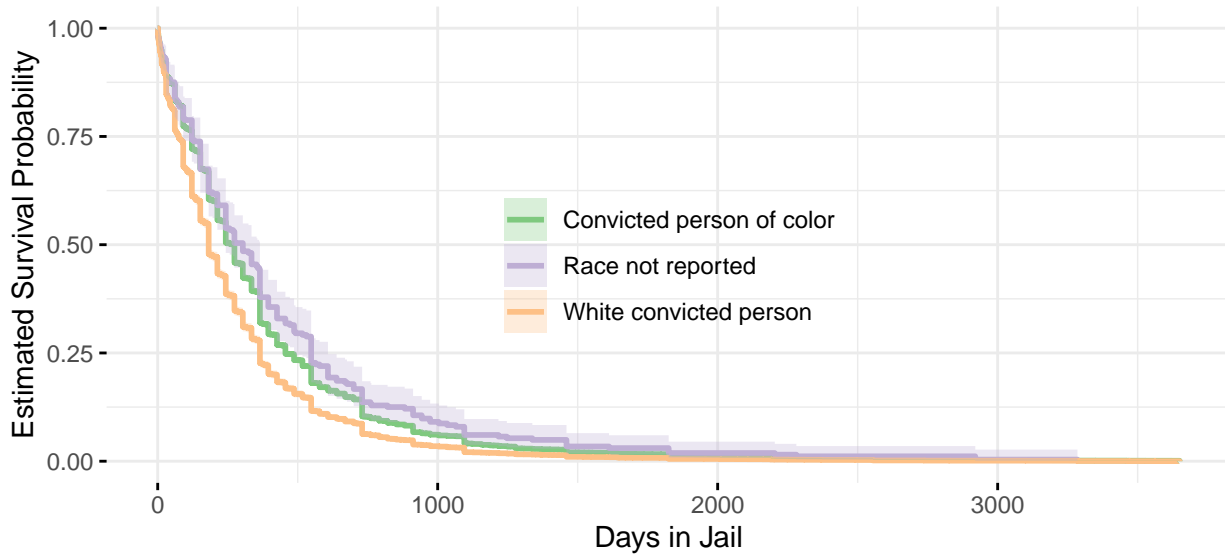
Our first goal is to understand whether jail time served is associated with the race of the incarcerated individual. While survival analysis will allow for incorporation of individuals who have not yet been sentenced into our model, roughly 8% of the data consists of people who reported serving no jail time and would have survival time 0. These individuals are important to consider. They likely represent a group that could afford to post bail or pay a bail bondsman, or that live in states with pretrial detention policies that don't heavily rely on money bail, places like New Jersey and Washington D.C. [10]. To consider those who were not detained pretrial before removing them from the data for survival analysis, we will first conduct multinomial logistic regression with the jail time served indicator as our response and policy, charge, and demographic covariates as predictors.

We opt for multinomial logistic regression over binary logistic regression with only jail time served/not served as outcome in order to account for potential meaning in missingness in the data. Instead of filtering out those with jail time not reported, we consider "Not Reported" as a third outcome in our model. See Appendix 1 for model assumptions and diagnostics.

2.2 Primary Analysis: Racial Discrepancies in Jail Time

Our next goal is to observe whether an individual's race is associated with jail time, and if an association does exist, to understand the effect size of race on days in jail.

Figure 4: Survival Curve for Race of Incarcerated Individual



We plot survival curves for the data from a non-parametric Kaplan-Meier estimate. When racial categories are simplified to white and non-white, as shown in Figure 4, the curves for different groups do not cross. They also remain roughly parallel at most survival times. This provides empirical evidence of proportional hazard and establishes the power of a log-rank test as a method to compare groups. Such a test of survival times for white incarcerated individuals, non-white individuals, and those who did not report their race has significant p-value < 0.001 . (See Appendix 2 for survival curves for disaggregated racial groups and full log-rank test results.) We will further explore this racial discrepancy with a survival model.

To further examine the scale of this difference and incorporate confounders, we built an accelerated failure time (AFT) model with error term ϵ_i normally distributed and survival time T_i log-normally distributed, specified as follows:

$$\log(T_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \epsilon_i$$

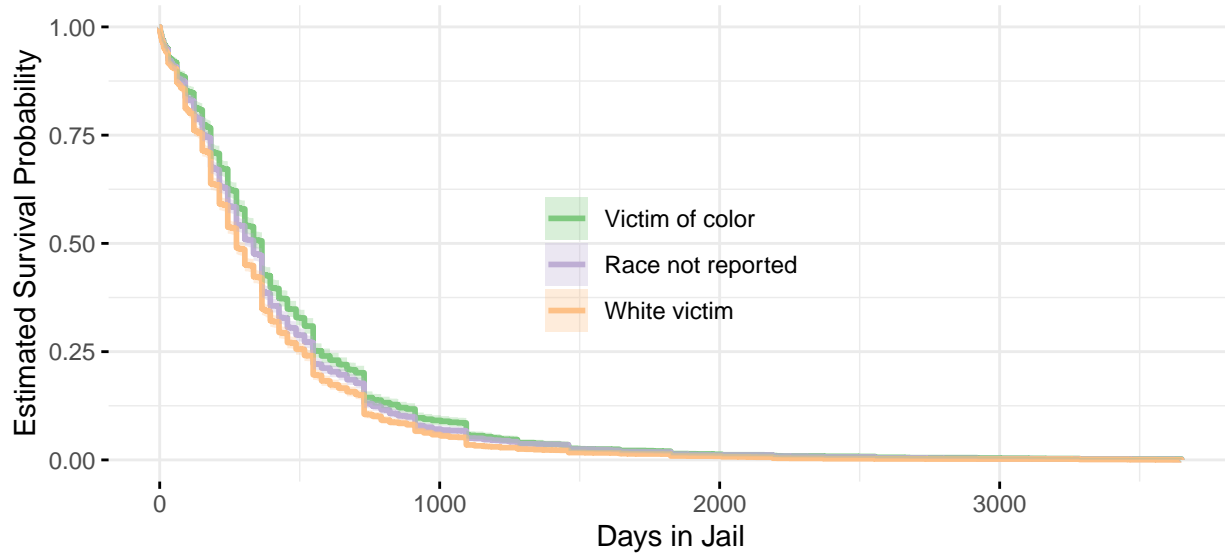
We included the following covariates: primary offense, legal status at arrest, firearm present at offense, under the influence of alcohol at offense, under the influence of drugs at offense, arrest year range, authority held by, state of incarceration, age at arrest, race, sex, citizenship status, veteran status, education level, and whether homeless in the year prior to offense. We believe the policy and charge-related covariates were important to include to correct for the effects as much as possible of the nature of the crimes people were accused of and how they were prosecuted, which can vary regionally and over time. The demographic-related covariates were selected for inclusion because of interest.

We compared AFT models with Weibull, log-normal, log-logistic, and exponential hazard distributions in Appendix 2 and conducted model selection with Kaplan-Meier residual plots under the survival functions of these distributions. These plots show the log-normal model performs well, that the curve of its distribution fits the residuals most closely and satisfies assumptions (see Appendix 2). As shown in the white/non-white survival curve above, there are several different ways race can be encoded: either as 1) white, Black, hispanic, other, American Indian/Alaska Native, Asian/Native Hawaiian/Other Pacific Islander, or not reported; 2) Black, non-Black, and not reported; and 3) white, non-white, and not reported. After model selection, we conducted variable selection via Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to determine which among these three variables to include as a confounder in our log-normal model. Both metrics select the model which labels individuals as white/non-white.

In lieu of an AFT model, we could have pursued a Cox proportional hazards model. Although a semi-parametric model may have done better to capture the complexity in our data, a proportional hazards model would not do well to estimate the magnitude of the difference in jail time served between groups. Our goal is to ascertain how long individuals spend detained pretrial, not their instantaneous hazard rate of sentencing. Therefore, an AFT model is more appropriate for our analysis. Estimating survival times is possible with a Cox proportional hazards model through Breslow estimator calculations, but AFT model coefficients provide a more straightforward approach. In this approach, we do assume that individuals with censored jail times have the same survival prospects as those without censoring at every point in time and that survival probability functions have remained roughly constant over the period of data collection.

