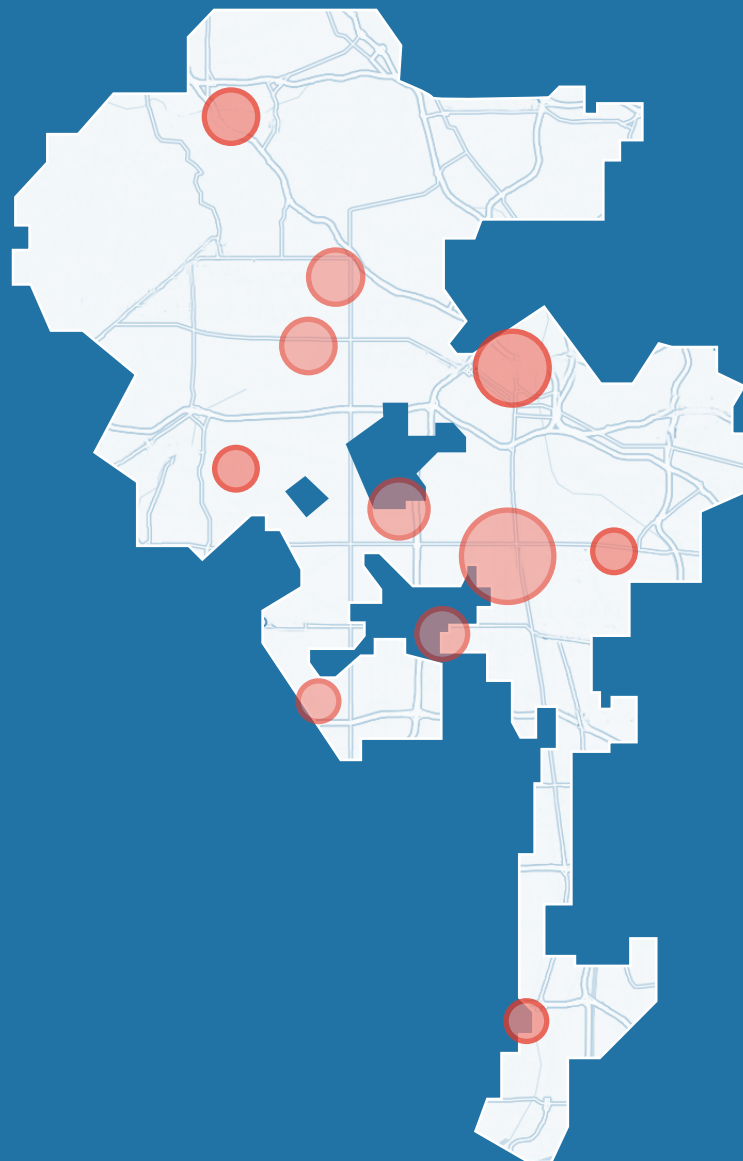


The Future of Crime in Los Angeles and the Impact of Reducing the Prison Population on Crime Rates

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Summary

We developed statistical models to “predict” past yearly changes in rates of violent and property crime from the early 1960s through 2021, employing a very small set of predictive variables known to be associated with levels of crime. The yearly changes projected for those years correspond quite closely to the actual changes. We then use the models to forecast crime trends through 2026. Our models forecast a rise in Los Angeles’s violent and property crime rates in 2022. (The actual 2022 rates are not known at time of publication.) Violent crime is then expected to fall and property crime to rise slowly during the next several years. We also project crime trends under a hypothetical policy of augmenting by 20% California’s recent reduction in its imprisonment rate. We find that this additional decrease in imprisonment would have a negligible effect on Los Angeles’s crime rates, with annual increases of less than 1% in violent crime and less than 2% in property crime. We conclude with recommendations for the optimal implementation of such a reduction in imprisonment: it should proceed in a measured way over a number of years and be counterbalanced by enhanced community-based monitoring and support.

Introduction

Major changes in America's crime rates have occurred since the 1960s. After several decades of relative stability, a significant, unanticipated uptick in crime began in the mid-1960s, reaching historic peaks in the early 1980s and then again in the early 1990s. Between 1960 and 1991, crime rates more than tripled. Just as unexpectedly, crime then started what became a long and steady decline, eventually returning to mid-1960s levels. Crime trends in Los Angeles have followed these national trends.

