Forecasting US Crime Rates and the Impact of Reductions in Imprisonment: 1960-2025

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Abstract

This is a follow-up to a report by the authors that developed a forecasting model for crime rates in the United States (Austin, Clear, and Rosenfeld 2020). The report argued that the twenty-five-year decline in crime should be expected to continue into 2021, absent unforeseen exogenous shocks to the factors associated with changes in crime rates. The analysis also showed that substantial reductions in imprisonment could be achieved without significantly increasing crime. In the current study, the authors revise the original model and extend crime forecasts to 2025 in light of two such unanticipated shocks: the worldwide COVID-19 pandemic and widespread unrest in reaction to police violence. The model continues to perform well and supports the expectation that in the near future the violent crime rate will increase modestly and then flatten, while the property crime rate will continue its longstanding decline. The authors again conclude that sizeable reductions in prison populations can be achieved without substantially increasing crime.

Introduction

Three years ago, we proposed two models for forecasting future crime rates (Austin et al. 2020). Our forecasts relied on demographic, economic, and criminal justice indicators that are related to historic changes in the nation's violent and property crime rates, which had been declining more or less steadily since the mid-1990s. Using these indicators, we projected that the nation's violent and property crime rates would continue to fall in the near future. We also showed that changes in the size of the nation's prison population would have little impact on either violent or property crime.

Our projections made assumptions about the stability of demographic and economic trends. We acknowledged the possibility that "substantial changes in factors not considered in our models — "exogenous shocks" — could drive crime rates above or below our projections." We could not have known it at the time, but the United States was about to experience just such a shock: the COVID-19 pandemic.

The economic and social impacts of the pandemic are still under study, but both have clearly been immense. There is also no doubt that the pandemic has affected factors that are associated with crime rates. Inflation, which plays a major role in our forecasts, increased dramatically during the pandemic, something that was wholly unexpected when we first wrote.

Our original projection that crime rates would continue to decline has, despite the effects of the pandemic, proven to remain generally accurate for property crime but somewhat less accurate for violent crime, which our current analysis indicates should increase very modestly over the next few years and then stabilize. In this follow-up study, we revisit our original crime projections, giving special attention to changes associated with the pandemic and the widespread social unrest following George Floyd's murder in 2020. We investigate how well our models account for recent patterns of both violent and property crime and extend the time period under investigation back to 1960 and forward to 2025. We also take a second look at the estimated impact of incarceration policies on crime.

Trends in US Crime

There are two primary ways that crime rates are estimated in the United States: the Uniform Crime Reports (UCR) compiled by the Federal Bureau of Investigation (FBI) and the National Crime Victimization Surveys (NCVS) conducted by the US Census and reported by the Bureau of Justice Statistics.[1] The UCR counts crimes reported to the police and has the advantage of long history and coverage of over eighteen thousand police agencies, representing 97% of the nation's population. The NCVS, through a representative sample of about 150,000 households, has the advantage of capturing crimes that were not reported to the police. Both methods have the disadvantage of delay in reporting, with about a year needed for each system to report its results.

The UCR violent crime rate includes homicides, rapes, robberies, and aggravated assaults and is expressed as the number of all violent crimes per 100,000 population. The UCR property crime measure includes burglaries, larcenies, and motor vehicle thefts per 100,000 population. Figure 1 shows the pattern of violent and property crime as estimated by the UCR from 1931 to 2020.

FIGURE 1. UCR CRIME RATES, 1931–2020
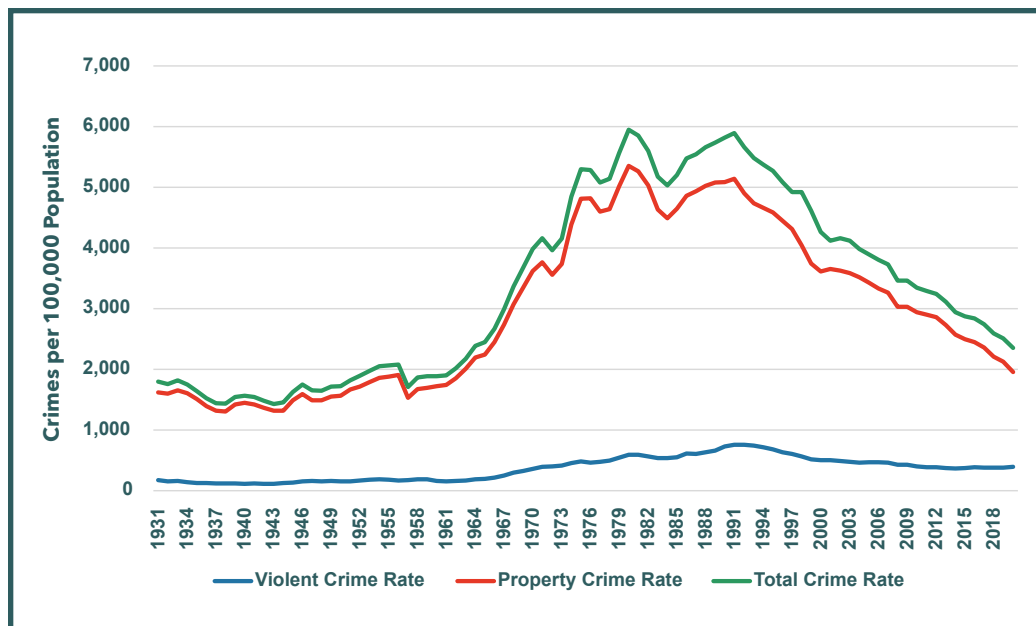
Source: FBI's Uniform Crime Reports.