2.3 Secondary Analysis: Jail Time by Victim Characteristics

Figure 5: Survival Curve for Race of Victim



Our methodology for our secondary analysis of victim characteristics is identical to the one above, with the exception of the initial inclusion of victim race, victim sex, victim age, victim hispanic ethnicity and whether the victim was known by the individual as additional covariates. The victim white/non-white survival curves appear to demonstrate proportional hazard, and a log-rank test of these groups has p-value < 0.001 . Our interpretation goals remain oriented on survival times, not hazards, so we build AFT models to investigate. We find a log-normal AFT model to be the best fit when its hazard distribution is compared to a plot of the Kaplan-Meier residuals, and comparing AIC and BIC leads us to select victim race white/non-white as our method of encoding race. (See Appendix 3.)

3. Results

3.1 Preliminary Analysis

Table 1: Multinomial Logistic Model Output

Y Level	Model Term	Estimate	Standard Error	Test Statistic	p-Value
Not Reported	raceAmerican Indian/Alaska Native	1.454	0.582	2.499	0.012
Not Reported	sexMale	0.589	0.279	2.111	0.035
Not Reported	educationLess Than High School	1.364	0.562	2.428	0.015
Not Reported	homeless_12mo_priorYes	0.724	0.311	2.330	0.020
Yes	age_at_arrest36-50	-0.126	0.060	-2.115	0.034
Yes	age_at_arrestOver 50	-0.528	0.087	-6.046	<0.001
Yes	sexMale	0.234	0.063	3.699	<0.001
Yes	citizenNon-citizen	0.472	0.121	3.917	<0.001
Yes	educationHigh School Graduate	0.479	0.097	4.962	<0.001
Yes	educationLess Than High School	0.738	0.094	7.868	<0.001
Yes	educationSome College	0.460	0.100	4.588	<0.001
Yes	homeless_12mo_priorYes	0.441	0.108	4.085	<0.001

Only demographic-related covariates found to be significant at the 0.05 alpha level are displayed above (see Appendix 1 for full model output and baseline values). Race only appears significant when comparing those who did not report whether they served jail time to those who did not serve jail time. Interestingly, holding all else constant, lack of citizenship and recent homelessness are associated with increased odds of serving jail time as compared to the baseline (U.S. citizenship and no recent homelessness). Education levels, again holding all else constant, appear to have some of the largest effect sizes when comparing those assigned jail time to those who were not detained pretrial. Also, we observe on average increased odds of not reporting jail time compared to serving no jail time for Indigenous individuals, holding all else constant.

3.2 Primary Analysis

Table 2: AFT (log-normal) Model Output (With Race White/Non-white)

Model Term	Estimate	Standard Error	Test Statistic	p-Value
age_at_arrest36-50	-0.049	0.021	-2.338	0.019
age_at_arrestOver 50	-0.156	0.038	-4.159	<0.001
race_whiteY	-0.047	0.020	-2.296	0.022
sexMale	0.226	0.023	9.834	<0.001
citizenNon-citizen	0.314	0.041	7.682	<0.001
educationHigh School Graduate	0.173	0.046	3.756	<0.001
educationLess Than High School	0.249	0.045	5.600	<0.001

Again, only demographic-related covariates found to be significant at the 0.05 alpha level are displayed above (see Appendix 2 for full model output and baseline values). As shown by the model output, certain values of age, race, sex, citizenship status, and education level are significant. Non-white race is the baseline for the model, so we can say that we expect white individuals to spend approximately 0.95 times fewer days in jail than individuals of color, holding all else constant. For the median non-zero jail time in the dataset, 243 days, a survival time multiplied by a factor of 0.95 would mean roughly 12 fewer days in jail. Thus, there is evidence that an individual's race is associated with the time they are detained pretrial.

3.3 Secondary Analysis

Table 3: AFT (log-normal) Model Output (With Race and Victim Race White/Non-white)

Model Term	Estimate	Standard Error	Test Statistic	p-Value
age_at_arrestOver 50	-0.134	0.054	-2.463	0.014
age_at_arrestUnder 18	0.111	0.052	2.138	0.033
race_whiteY	-0.117	0.030	-3.973	<0.001
sexMale	0.169	0.034	4.945	<0.001
educationHigh School Graduate	0.157	0.064	2.451	0.014
educationLess Than High School	0.227	0.063	3.625	<0.001
homeless_12mo_priorYes	0.081	0.041	1.982	0.048
victim_ageUnder 12 Years	0.119	0.058	2.060	0.039

See Appendix 3 for full model output and baseline values – the results shown above are again limited to significant demographic covariates. Only one level of victim age (under 12 years old) is significant when compared to the baseline (victim 12 to 18 years old). All other victim traits were not significant at the 0.05 alpha level. However, adding victim traits to the model did produce a different effect size for white race of incarcerated individual compared to non-white race. With this model, we can say that we expect white individuals to spend approximately 0.89 times fewer days in jail than individuals of color, holding all else constant. For the median non-zero jail time in the dataset, this multiplication of survival time would mean roughly 27 fewer days in jail.

4. Discussion

4.1 Conclusions

We have examined the relationship between incarcerated individuals’ race, the traits of their victims, and the length of time they were detained pretrial (as well as whether they were detained pretrial at all). Although we did not observe significant racial discrepancies between those detained and not detained in a preliminary multinomial logistic model, we did conclude that there is a slight negative association between white race (as compared to non-white race) and length of jail time in our primary and secondary analyses. Both survival models excluding and including victim traits confirmed the spirit of our primary hypothesis, although we sacrificed some racial granularity by grouping individuals into white and non-white groups during variable selection and cannot say specifically that Black, Hispanic and Indigenous individuals were detained for longer times pretrial. Although the effect size we found may not seem large, even a discrepancy of several days in jail a) affects the lives of the people in the system and b) serves as an important metric of racial inequality. This finding supports previous research on the ways racial bias is embedded in our criminal legal system.

We did not find a significant effect of victim race and ethnicity on times spent in jail and fail to reject the null hypothesis in favor of our secondary alternate hypothesis where victim characteristics are concerned. When controlling for confounders, it does not appear that a victim’s race is associated with the time the accused spends detained pretrial.

Survival analysis allowed us to account for those individuals who reported that they had not yet been sentenced and were still being detained pre-trial, and using AFT models as opposed to proportional hazards models allowed us to measure the effect size of covariates on survival time (time in jail) instead of the hazard of release.

4.2 Limitations and Future Directions

In order to account for potentially important trends among data that was not reported (such as the increased odds of a failure to report jail time for Indigenous individuals in the data, holding all else constant, as we found in our preliminary analysis), all missing values, with the exception of length of jail time, were encoded as “Not Reported”. Survey data is far from perfect and can contain a number of biases, including non-response bias, which may have affected our conclusions drawn. Court-reported pretrial detention lengths would be a more reliable source of outcome data for future exploration, but this data is not available in Durham County, North Carolina, much less nationally. As many other researchers have recommended, increased data collection around the experiences of individuals who come in contact with the courts will be essential in appraising and attempting to repair the broken, racially-biased mechanisms of our criminal legal system.

Since the dataset was sufficiently large, we were able to conduct a complete-case analysis. This did reduce the sample size and lead to lower power; however, imputation of missing lengths of time spent in jail, perhaps via the

Multiple Imputation via Chained Equations (MICE) algorithm, could be conducted to avoid sample size reduction in further study. Performing a complete-case analysis can also lead to biased parameter estimates under the Missing at Random (MAR assumption). Though the missing length of jail time did not exactly align with the “Not Reported” category for whether jail time was served, the two groups were near one and the same. Covariates in our preliminary multinomial model output may be indicators of biased parameter estimates in the survival models that followed. Another opportunity for further expansion would be a sensitivity analysis considering the data with and without jail times greater than ten years (which we filtered out). We chose the covariates to include in our analyses based on prior research and interest, but potential multicollinearity may obscure their effects and a test of Spearman rank correlation coefficients for ordinal variables and chi-square test for nominal variables would serve as a beneficial way to evaluate and improve on our models [11].

Our use of jail time as a proxy for pretrial detention relies on the assumption that people incarcerated in prisons spent their time in jail awaiting trial, after which they were sentenced and transferred to prisons. Further research into the validity of this assumption and the frequency of violations of the above protocol would do well to develop and add necessary nuance to our conclusions. Finally, frailty models and their ability to account for clustering by independent variables (e.g. state) without including those as factors in the model output promise another opportunity for further refinement.