This historical volatility means policymakers are uncertain whether crime rates will continue their current long-term decline, stabilize, or begin once again to increase. The ability to forecast near-term changes would be immensely useful to those responsible for choosing among crime policy options. While a reasonable body of research has identified factors associated with past crime rates (e.g., Rosenfeld 2011; Rosenfeld and Levin 2016), comparatively little attention has been paid to projecting future crime rates.

With funding from The Harry Frank Guggenheim Foundation (HFG), we developed a model for forecasting crime rates based on factors that were associated with the rapid increase and subsequent decline in US crime rates from 1960 to 2021, with forecasts to 2025 (Austin and Rosenfeld 2023). While a national-level overview is useful, it is simply the weighted average of the conditions that influence crime rates and the decisions reflected in crime-control policies in smaller jurisdictions, which may vary widely. State and local studies are needed to analyze the conditions and policies that affect local crime trends.

The current study examines the effects of a small set of factors on violent crime and property crime rates in Los Angeles.¹ We found that a statistical model incorporating the state imprisonment rate and a measure of the cost of living (inflation divided by median household income) explained past variation in crime rates with minimal error. Different substantive variables were not needed to explain the year-to-year variation in violent and property crime: the results are robust not only within crime types, but also between them.

¹ The violent crime rate is the sum of the homicide, aggravated assault, rape, and robbery rates. The property crime rate is the sum of the burglary, larceny, and motor vehicle theft rates.

We then used the model to forecast crime rates through 2026. We also conducted a hypothetical policy experiment to estimate the impact on the forecasted crime rates of a sizable reduction in the California state prison population. We found negligible effects on Los Angeles crime rates of decreasing the incarceration rate.

Modeling Crime Rates

A statistical model that would guide policymaking must meet two requirements: (1) it must include factors that not only explain the outcome but also are modifiable by policy, and (2) it must be accurate. Our forecasting model of Los Angeles crime rates stands up well against both of these criteria. It incorporates policy variables with robust effects on violent and property crime rates, and it produces estimates that are generally close to the observed values of the crime rates.

With just sixty annual observations, the effects of a large number of variables cannot be reliably estimated in a forecasting model. With a longer time series we could have included in our model several additional variables known to affect crime trends. These include the age composition of the population, lagged and contemporaneous birth rates, numerous economic indicators, such as poverty and economic growth rates, and several criminal justice indicators. We experimented with a large number of models containing a varying mix of demographic, socioeconomic, and criminal justice variables before settling on a model that contains only the past year's imprisonment rate and the current year's inflation rate, adjusted by median household income. Prior research has shown that each of these variables is associated with changes in crime rates over time, and the logic for including them in our model is fairly straightforward. Increases in the imprisonment rate are expected to reduce crime on the assumption that punishment incapacitates offenders and deters criminal behavior. The magnitude of the effect of imprisonment on crime varies widely across studies, however, and some studies indicate that it weakens at high levels of imprisonment (National Research Council 2014).

Prior research indicates that inflation has strong and consistent effects on crime committed for monetary gain: as retail prices increase, so does the demand for cheaper stolen goods (Rosenfeld and Levin 2016). Inflation is also expected to contribute to both violent and property crime by reducing confidence in government and other institutions (LaFree 1999). Crime rates, especially the property rate, should vary with purchasing power, which is the rationale for adjusting the inflation rate by median income (inflation/median household income). The imprisonment rate and income-adjusted inflation rate are incorporated in the multivariate forecasting models described below.

The Near Future of Crime in Los Angeles

Forecasting the future of crime is always risky because such predictions are based on crime-related factors whose future values are unknown. Projecting changes in crime rates, even in the near term, is especially difficult in the current period. The social response to the COVID-19 pandemic and the widespread unrest surrounding violent police actions influenced crime rates in ways that were difficult to foresee (Rosenfeld et al. 2022). If the study of crime trends is to have policy relevance, however, it will come mainly from forecasting. Policymakers have an interest in past crime rates mainly insofar as they portend future rates. The planning horizon for criminal justice policy rarely extends beyond a few years, and forecasting models should be calibrated accordingly.

Forecasting models will always contain error. They may be *inaccurate* (the crime rate falls outside the forecast range) or *imprecise* (the crime rate is within the forecast range, but the range is so broad it has little practical utility). Useful and reliable forecasting always involves a tradeoff between precision and accuracy.

Finally, crime forecasting is the most exacting way to test hypotheses about changes in crime rates. To avoid overfitting the data used to develop it, an empirical model should always be evaluated with “out-of-sample” observations. The typical way of testing a statistical model of the change over time in crime rates is to determine how it fits the data used to generate the model—in other words, data on *past* crime rates. This is a necessary but not sufficient method of theory testing. An adequate test will assess how well the model predicts values that were not used in its construction. This test does not require waiting until the future arrives. It simply requires reserving some data from the sample used to generate the model and measuring how well it predicts these out-of-sample observations. We perform such a validation exercise and then use our model to forecast Los Angeles’s violent and property crime rates through 2026.

Forecasting Method

We derive our forecasts of Los Angeles crime rates from sample data spanning the period 1960 to 2016. Two out-of-sample forecast periods are examined. The first is the period between 2017 and 2021. This five-year out-of-sample period, for which the violent and property crime rates are known, is used to validate the forecasts derived from a model based on the 1960–2016 data. We chose a five-year validation window to minimize “continuity bias” (i.e., the disproportionate influence of very recent values of the crime rates) in our forecasts. The violent and property crime rates for 2022 to 2026 are then forecasted.² The forecasting exercise is summarized in the text, and technical details can be found in the Appendix.

A first step in forecasting the values of a time series is to evaluate the series for “stationarity.” A stationary series is one in which the mean and variance of the series are constant or nearly so over time. Forecasts of a stationary time series are more reliable than those of a nonstationary series. Statistical tests showed that Los Angeles’s violent and property crime rates between 1960 and 2016 are nonstationary.

A common approach to transforming a nonstationary time series to a stationary series is to first-difference the series. First-differencing transforms a series measured in levels (in this case, crime rates) to one in which each data point is the difference between the variable’s current and previous level (i.e., this year’s crime rate minus last year’s crime rate). Second- and higher-order-differencing can be applied if first-differencing does not produce stationarity. First-differencing was sufficient to produce stationarity in both the violent and property crime series (see Appendix).

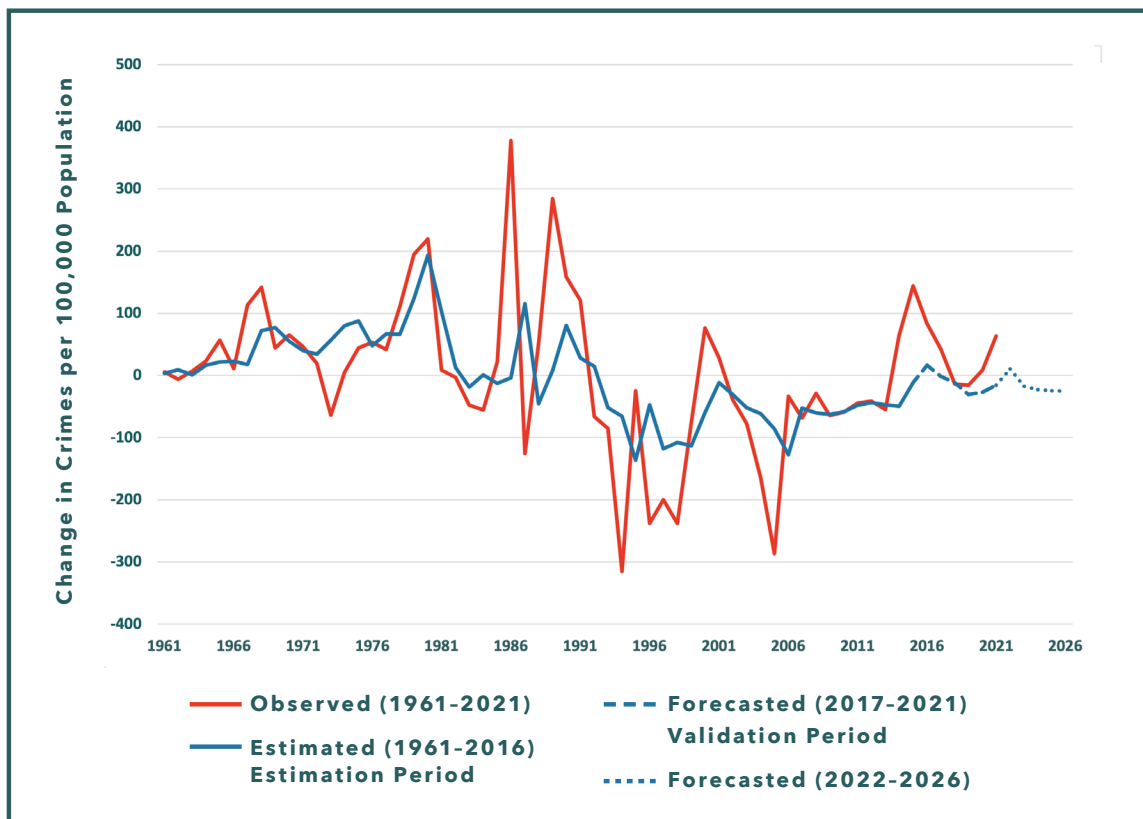
Autoregressive integrated moving average (ARIMA) models were used to forecast the first-differenced violent and property crime rates. ARIMA models are commonly used in forecasting because they offer a thorough assessment of the key statistical properties of a time series. A parsimonious multivariate ARIMA model was created that contains the two variables with the most robust effects on crime rates in the Rosenfeld and Levin (2016) study: the inflation rate (adjusted by median household income) and the imprisonment rate.³