4.3 Summary

As bail reform spreads slowly across a landscape of overworked district attorneys and public defenders, courts still struggling with a backlog of cases only exacerbated by time lost to months of COVID-19 closures, pretrial detention enmires hundreds of thousands of individuals in the United States. In some cases, people wait months or years before they are given the chance to argue their innocence to a judge. Many of those individuals are incarcerated prior to their trials or assigned secured bond, through which they may or may not be able to pay their way to freedom. The legal justification for pre-trial incarceration varies state by state, but in North Carolina, individuals have the right to release on written promise to appear unless a judge deems money bond necessary to prevent them from fleeing or to protect the community. In reality, despite regional reforms, money bond is more widespread than that high legal standard would allow, were it appropriately applied. The racial inequality in pretrial detention suggested by this study matters because it indicates that at least among those eventually convicted and serving time in prison, people of color spend longer in limbo before sentencing, where they are subject to the destabilizing effects of jail incarceration.

References

- [1] “United States of America.” United States of America Overview. World Prison Brief, December 2019. <https://www.prisonstudies.org/country/united-states-america>.
- [2] “Pretrial Detention.” Prison Policy Initiative. Accessed December 8, 2021. https://www.prisonpolicy.org/research/pretrial_detention/.
- [3] Lowenkamp, Christopher T., Alexander M. Holsinger, and Marie VanNostrand. “Investigating the Impact of Pretrial Detention on Sentencing Outcomes.” National Institute of Corrections, January 5, 2021. <https://nicic.gov/investigating-impact-pretrial-detention-sentencing-outcomes>.
- [4] Digard, Léon, and Elizabeth Swavola. “Justice Denied: The Harmful and Lasting Effects of Pretrial Detention.” Vera Evidence Brief. Vera Institute of Justice, April 2019. <https://www.vera.org/downloads/publications/Justice-Denied-Evidence-Brief.pdf>.
- [5] Sawyer, Wendy. “How Race Impacts Who Is Detained Pretrial.” Prison Policy Initiative, October 9, 2019. https://www.prisonpolicy.org/blog/2019/10/09/pretrial_race/.
- [6] Kovalski, Serge F. “Justice Delayed: 10 Years in Jail, but Still Awaiting Trial.” The New York Times, September 19, 2017. <https://www.nytimes.com/2017/09/19/us/alabama-kharon-davis-speedy.html>.
- [7] Crozier, William, Brandon L. Garrett, and Arvind Krishnamurthy. “The Transparency Of Jail Data.” SSRN, January 24, 2021. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3741638.
- [8] United States Bureau of Justice Statistics. “Survey of Prison Inmates, United States, 2016.” Survey of Prison Inmates, United States, 2016. Inter-university Consortium for Political and Social Research, September 15, 2021. <https://www.icpsr.umich.edu/web/NACJD/studies/37692>.
- [9] Stevenson, Bryan. Just Mercy: A Story of Justice and Redemption. Spiegel & Grau, 2014.
- [10] “What Changed after D.C. Ended Cash Bail.” NPR, September 2, 2018. <https://www.npr.org/2018/09/02/644085158/what-changed-after-d-c-ended-cash-bail>.
- [11] Bhalla, Deepanshu. “Detecting Multicollinearity in Categorical Variables.” ListenData. Accessed December 8, 2021. <https://www.listendata.com/2015/04/detecting-multicollinearity-in-categorical-variables.html>.
- [12] “Multinomial Logistic Regression.” Wikipedia. Wikimedia Foundation, August 23, 2021. https://en.wikipedia.org/wiki/Multinomial_logistic_regression#.

Appendix

Appendix 1: Preliminary Multinomial Logistic Analysis

We assume the data in our multinomial logistic model are case specific, where each independent variable has a singular value for each case [12]. We also assume the outcome, whether jail time was served, is impossible to predict perfectly from the covariates for any case.

Figure 6: Model Diagnostics: Binned Residuals vs. Predicted Probabilities

Figure 7: Model Diagnostics: Average Residuals for Categorical Predictor Variables

Table 4: Full Multinomial Logistic Results

Table 4: Multinomial Logistic Model Output

Y Level	Model Term	Estimate	Standard Error	p-Value
Not Reported	(Intercept)	-3.086	1.405	0.028
Not Reported	controlling_offenseBurglary	0.184	0.573	0.748
Not Reported	controlling_offenseDrug Possession	0.317	0.558	0.571
Not Reported	controlling_offenseDrug Trafficking	-0.113	0.473	0.810
Not Reported	controlling_offenseHomicide	0.634	0.454	0.163
Not Reported	controlling_offenseNot Reported	0.922	0.544	0.090
Not Reported	controlling_offenseOther Drug	0.967	0.753	0.199
Not Reported	controlling_offenseOther Property	-0.373	0.489	0.445
Not Reported	controlling_offenseOther Public Order	-0.063	0.468	0.893
Not Reported	controlling_offenseOther Unspecified	0.281	1.118	0.802
Not Reported	controlling_offenseOther Violent	-0.270	0.838	0.747
Not Reported	controlling_offenseRape Sexual Assault	0.153	0.471	0.746
Not Reported	controlling_offenseRobbery	0.465	0.460	0.312
Not Reported	controlling_offenseWeapons	0.979	0.547	0.074
Not Reported	arrested_during_statusNone	-0.768	0.697	0.271
Not Reported	arrested_during_statusNot Reported	-0.022	0.906	0.981
Not Reported	arrested_during_statusParole	-0.930	0.722	0.197
Not Reported	arrested_during_statusProbation	-0.693	0.712	0.331
Not Reported	firearm_at_offenseNot Reported	1.067	0.384	0.005
Not Reported	firearm_at_offenseYes	-0.404	0.305	0.186
Not Reported	alc_at_offenseNot Reported	0.494	0.263	0.060
Not Reported	alc_at_offenseYes	-0.265	0.239	0.269
Not Reported	drug_at_offenseNot Reported	-0.256	0.266	0.337
Not Reported	drug_at_offenseYes	-0.272	0.237	0.251
Not Reported	arrest_year_range1981-1984	-0.040	1.040	0.969
Not Reported	arrest_year_range1985-1988	-1.513	1.304	0.246
Not Reported	arrest_year_range1989-1992	-0.944	1.109	0.394
Not Reported	arrest_year_range1993-1996	-0.287	0.926	0.757
Not Reported	arrest_year_range1997-2000	-0.612	0.909	0.501
Not Reported	arrest_year_range2001-2004	-1.267	0.938	0.177
Not Reported	arrest_year_range2005-2008	-0.868	0.866	0.316
Not Reported	arrest_year_range2009-2012	-1.118	0.853	0.190
Not Reported	arrest_year_range2013-2016	-1.936	0.862	0.025
Not Reported	arrest_year_rangeNot Reported	0.399	0.423	0.346
Not Reported	held_byICE	1.364	0.622	0.028
Not Reported	held_byLocal	1.440	0.652	0.027
Not Reported	held_byNot Reported	2.620	0.983	0.008
Not Reported	held_byOther	-2.259	7.205	0.754

Table 4: Multinomial Logistic Model Output (*continued*)