² Although the start of this period precedes the time of publication, the crime rates for these years were not known when the report was written.

³ The inflation data are from the Bureau of Labor Statistics (<https://www.bls.gov>), and the imprisonment data are from the Bureau of Justice Statistics (<https://bjs.ojp.gov>). The inflation rates for 2023 to 2026 and the income and imprisonment rates for 2022 to 2026 were unknown at the time of this writing. The 2023–2026 inflation rates were assumed to be equal to national inflation forecasts from the Congressional Budget Office (<https://www.cbo.gov/data/budget-economic-data#4>). The forecasted 2022–2026 income and imprisonment values are based on the average yearly rate of change in these measures between 2017 and 2021 (3.4% and -4.4%, respectively). For example, the median household income forecast for 2022 is assumed to be 3.4% greater than median household income in 2021, the forecast for 2023 to be 3.4% greater than the 2022 forecast, and so on.

The forecast models were fit to the first-differenced violent crime rate and to the property crime rates between 1960 and 2016. The years 2017 to 2021 were “held back” from the models so they could be used to validate the forecasts from the 1960–2016 baseline period. The closer the forecasted crime rates are to the observed rates during the validation period, the greater our confidence in the forecasts for 2022 to 2026, when the crime rates are unknown. The forecast results are presented in Figures 1 and 2.

FIGURE 1. OBSERVED AND FORECASTED YEAR-OVER-YEAR CHANGE IN LOS ANGELES VIOLENT CRIME RATE, 1961-2026

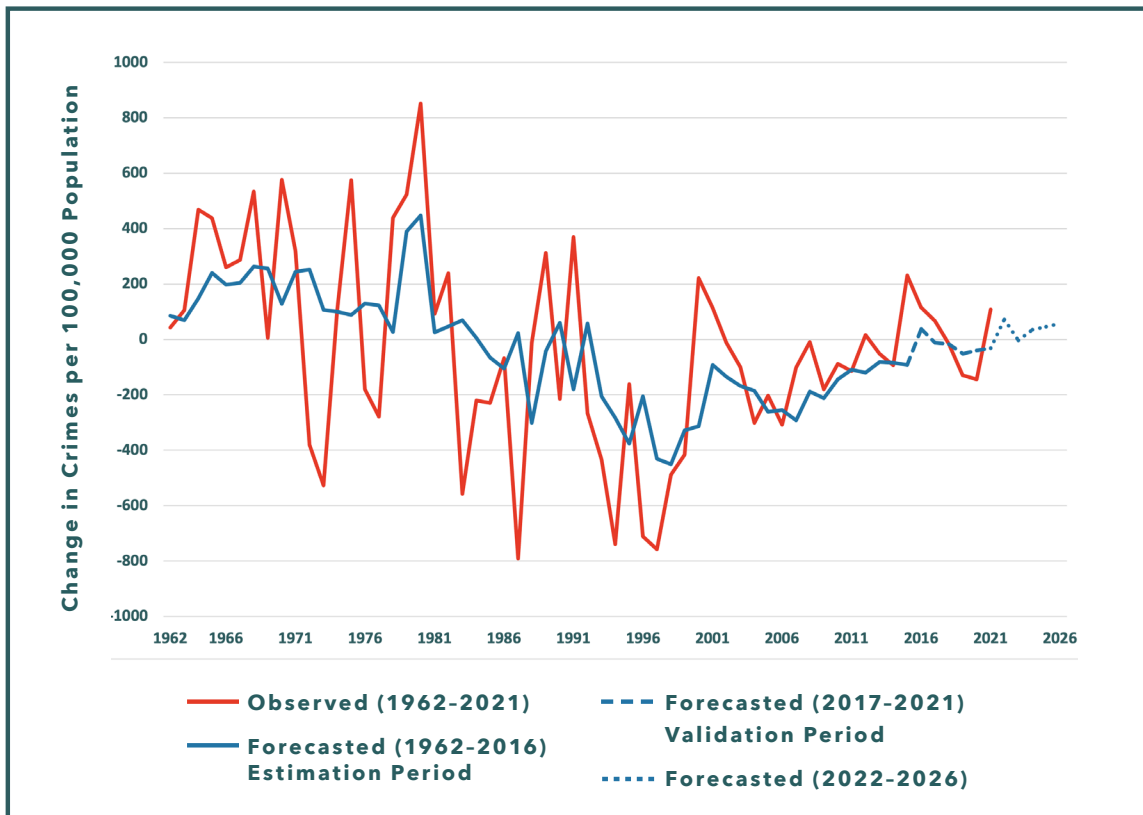


Source: FBI's Uniform Crime Reports.

Figure 1 displays the observed and forecasted annual changes in the violent crime rate. The observed changes, denoted by the red line, extend from 1961 to 2021.⁴ The in-sample estimated changes through 2016 are denoted by the solid blue line, and the dashed blue line represents the forecasted changes during the 2017–2021 out-of-sample validation period. The dotted blue line represents the forecasted changes in the violent crime rate between 2022 and 2025.

The forecasted yearly changes in violent crime generally correspond with the observed changes during the 2017–2021 validation period, with one exception: the difference between the observed and forecasted change in violent crime in 2021 (discussed below). The results suggest that Los Angeles’s violent crime rate will increase in 2022 and then fall through 2026.

FIGURE 2. OBSERVED AND FORECASTED YEAR-OVER-YEAR CHANGE IN LOS ANGELES PROPERTY CRIME RATE, 1962-2026



Source: FBI's Uniform Crime Reports.

⁴ Given how the respective ARIMA forecast models are specified, the violent crime series and property crime series shown in Figures 1 and 2 begin in 1961 and 1962, respectively (see Appendix).

The observed and forecasted property crime rates during the validation period are also very similar. The results shown in Figure 2 suggest that the property crime rate will rise in 2022 and then increase modestly through 2026.

Forecasts of an unknowable future will always contain error. This means that the policymaker will have to decide how much forecast error is tolerable, which is a substantive and not a statistical decision. We will assume for current purposes that forecasted crime rates that diverge from the observed rates by no more than 10% are sufficiently accurate and precise for both policy and theory evaluation. A forecasted annual rate that fell outside of these limits would be uninformative and suggest that the forecast model needed to be revised.

Appendix Table A displays the observed and forecasted Los Angeles crime rates during the validation period. Averaged over the 5 years of the validation period, the forecast error for violent crime—the difference between the observed and forecasted rates in either direction—is 4.6%, well within the 10% tolerance limits. The forecast error falls within the 10% tolerance limits in each of the five years of the validation period, although the -9.8% error in 2021 is substantial. The Los Angeles violent crime rate rose by 8.5% between 2020 and 2021, from 741 to 804 violent crimes per 100,000 population. By contrast, the forecasted 2021 rate increased by only 2.8% from the forecasted rate for 2020. The forecasted violent crime rate rises in 2022 and then falls over the next four years to its level in 2019, the year before the onset of the pandemic.

An unanticipated 8.5% rise in the violent crime rate in a single year would have caught policymakers and law enforcement officials off guard had they relied for planning purposes on the crime forecasting model used here. The increase in Los Angeles's violent crime rate could well have resulted from the murder of George Floyd by a Minneapolis police officer in late May of 2020 and ensuing mass protests around the country. These events reduced nationwide trust in the police.⁵ When police legitimacy declines, acceptance of private violence to settle disputes grows (Tyler, Goff, and MacCoun 2015). Such unexpected “exogenous shocks” to crime rates would be difficult for any forecast model to capture.