Y Level	Model Term	Estimate	Standard Error	p-Value
Not Reported	held_byState	0.877	0.276	0.001
Not Reported	stateAL	-6.315	11.793	0.592
Not Reported	stateAR	0.189	0.848	0.823
Not Reported	stateAZ	-6.704	14.152	0.636
Not Reported	stateCA	-0.112	0.640	0.861
Not Reported	stateCO	-4.819	8.307	0.562
Not Reported	stateCT	-1.992	0.872	0.022
Not Reported	stateDC	-4.866	6.529	0.456
Not Reported	stateDE	-4.231	6.315	0.503
Not Reported	stateFL	-1.273	0.758	0.093
Not Reported	stateGA	-0.758	0.770	0.324
Not Reported	stateHI	-0.961	0.808	0.234
Not Reported	stateIA	0.429	1.179	0.716
Not Reported	stateID	-2.856	6.225	0.646
Not Reported	stateIL	0.371	0.675	0.583
Not Reported	stateIN	1.622	0.773	0.036
Not Reported	stateKS	-3.373	7.311	0.645
Not Reported	stateKY	-4.297	7.558	0.570
Not Reported	stateLA	-1.112	0.924	0.229
Not Reported	stateMA	-1.888	0.961	0.049
Not Reported	stateMD	-1.175	0.916	0.199
Not Reported	stateME	-0.843	7.136	0.906
Not Reported	stateMI	0.516	0.664	0.437
Not Reported	stateMN	0.606	1.198	0.613
Not Reported	stateMO	-0.526	0.710	0.459
Not Reported	stateMS	-0.271	0.776	0.727
Not Reported	stateMT	-1.963	5.886	0.739
Not Reported	stateNC	-1.146	1.150	0.319
Not Reported	stateND	-0.998	6.413	0.876
Not Reported	stateNE	1.156	1.211	0.340
Not Reported	stateNH	-1.579	5.861	0.788
Not Reported	stateNJ	-0.899	1.164	0.440
Not Reported	stateNM	-0.250	1.201	0.835
Not Reported	stateNot Reported	0.922	0.718	0.199
Not Reported	stateNV	-0.804	1.167	0.490
Not Reported	stateNY	-0.927	0.738	0.209
Not Reported	stateOH	-0.427	0.821	0.603
Not Reported	stateOK	-5.365	10.071	0.594
Not Reported	stateOR	0.151	0.839	0.857
Not Reported	statePA	-1.811	0.760	0.017
Not Reported	statePR	-0.155	0.974	0.873
Not Reported	stateRI	-3.023	5.997	0.614
Not Reported	stateSC	0.199	0.848	0.814
Not Reported	stateSD	-2.912	7.296	0.690
Not Reported	stateTN	-1.415	1.132	0.211
Not Reported	stateTX	-0.333	0.653	0.611
Not Reported	stateUT	-2.413	6.441	0.708
Not Reported	stateVA	0.590	0.741	0.426
Not Reported	stateVT	-1.322	1.345	0.326

Table 4: Multinomial Logistic Model Output (*continued*)

Y Level	Model Term	Estimate	Standard Error	p-Value
Not Reported	stateWA	0.661	0.932	0.478
Not Reported	stateWI	0.736	0.843	0.383
Not Reported	stateWV	-0.122	1.198	0.919
Not Reported	stateWY	-1.423	6.220	0.819
Not Reported	age_at_arrest36-50	0.439	0.241	0.068
Not Reported	age_at_arrestNot Reported	0.399	0.423	0.346
Not Reported	age_at_arrestOver 50	-0.503	0.496	0.311
Not Reported	age_at_arrestUnder 18	-0.045	0.574	0.937
Not Reported	raceAmerican Indian/Alaska Native	1.454	0.582	0.012
Not Reported	raceAsian/Native Hawaiian/Other Pacific Islander	0.447	0.650	0.491
Not Reported	raceBlack	0.162	0.256	0.528
Not Reported	raceHispanic	0.413	0.297	0.165
Not Reported	raceNot Reported	0.501	0.659	0.447
Not Reported	raceOther	-0.321	0.366	0.380
Not Reported	sexMale	0.589	0.279	0.035
Not Reported	sexNot Reported	0.670	1.036	0.518
Not Reported	sexTransgender/Other	1.116	1.207	0.355
Not Reported	citizenNon-citizen	-0.052	0.424	0.902
Not Reported	citizenNot Reported	0.882	1.245	0.479
Not Reported	militaryVeteran	0.085	0.381	0.824
Not Reported	educationHigh School Graduate	0.911	0.577	0.114
Not Reported	educationLess Than High School	1.364	0.562	0.015
Not Reported	educationNot Reported	0.845	0.842	0.315
Not Reported	educationSome College	0.847	0.608	0.164
Not Reported	homeless_12mo_priorNot Reported	0.526	0.384	0.170
Not Reported	homeless_12mo_priorYes	0.724	0.311	0.020
Yes	(Intercept)	-1.818	0.551	<0.001
Yes	controlling_offenseBurglary	-0.012	0.168	0.941
Yes	controlling_offenseDrug Possession	-0.579	0.163	<0.001
Yes	controlling_offenseDrug Trafficking	-0.118	0.121	0.333
Yes	controlling_offenseHomicide	0.099	0.140	0.481
Yes	controlling_offenseNot Reported	-0.173	0.221	0.433
Yes	controlling_offenseOther Drug	-0.221	0.244	0.366
Yes	controlling_offenseOther Property	-0.865	0.120	<0.001
Yes	controlling_offenseOther Public Order	-0.572	0.121	<0.001
Yes	controlling_offenseOther Unspecified	-0.486	0.280	0.082
Yes	controlling_offenseOther Violent	0.289	0.232	0.212
Yes	controlling_offenseRape Sexual Assault	-0.103	0.142	0.467
Yes	controlling_offenseRobbery	0.015	0.139	0.912
Yes	controlling_offenseWeapons	-0.088	0.156	0.573
Yes	arrested_during_statusNone	1.171	0.327	<0.001
Yes	arrested_during_statusNot Reported	0.902	0.403	0.025
Yes	arrested_during_statusParole	0.685	0.332	0.039
Yes	arrested_during_statusProbation	1.177	0.330	<0.001
Yes	firearm_at_offenseNot Reported	-0.255	0.201	0.206
Yes	firearm_at_offenseYes	0.089	0.087	0.308
Yes	alc_at_offenseNot Reported	-0.111	0.085	0.189
Yes	alc_at_offenseYes	-0.077	0.060	0.198
Yes	drug_at_offenseNot Reported	-0.194	0.073	0.008

Table 4: Multinomial Logistic Model Output (*continued*)

Y Level	Model Term	Estimate	Standard Error	p-Value
Yes	drug_at_offenseYes	0.382	0.061	<0.001
Yes	arrest_year_range1981-1984	-0.395	0.488	0.418
Yes	arrest_year_range1985-1988	-0.258	0.442	0.559
Yes	arrest_year_range1989-1992	0.539	0.446	0.227
Yes	arrest_year_range1993-1996	0.447	0.406	0.271
Yes	arrest_year_range1997-2000	0.311	0.389	0.423
Yes	arrest_year_range2001-2004	0.368	0.379	0.332
Yes	arrest_year_range2005-2008	0.450	0.371	0.226
Yes	arrest_year_range2009-2012	0.344	0.367	0.348
Yes	arrest_year_range2013-2016	0.254	0.367	0.490
Yes	arrest_year_rangeNot Reported	-0.186	0.190	0.327
Yes	held_byICE	0.050	0.248	0.839
Yes	held_byLocal	0.702	0.190	<0.001
Yes	held_byNot Reported	1.145	0.541	0.034
Yes	held_byOther	-0.072	0.596	0.903
Yes	held_byState	1.341	0.066	<0.001
Yes	stateAL	1.516	0.277	<0.001
Yes	stateAR	1.633	0.309	<0.001
Yes	stateAZ	1.797	0.294	<0.001
Yes	stateCA	1.472	0.228	<0.001
Yes	stateCO	1.811	0.359	<0.001
Yes	stateCT	-1.218	0.254	<0.001
Yes	stateDC	1.002	0.373	0.007
Yes	stateDE	-0.923	0.338	0.006
Yes	stateFL	1.488	0.227	<0.001
Yes	stateGA	1.583	0.239	<0.001
Yes	stateHI	-0.426	0.273	0.119
Yes	stateIA	1.938	0.373	<0.001
Yes	stateID	1.659	0.469	<0.001
Yes	stateIL	1.690	0.250	<0.001
Yes	stateIN	2.470	0.352	<0.001
Yes	stateKS	2.159	0.426	<0.001
Yes	stateKY	1.731	0.353	<0.001
Yes	stateLA	0.893	0.258	<0.001
Yes	stateMA	0.142	0.253	0.576
Yes	stateMD	0.563	0.253	0.026
Yes	stateME	2.561	1.065	0.016
Yes	stateMI	1.557	0.252	<0.001
Yes	stateMN	1.725	0.413	<0.001
Yes	stateMO	1.003	0.234	<0.001
Yes	stateMS	1.035	0.261	<0.001
Yes	stateMT	1.246	0.555	0.025
Yes	stateNC	2.080	0.271	<0.001
Yes	stateND	1.520	0.834	0.068
Yes	stateNE	1.797	0.435	<0.001
Yes	stateNH	0.808	0.863	0.349
Yes	stateNJ	1.126	0.311	<0.001
Yes	stateNM	1.995	0.404	<0.001
Yes	stateNot Reported	1.866	0.292	<0.001