The average forecast error for property crime during the 2017–2021 validation period is 3.3%, and none of the errors during the validation period is above 6%, well within the tolerable forecast range. With the exception of motor vehicle theft, property crime rates fell in cities

5 <https://news.gallup.com/poll/183704/confidence-police-lowest-years.aspx>

across the country at the height of pandemic lockdowns in 2020. Property crime and robbery rates increased in 2021 and 2022, as the pandemic response wound down and inflation increased (Rosenfeld et al. 2022). Los Angeles's property crime rate is forecasted to rise by 9.3% from 2021 to 2022 and then increase more slowly through 2026.

We cannot be certain, of course, that our forecasts will be sufficiently accurate and precise to serve as reliable policy guides, and policymakers may choose to set more restrictive tolerance limits around the forecast errors than the illustrative 10% limits we have used. Our results suggest, however, that Los Angeles is unlikely to experience large and sustained crime increases during the next several years. As of this writing, the pandemic's disruptive consequences have wound down, and social unrest of the intensity and scale seen in 2020 and 2021 has not returned. But the last few years serve as a reminder that crime rates are subject to unanticipated jolts that can throw off even the most reliable predictions of the future.

Key Takeaway

Our models forecast a rise in Los Angeles's violent crime rate and property crime rate in 2022. Violent crime is then expected to fall and property crime to rise slowly during the next several years. The generally small forecast errors during the validation period inspire confidence in the violent and property crime forecasts for 2022 and 2026.

The Impact on Los Angeles Crime Rates of Reducing the Prison Population

We have suggested that the policy relevance of any statistical model depends on whether the elements of the model are, in fact, modifiable by policy. The size of the prison population is clearly a modifiable policy outcome. It can be reduced by altering the policies that determine prison admissions and the sentencing and parole policies that regulate length of stay and releases. Such proposals, however, invariably run up against concerns that reducing the incarcerated population will increase crime. These concerns are not unreasonable. We would not have included the imprisonment rate in our forecasting models if we believed it had no impact on crime rates. But the size of this impact is an empirical question that continues to occupy researchers.

Suppose that in 2022, state policymakers had decided to reduce the California state imprisonment rate, which had been declining for over a decade, by an *additional* 20%? What impact would such a reduction have on Los Angeles crime rates? We assume that a reduction in imprisonment of this magnitude would not occur in a single year but would unfold in a five-year planned decline. This time frame is realistic, and it has the added benefit of providing ample time for policymakers and criminal justice officials to make mid-course corrections as needed.

Figures 3 and 4 compare two forecasts of Los Angeles's violent and property crime rates between 2022 and 2026: the original forecast, as shown in Appendix Table A, and the forecast assuming an additional 20% reduction in the imprisonment rate over the five years. The other variables in the model remained at their forecasted values.

FIGURE 3. LOS ANGELES VIOLENT CRIME RATE FORECASTS, WITH AND WITHOUT ADDITIONAL 25% IMPRISONMENT REDUCTION

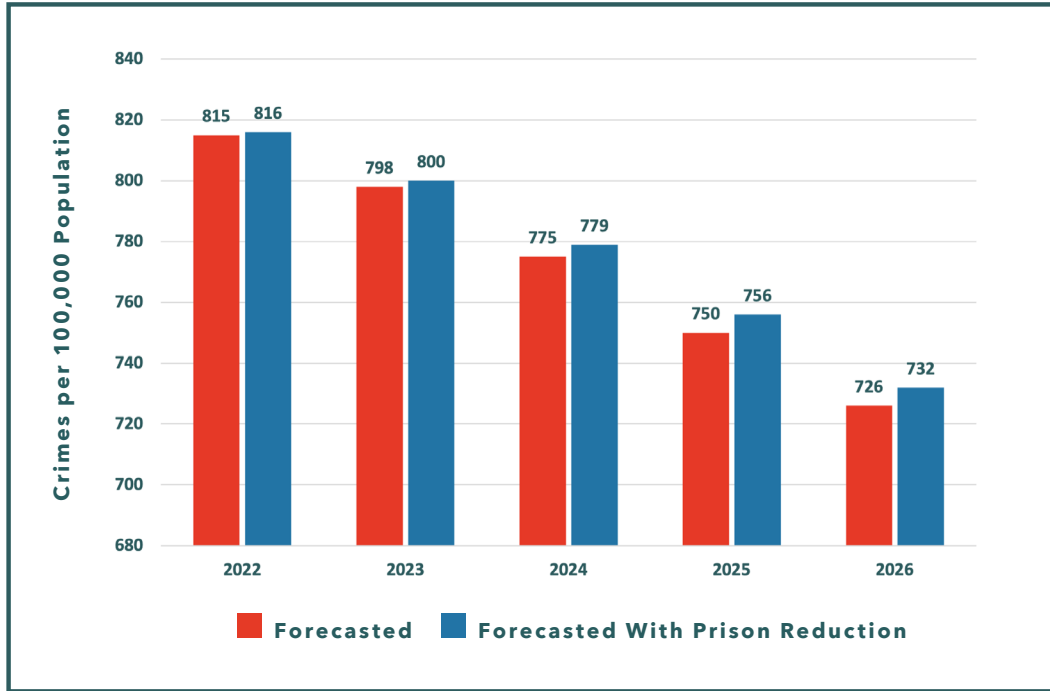
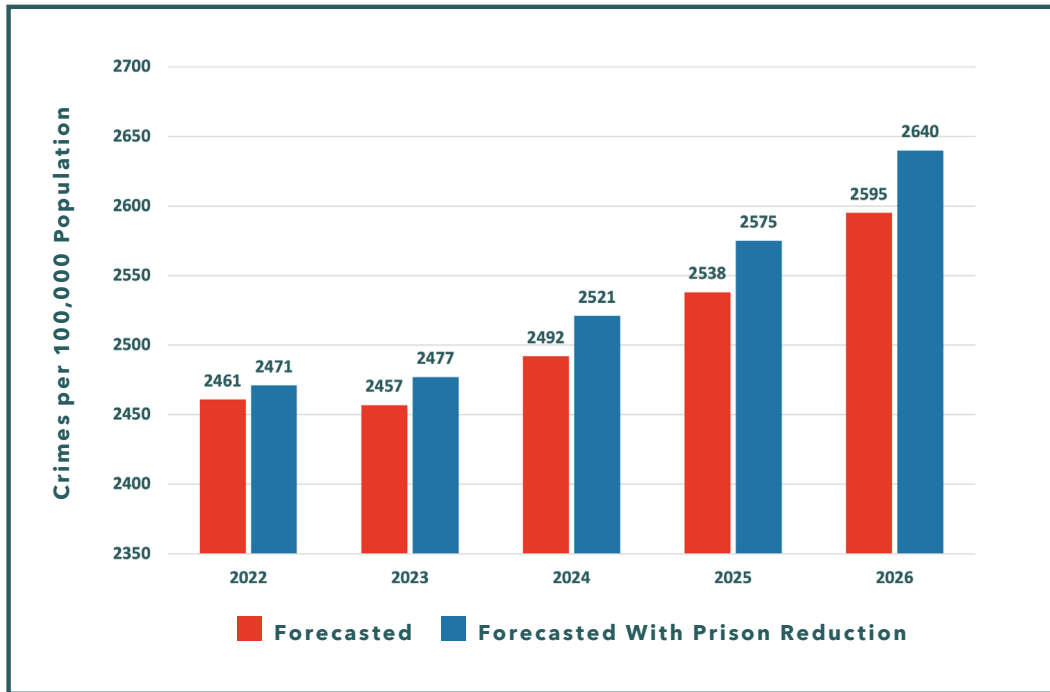


FIGURE 4. LOS ANGELES PROPERTY CRIME RATE FORECASTS, WITH AND WITHOUT ADDITIONAL 25% IMPRISONMENT REDUCTION



The reduction in the state imprisonment rate between 2022 and 2026 would have a negligible effect on Los Angeles's crime rates: an annual increase of less than 1% in violent crime and less than 2% in property crime. And there are reasons to believe that even these very small forecasted increases are overestimates. First, this exercise assumes that the *total* prison population is reduced by 20%. The policy change, however, would almost certainly be more selective, for example by limiting early release from prison to older inmates and others at relatively low risk of reoffending.

Second, the exercise assumes that no more provision would be made than in past practice to monitor or assist those who would be released from prison, which seems unlikely. Conscientious reform proposals should include additional community supervision as an alternative to incarceration and increases in vocational training, job placement, and mental health and substance abuse treatment for releasees (Rosenfeld and Grigg 2022). A responsible approach to decarceration would implement evidence-based forms of supervision and support at the same time.

Key Takeaway

An additional 20% reduction in the state imprisonment rate between 2022 and 2026 would have a negligible effect on Los Angeles's crime rates: an annual increase of less than 1% in violent crime and less than 2% in property crime.