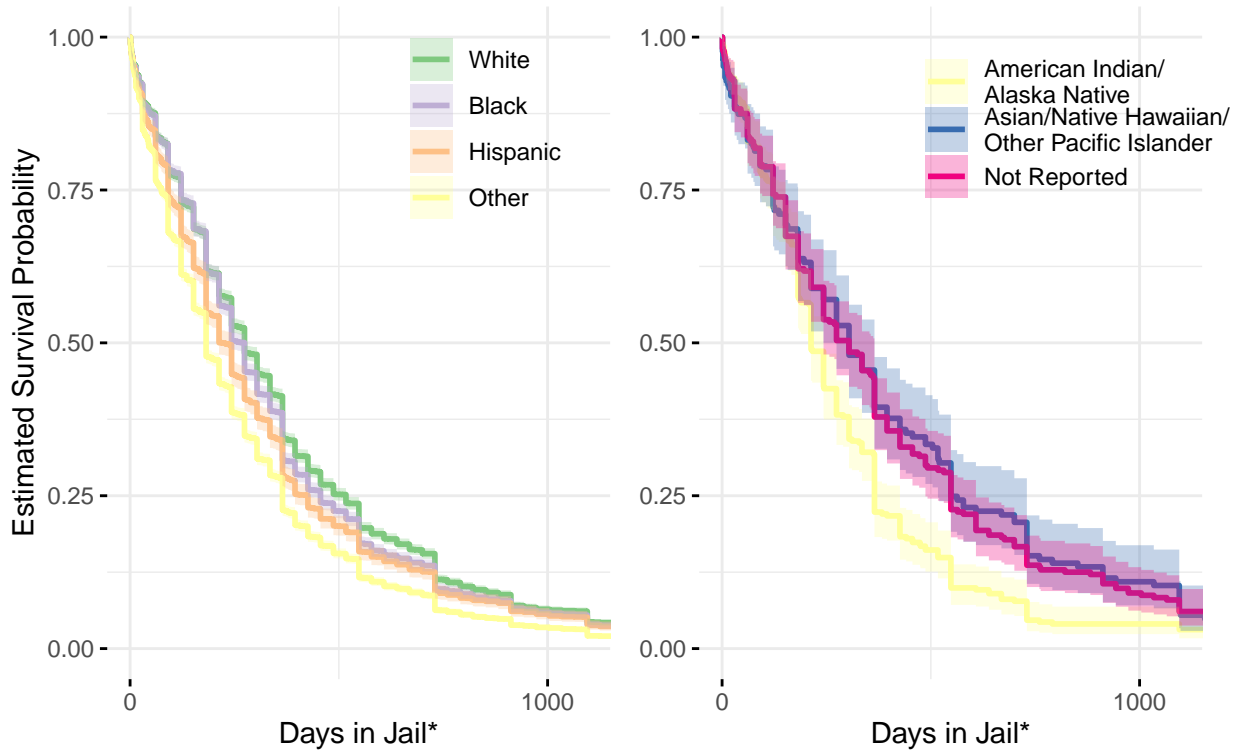
Table 4: Multinomial Logistic Model Output (*continued*)

Y Level	Model Term	Estimate	Standard Error	p-Value
Yes	stateNV	1.383	0.306	<0.001
Yes	stateNY	1.202	0.238	<0.001
Yes	stateOH	1.628	0.252	<0.001
Yes	stateOK	1.893	0.333	<0.001
Yes	stateOR	1.183	0.291	<0.001
Yes	statePA	0.623	0.222	0.005
Yes	statePR	0.018	0.313	0.954
Yes	stateRI	0.992	0.628	0.114
Yes	stateSC	1.826	0.302	<0.001
Yes	stateSD	2.840	0.630	<0.001
Yes	stateTN	1.506	0.266	<0.001
Yes	stateTX	1.976	0.226	<0.001
Yes	stateUT	2.272	0.515	<0.001
Yes	stateVA	2.043	0.277	<0.001
Yes	stateVT	-0.817	0.422	0.053
Yes	stateWA	1.841	0.324	<0.001
Yes	stateWI	2.332	0.336	<0.001
Yes	stateWV	1.330	0.363	<0.001
Yes	stateWY	1.837	0.595	0.002
Yes	age_at_arrest36-50	-0.126	0.060	0.034
Yes	age_at_arrestNot Reported	-0.186	0.190	0.327
Yes	age_at_arrestOver 50	-0.528	0.087	<0.001
Yes	age_at_arrestUnder 18	-0.238	0.198	0.229
Yes	raceAmerican Indian/Alaska Native	0.202	0.254	0.427
Yes	raceAsian/Native Hawaiian/Other Pacific Islander	-0.341	0.214	0.111
Yes	raceBlack	0.026	0.070	0.711
Yes	raceHispanic	0.076	0.082	0.352
Yes	raceNot Reported	-0.385	0.207	0.063
Yes	raceOther	-0.020	0.090	0.823
Yes	sexMale	0.234	0.063	<0.001
Yes	sexNot Reported	0.028	0.429	0.948
Yes	sexTransgender/Other	-0.123	0.490	0.802
Yes	citizenNon-citizen	0.472	0.121	<0.001
Yes	citizenNot Reported	0.719	0.622	0.247
Yes	militaryVeteran	0.189	0.106	0.075
Yes	educationHigh School Graduate	0.479	0.097	<0.001
Yes	educationLess Than High School	0.738	0.094	<0.001
Yes	educationNot Reported	0.026	0.245	0.915
Yes	educationSome College	0.460	0.100	<0.001
Yes	homeless_12mo_priorNot Reported	0.133	0.132	0.313
Yes	homeless_12mo_priorYes	0.441	0.108	<0.001

The baseline individual for the multinomial logistic model has

Appendix 2: Primary Survival Analysis

Figure 8: Additional Survival Curves for Race of Incarcerated Individual



*Survival curves plotted separately for most/least common racial groups in data and truncated to jail times 3 years and under for readability

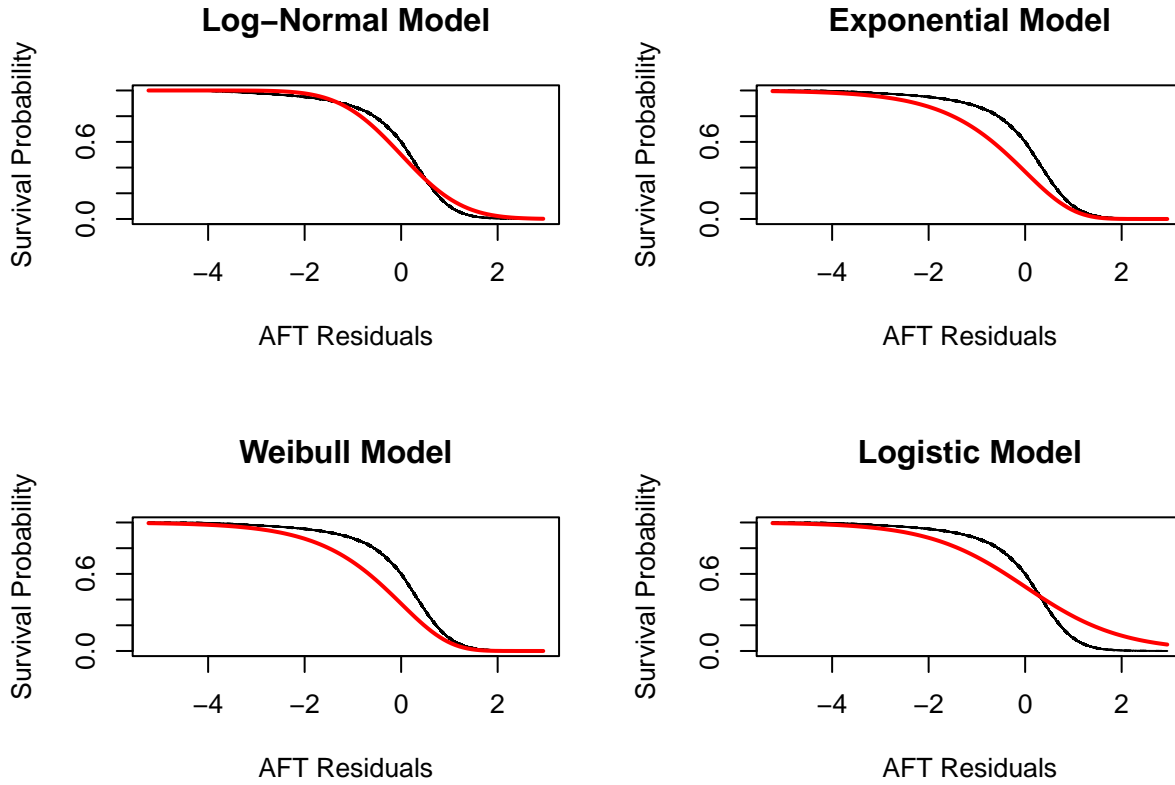
Table 5: Log-rank Test for White/Non-white Incarcerated Individual

Table 5: Log-Rank Test Output

Race	Number of Individuals	Observed	Expected	$(O-E)^2/E$	$(O-E)^2/V$
Non-white	14416	14355	15499.08	84.45	310.87
Not Reported	264	264	322.48	10.61	11.79
White	7424	7397	6194.44	233.46	354.14

A log-rank test of jailtime by race white/non-white reveals a difference between the two groups, a powerful observation because we find empirical evidence of proportional hazard and further modeling confirms this discrepancy.

Figure 9: Kaplan-Meier Residual Plots of AFT Model Candidates



We assume predictors have a multiplicative effect on survival time, and a KM residual plot for the log-normal AFT model shows this is satisfied. The fit is not perfect, but a log-normal model outperforms the other models evaluated above.

Table 6: Race Variable Selection

Table 6: AIC and BIC for Log-normal AFT Models by Race Encoding Method

	Race complete	Race Black/non-Black	Race white/non-white
AIC	301789.7	301786.8	301782.9
BIC	302702.1	302667.2	302663.3

Variable selection among AFT log-normal models with different race encoding methods was performed as discussed in methodology, via AIC and BIC.

Table 7: Full Primary Survival Analysis Results

Table 7: AFT (log-normal) Model Output (with race white/non-white)

Model Term	Estimate	Standard Error	Test Statistic	p-Value
(Intercept)	5.115	0.247	20.720	<0.001
controlling_offenseBurglary	-0.082	0.045	-1.797	0.072
controlling_offenseDrug Possession	-0.496	0.053	-9.305	<0.001
controlling_offenseDrug Trafficking	-0.266	0.037	-7.124	<0.001
controlling_offenseHomicide	0.470	0.039	12.046	<0.001
controlling_offenseNot Reported	-0.048	0.083	-0.573	0.567
controlling_offenseOther Drug	-0.287	0.098	-2.913	0.004
controlling_offenseOther Property	-0.424	0.041	-10.227	<0.001
controlling_offenseOther Public Order	-0.396	0.040	-9.786	<0.001
controlling_offenseOther Unspecified	-0.185	0.127	-1.454	0.146

Table 7: AFT (log-normal) Model Output (with race white/non-white) (*continued*)

Model Term	Estimate	Standard Error	Test Statistic	p-Value
controlling_offenseOther Violent	0.091	0.061	1.506	0.132
controlling_offenseRape Sexual Assault	-0.025	0.042	-0.603	0.546
controlling_offenseRobbery	0.129	0.039	3.318	<0.001
controlling_offenseWeapons	-0.211	0.052	-4.057	<0.001
arrested_during_statusNone	-0.080	0.171	-0.467	0.641
arrested_during_statusNot Reported	1.807	0.318	5.674	<0.001
arrested_during_statusParole	-0.105	0.173	-0.606	0.544
arrested_during_statusProbation	-0.027	0.172	-0.157	0.875
firearm_at_offenseNot Reported	0.234	0.075	3.119	0.002
firearm_at_offenseYes	0.078	0.026	3.008	0.003
alc_at_offenseNot Reported	0.052	0.032	1.662	0.097
alc_at_offenseYes	-0.065	0.020	-3.170	0.002
drug_at_offenseNot Reported	-0.059	0.030	-1.975	0.048
drug_at_offenseYes	0.077	0.020	3.895	<0.001
arrest_year_range1981-1984	0.049	0.159	0.312	0.755
arrest_year_range1985-1988	0.001	0.142	0.007	0.995
arrest_year_range1989-1992	0.082	0.129	0.638	0.523
arrest_year_range1993-1996	0.225	0.122	1.845	0.065
arrest_year_range1997-2000	0.342	0.119	2.869	0.004
arrest_year_range2001-2004	0.365	0.117	3.122	0.002
arrest_year_range2005-2008	0.335	0.115	2.924	0.003
arrest_year_range2009-2012	0.204	0.113	1.794	0.073
arrest_year_range2013-2016	-0.191	0.114	-1.679	0.093
arrest_year_rangeNot Reported	-0.265	0.122	-2.165	0.030
held_byICE	-0.228	0.105	-2.160	0.031
held_byLocal	-0.476	0.093	-5.119	<0.001
held_byNot Reported	-0.395	0.203	-1.945	0.052
held_byOther	-0.114	0.290	-0.395	0.693
held_byState	-0.293	0.028	-10.353	<0.001
stateAL	-0.162	0.139	-1.167	0.243
stateAR	-0.172	0.141	-1.227	0.220
stateAZ	0.092	0.136	0.677	0.498
stateCA	0.272	0.126	2.160	0.031
stateCO	0.057	0.149	0.379	0.705
stateCT	-0.300	0.179	-1.676	0.094
stateDC	0.086	0.198	0.435	0.664
stateDE	-0.304	0.259	-1.174	0.240
stateFL	0.077	0.126	0.616	0.538
stateGA	0.112	0.128	0.878	0.380
stateHI	0.148	0.177	0.833	0.405
stateIA	-0.151	0.155	-0.972	0.331
stateID	0.153	0.192	0.798	0.425
stateIL	0.140	0.129	1.088	0.276
stateIN	0.179	0.134	1.339	0.180
stateKS	0.180	0.156	1.152	0.249
stateKY	0.414	0.154	2.685	0.007
stateLA	0.315	0.137	2.301	0.021
stateMA	0.098	0.146	0.669	0.504

Table 7: AFT (log-normal) Model Output (with race white/non-white) (*continued*)