Conclusion

The hazards of predicting the future of crime are obvious, even when the predictions are based on a reliable statistical model of past crime trends. Some conditions affecting crime rates, such as the aging of the population, can be forecasted with reasonable accuracy. But many others cannot. No one to our knowledge predicted the coronavirus pandemic, George Floyd's murder and the following period of widespread social unrest, or the momentous recent increase in inflation. While we have assumed that the effects of the COVID-19 pandemic on crime rates were temporary, it could have lingering or even permanent effects in the form of educational deficits resulting from school closures and online instruction and changes in population mobility as more people choose to work from home. It would be a mistake to discount the possibility of another inflammatory episode of police violence and social unrest. And, despite optimistic forecasts, the pace at which the current spike in inflation will subside remains uncertain. The lesson is to proceed cautiously, acknowledge the error that accompanies all forecasts, and decide how much error is acceptable for policy planning and evaluation. Most important, predicting the future of crime should be based on models that are continuously recalibrated to take account of new information and of the variation in local conditions to which crime policy must respond.

Appendix: Forecast Methods and Models

Testing the Crime Series for Stationarity

Two formal tests were conducted to determine whether the Los Angeles violent and property crime time series contain a unit root (i.e., are nonstationary). Both the augmented Dickey–Fuller (ADF) test and the Phillips–Perron (PP) test failed to reject the null hypothesis of a unit root for violent crime and for property crime. Los Angeles violent and property crime rates between 1960 and 2016 are nonstationary and conform to a random walk. Both series were therefore converted to first differences and the same tests were conducted. The tests revealed that both violent crime and property crime are stationary in first differences.

ARIMA Models and Forecasting Results

ARIMA models estimate the autoregressive (denoted p), differencing (denoted d), and moving average (denoted q) properties of a time series. Several multivariate ARIMA(p,d,q) models containing the income-adjusted inflation rate and the imprisonment rate were estimated on the violent and property crime rates. The models that minimized the mean-squared errors and mean absolute errors of the estimates for both the estimation period (1960–2016) and validation period (2017–2021) of the time series were retained. These models were then used to forecast Los Angeles’s violent and property crime rates for 2022 to 2026.

In Table A, the year-to-year forecasted changes in Los Angeles’s violent crime rate are added to the previous year’s rates to generate forecasts of the current year’s rates during the validation period. The best-fitting forecast model for violent crime is an ARIMA(1,0,0) model, which contains a first-order autoregressive term in addition to the substantive covariates. Given the inclusion of the autoregressive term, the violent crime time series shown in Figure 1 begins in 1961. The model forecasts violent crime rates during the 2017–2021 validation period that diverge in either direction from the observed rates by an average of 4.56%. The largest divergence is in 2021. The forecasted violent crime rate is nearly 10% lower than the observed rate in that year. The forecasts through 2025 suggest that violent crime rates will increase in 2022 and then fall through 2026.

TABLE A. ARIMA FORECASTS OF LOS ANGELES VIOLENT AND PROPERTY CRIME RATES, 2017-2026

	Violent Crime (ARIMA _(1,0,0))			Property Crime (ARIMA _(1,1,1))		
	Observed Rate	Forecasted Rate	Percentage Error	Observed Rate	Forecasted Rate	Percentage Error
	Validation Period					
2017	761	717	-5.78%	2571	2493	-3.03%
2018	748	750	.27%	2554	2554	.00%
2019	732	717	-2.05%	2425	2502	3.18%
2020	741	705	-4.86%	2281	2386	4.60%
2021	804	725	-9.83%	2389	2250	-5.82%
MAPE ¹			4.56%			3.33%
	Forecast Period (Observed Rate Unknown)					
2022	815		2461			
2023	798		2457			
2024	775		2492			
2025	750		2538			
2026	726		1809			

MAPE¹ = Mean absolute percentage error

The best-fitting forecast model for property crime is an ARIMA(1,1,1) model that contains a first-order autoregressive term, a first-order moving average term, and a first-difference term, in addition to the substantive covariates. For this reason, the property crime time series shown in Figure 2 begins in 1962. On average, the forecasted property crime rates diverge from the observed rates by 3.33% during the validation period. The largest divergence is in 2021, when the forecasted property crime rate is nearly 6% lower than the observed rate. The forecasts suggest that Los Angeles’s property crime rate should rise between 2021 and 2022 and then increase more slowly through 2026.

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