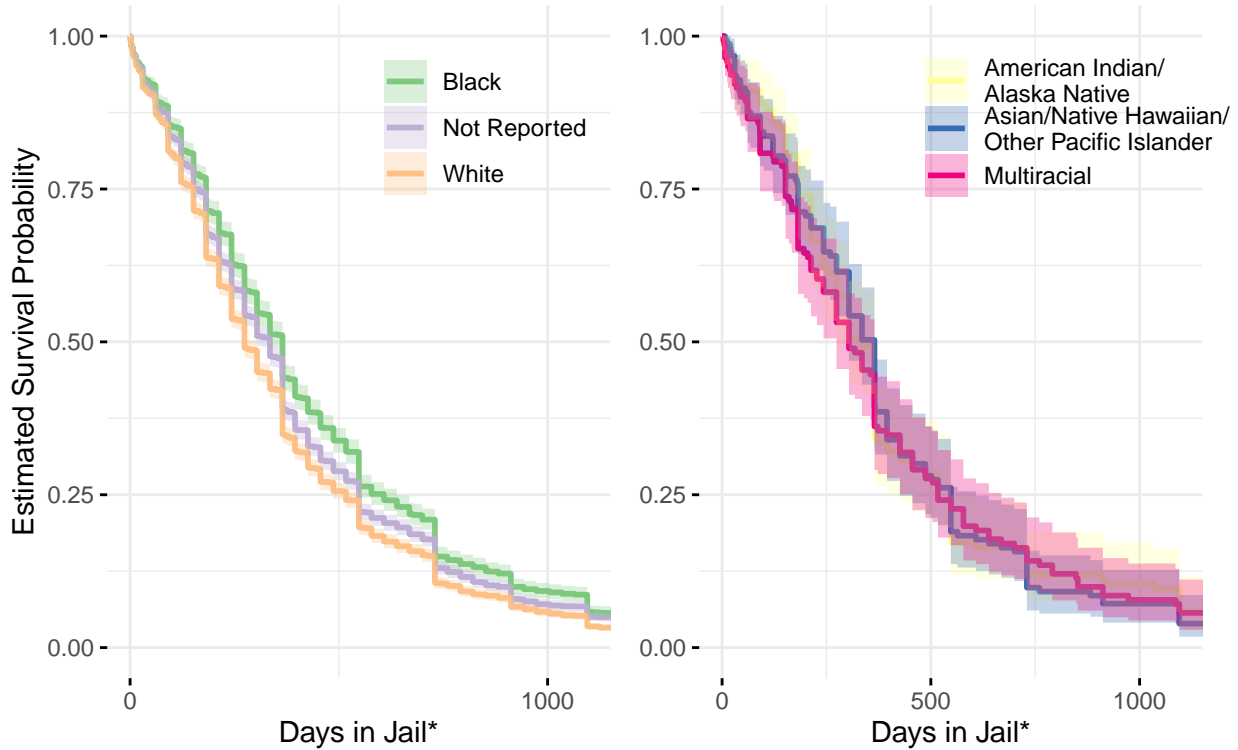
Model Term	Estimate	Standard Error	Test Statistic	p-Value
stateMD	-0.017	0.139	-0.119	0.905
stateME	-0.096	0.327	-0.293	0.770
stateMI	-0.355	0.129	-2.745	0.006
stateMN	-0.025	0.177	-0.144	0.886
stateMO	-0.233	0.130	-1.796	0.073
stateMS	-0.175	0.136	-1.289	0.197
stateMT	0.091	0.307	0.298	0.766
stateNC	-0.096	0.130	-0.737	0.461
stateND	-0.342	0.377	-0.907	0.364
stateNE	-0.022	0.181	-0.121	0.904
stateNH	-0.370	0.446	-0.829	0.407
stateNJ	0.248	0.150	1.654	0.098
stateNM	0.074	0.155	0.480	0.631
stateNot Reported	-0.046	0.146	-0.318	0.751
stateNV	0.105	0.143	0.735	0.462
stateNY	0.202	0.129	1.560	0.119
stateOH	-0.467	0.128	-3.650	<0.001
stateOK	0.104	0.141	0.738	0.461
stateOR	-0.354	0.142	-2.498	0.012
statePA	0.169	0.127	1.330	0.183
statePR	-0.480	0.220	-2.182	0.029
stateRI	0.111	0.354	0.314	0.753
stateSC	-0.277	0.136	-2.041	0.041
stateSD	-0.141	0.163	-0.867	0.386
stateTN	0.400	0.134	2.986	0.003
stateTX	0.029	0.124	0.233	0.816
stateUT	0.091	0.183	0.494	0.621
stateVA	0.629	0.130	4.835	<0.001
stateVT	0.606	0.334	1.812	0.070
stateWA	-0.286	0.144	-1.987	0.047
stateWI	-0.176	0.136	-1.297	0.194
stateWV	0.642	0.161	3.999	<0.001
stateWY	0.322	0.276	1.164	0.244
age_at_arrest36-50	-0.049	0.021	-2.338	0.019
age_at_arrestNot Reported	0.000	0.000	NaN	NA
age_at_arrestOver 50	-0.156	0.038	-4.159	<0.001
age_at_arrestUnder 18	0.098	0.052	1.867	0.062
race_whiteNot Reported	0.066	0.080	0.822	0.411
race_whiteY	-0.047	0.020	-2.296	0.022
sexMale	0.226	0.023	9.834	<0.001
sexNot Reported	0.356	0.186	1.911	0.056
sexTransgender/Other	0.235	0.196	1.200	0.230
citizenNon-citizen	0.314	0.041	7.682	<0.001
citizenNot Reported	-0.203	0.266	-0.765	0.444
militaryVeteran	0.062	0.038	1.654	0.098
educationHigh School Graduate	0.173	0.046	3.756	<0.001
educationLess Than High School	0.249	0.045	5.600	<0.001
educationNot Reported	0.141	0.113	1.247	0.212

Table 7: AFT (log-normal) Model Output (with race white/non-white) (*continued*)

Model Term	Estimate	Standard Error	Test Statistic	p-Value
educationSome College	0.073	0.048	1.506	0.132
homeless_12mo_priorNot Reported	0.052	0.043	1.195	0.232
homeless_12mo_priorYes	0.045	0.030	1.492	0.136
Log(scale)	0.252	0.005	52.856	<0.001

Appendix 3: Secondary Survival Analysis (Victim Traits)

Figure 10: Additional Survival Curves for Race of Victim



*Survival curves plotted separately for most/least common racial groups in data and truncated to jail times 3 years and under for readability

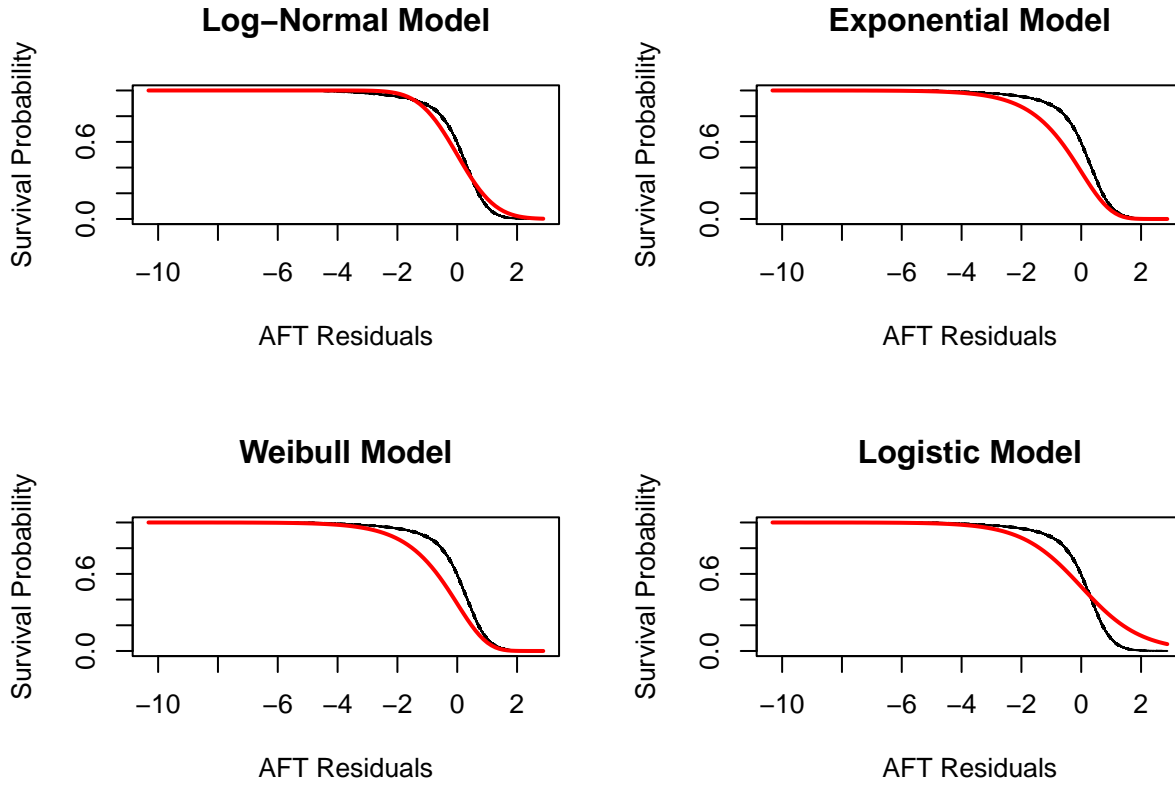
Table 8: Log-rank Test for White/Non-white Victim

Table 8: Log-Rank Test Output

Victim Race	Number of Individuals	Observed	Expected	$(O-E)^2/E$	$(O-E)^2/V$
Non-white	2558	2550	2809.53	23.97	16.00
Not Reported	3587	3583	3655.41	1.43	18.08
White	4069	4060	3728.06	29.56	26.98

A log-rank test of jail time by victim race white/non-white reveals a difference between the two groups, however, this is contradicted by later modeling with additional confounders.

Figure 11: Kaplan-Meier Residual Plots of AFT Model Candidates



We assume predictors have a multiplicative effect on survival time, and a KM residual plot for the log-normal AFT model shows this is satisfied. The fit is not perfect, but a log-normal model outperforms the other models evaluated above.

Table 9: Race Variable Selection

Table 9: AIC and BIC for Log-normal AFT Models Including Victim Traits by Race Encoding Method

	Race complete	Race Black/non-Black	Race white/non-white
AIC	144444.9	144443.1	144441.5
BIC	145298.2	145274.7	145273.2

Variable selection among AFT log-normal models with different race encoding methods was performed as discussed in methodology, via AIC and BIC.

Table 10: Full Primary Survival Analysis Results

Table 10: AFT (log-normal) Model Output (with race and victim race white/non-white)

Model Term	Estimate	Standard Error	Test Statistic	p-Value
(Intercept)	5.348	0.435	12.282	<0.001
controlling_offenseHomicide	0.486	0.037	13.155	<0.001
controlling_offenseOther Violent	0.104	0.057	1.844	0.065
controlling_offenseRape Sexual Assault	0.019	0.045	0.421	0.674
controlling_offenseRobbery	0.152	0.037	4.092	<0.001
arrested_during_statusNone	-0.232	0.372	-0.624	0.533
arrested_during_statusNot Reported	7.402	138.525	0.053	0.957
arrested_during_statusParole	-0.350	0.373	-0.939	0.348
arrested_during_statusProbation	-0.279	0.373	-0.748	0.454
firearm_at_offenseNot Reported	0.238	0.079	3.013	0.003

Table 10: AFT (log-normal) Model Output (with race and victim
race white/non-white) (*continued*)

Model Term	Estimate	Standard Error	Test Statistic	p-Value
firearm_at_offenseYes	0.037	0.029	1.283	0.199
alc_at_offenseNot Reported	0.036	0.041	0.879	0.379
alc_at_offenseYes	-0.099	0.027	-3.701	<0.001
drug_at_offenseNot Reported	-0.011	0.038	-0.292	0.770
drug_at_offenseYes	0.040	0.027	1.496	0.135
arrest_year_range1981-1984	0.062	0.146	0.422	0.673
arrest_year_range1985-1988	-0.045	0.132	-0.341	0.733
arrest_year_range1989-1992	0.061	0.120	0.506	0.613
arrest_year_range1993-1996	0.222	0.113	1.955	0.051
arrest_year_range1997-2000	0.329	0.111	2.952	0.003
arrest_year_range2001-2004	0.331	0.110	3.016	0.003
arrest_year_range2005-2008	0.313	0.108	2.913	0.004
arrest_year_range2009-2012	0.214	0.107	2.009	0.045
arrest_year_range2013-2016	-0.157	0.107	-1.467	0.143
arrest_year_rangeNot Reported	-0.118	0.124	-0.952	0.341
held_byICE	-0.457	0.240	-1.904	0.057
held_byLocal	-0.533	0.145	-3.669	<0.001
held_byNot Reported	-0.275	0.281	-0.976	0.329
held_byOther	0.184	0.394	0.468	0.640
held_byState	-0.271	0.057	-4.801	<0.001
stateAL	-0.350	0.190	-1.840	0.066
stateAR	-0.330	0.193	-1.711	0.087
stateAZ	0.077	0.186	0.412	0.681
stateCA	0.331	0.173	1.913	0.056
stateCO	0.147	0.209	0.704	0.481
stateCT	-0.593	0.251	-2.359	0.018
stateDC	0.093	0.238	0.390	0.696
stateDE	0.035	0.424	0.083	0.934
stateFL	0.180	0.174	1.032	0.302
stateGA	0.076	0.176	0.434	0.664
stateHI	-0.877	0.322	-2.719	0.007
stateIA	-0.397	0.227	-1.750	0.080
stateID	0.028	0.296	0.093	0.926
stateIL	0.252	0.178	1.413	0.158
stateIN	0.060	0.187	0.320	0.749
stateKS	-0.022	0.227	-0.099	0.921
stateKY	0.242	0.207	1.167	0.243
stateLA	0.260	0.185	1.408	0.159
stateMA	0.145	0.194	0.748	0.454
stateMD	-0.095	0.186	-0.509	0.611
stateME	-0.312	1.177	-0.265	0.791
stateMI	-0.423	0.177	-2.390	0.017
stateMN	-0.005	0.322	-0.016	0.987
stateMO	-0.098	0.180	-0.546	0.585
stateMS	-0.277	0.188	-1.470	0.141
stateMT	0.270	0.551	0.490	0.624
stateNC	-0.109	0.180	-0.603	0.547
stateND	0.824	0.607	1.359	0.174

Table 10: AFT (log-normal) Model Output (with race and victim
race white/non-white) (*continued*)

Model Term	Estimate	Standard Error	Test Statistic	p-Value
stateNE	-0.489	0.296	-1.649	0.099
stateNH	0.439	0.505	0.869	0.385
stateNJ	0.158	0.205	0.770	0.441
stateNM	0.179	0.227	0.789	0.430
stateNot Reported	-0.006	0.245	-0.023	0.982
stateNV	0.024	0.195	0.122	0.903
stateNY	0.075	0.179	0.420	0.674
stateOH	-0.544	0.176	-3.091	0.002
stateOK	-0.060	0.199	-0.302	0.763
stateOR	-0.318	0.190	-1.669	0.095
statePA	0.097	0.175	0.555	0.579
statePR	0.234	0.426	0.548	0.584
stateRI	0.205	0.694	0.295	0.768
stateSC	-0.313	0.186	-1.678	0.093
stateSD	-0.281	0.232	-1.209	0.227
stateTN	0.339	0.183	1.855	0.064
stateTX	-0.036	0.172	-0.210	0.833
stateUT	0.404	0.296	1.362	0.173
stateVA	0.395	0.180	2.193	0.028
stateVT	-0.042	0.473	-0.089	0.929
stateWA	-0.096	0.202	-0.477	0.634
stateWI	-0.333	0.189	-1.759	0.079
stateWV	0.677	0.211	3.210	0.001
stateWY	-0.572	0.505	-1.131	0.258
age_at_arrest36-50	-0.040	0.030	-1.325	0.185
age_at_arrestNot Reported	0.000	0.000	NaN	NA
age_at_arrestOver 50	-0.134	0.054	-2.463	0.014
age_at_arrestUnder 18	0.111	0.052	2.138	0.033
race_whiteNot Reported	0.134	0.104	1.290	0.197
race_whiteY	-0.117	0.030	-3.973	<0.001
sexMale	0.169	0.034	4.945	<0.001
sexNot Reported	0.299	0.230	1.300	0.193
sexTransgender/Other	0.330	0.231	1.431	0.153
citizenNon-citizen	0.100	0.060	1.673	0.094
citizenNot Reported	-0.095	0.357	-0.266	0.790
militaryVeteran	-0.010	0.044	-0.234	0.815
educationHigh School Graduate	0.157	0.064	2.451	0.014
educationLess Than High School	0.227	0.063	3.625	<0.001
educationNot Reported	0.114	0.153	0.746	0.456
educationSome College	0.095	0.068	1.386	0.166
homeless_12mo_priorNot Reported	0.057	0.062	0.927	0.354
homeless_12mo_priorYes	0.081	0.041	1.982	0.048
victim_race_whiteNot Reported	0.044	0.072	0.606	0.544
victim_race_whiteY	-0.045	0.034	-1.351	0.177
victim_sexMale	0.048	0.031	1.532	0.125
victim_sexNot Reported	0.121	0.205	0.589	0.556
victim_knownNot Reported	0.085	0.198	0.433	0.665
victim_knownStranger	-0.019	0.032	-0.575	0.565

Table 10: AFT (log-normal) Model Output (with race and victim
race white/non-white) (*continued*)

Model Term	Estimate	Standard Error	Test Statistic	p-Value
victim_hispanicNot Reported	-0.191	0.109	-1.747	0.081
victim_hispanicYes	0.035	0.044	0.793	0.428
victim_age18 to 24	0.050	0.059	0.847	0.397
victim_age25 to 34	0.033	0.054	0.604	0.546
victim_age35 to 54	0.076	0.053	1.435	0.151
victim_age55 or Older	0.087	0.069	1.269	0.204
victim_ageNot Reported	0.003	0.090	0.039	0.969
victim_ageUnder 12 Years	0.119	0.058	2.060	0.039
Log(scale)	0.150	0.007	21.359	<0.001