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1 As of January 1, 2021, the UCR "summary system" was replaced by the FBI's National Incident-Based Reporting System (NIBRS), which requires law-enforcement agencies to report a greater range of crimes and more detail on each crime. However, only about two-thirds of the US population was covered by the agencies reporting in that year, so that at the time the current analysis was conducted, reliable estimates of US crime rates were not available for the years after 2020.

The overall story of the UCR police-recorded crime rates is a dramatic four-decade increase, followed by an equally dramatic three-decade decline. After an initial period of relative stability, UCR crime rates began to rise in the 1960s, peaking twice, first around 1980 and again around 1990. Since the early 1990s, there has been a steady decline. By 2020, the UCR property crime rate had fallen to levels not seen since the 1960s. Violent crime has fallen by half since the 1990s peak.

**FIGURE 2. NCVS CRIME RATES, 1993–2020**
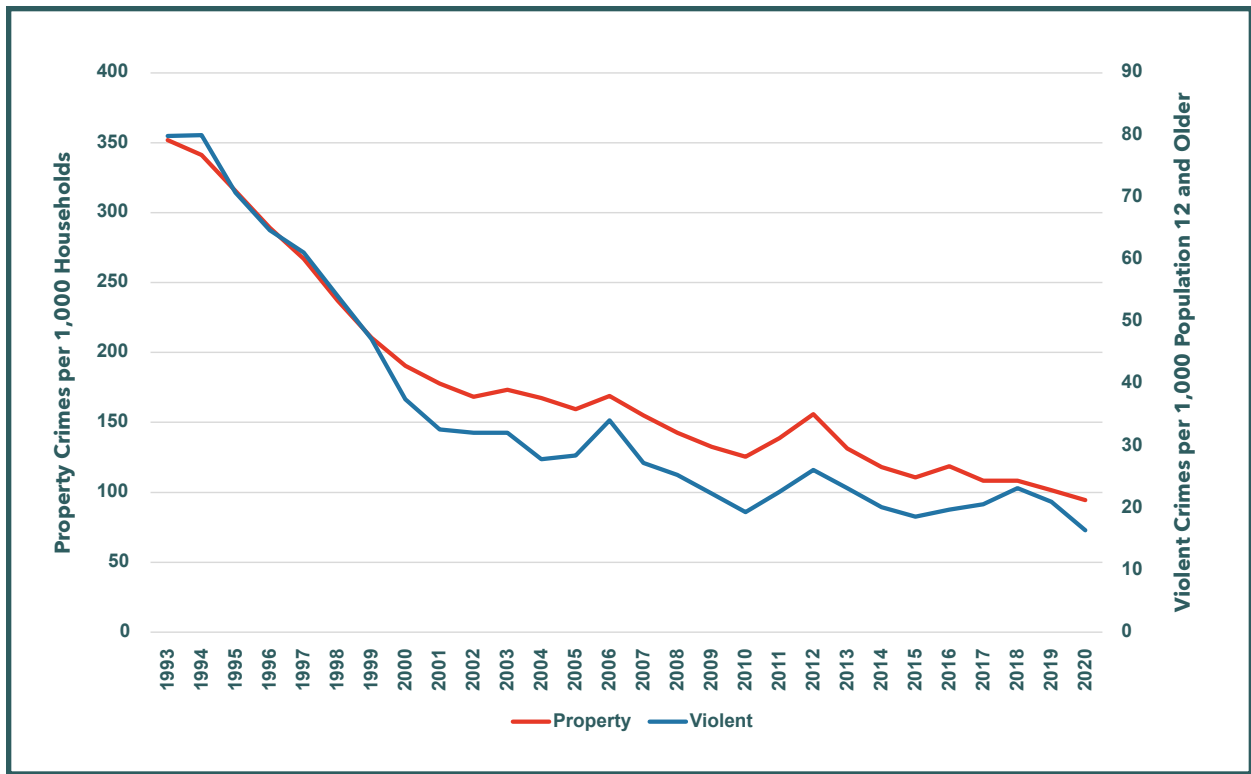
Source: National Crime Victimization Survey, US Bureau of Justice Statistics.

Figure 2 shows the NCVS estimates from 1993 to 2020. The NCVS estimates crime rates based on surveys of representative samples of households. Residents aged twelve or older are asked if they have been a victim of a crime during the past six months. For those who have been, the survey records the details of the crime or crimes. Because crimes that are not reported to police and less serious crimes (such as simple assault) are included, the volume of crimes captured in the NCVS is much higher than the numbers in the UCR data. For example, in 2019, the NCVS estimated a total of 18.6 million property and violent crimes while the UCR total was 8.1 million.

Despite these differences in how crime is measured and in the total amount of crime estimated, the recent trends are similar according to the UCR and the NCVS. The data sets show equivalent declines in property and violent crime from 1993 to 2020, confirming that the country has been experiencing a lengthy period of steadily declining crime. The UCR reported a small increase in violent crime in 2020, though property crime continued to decline. As has been much discussed in the media and by national advisory groups, however, the last two years have seen a spike in the most serious violent crime: homicide (Rosenfeld and Lopez 2022). The homicide surge, while obviously very serious, contributed little to the overall rise in the violent crime rate because homicides constitute a small fraction of all violent crimes (less than 2% in 2020).

FIGURE 3. IMPRISONMENT RATES AND UCR CRIME RATES, 1931–2020
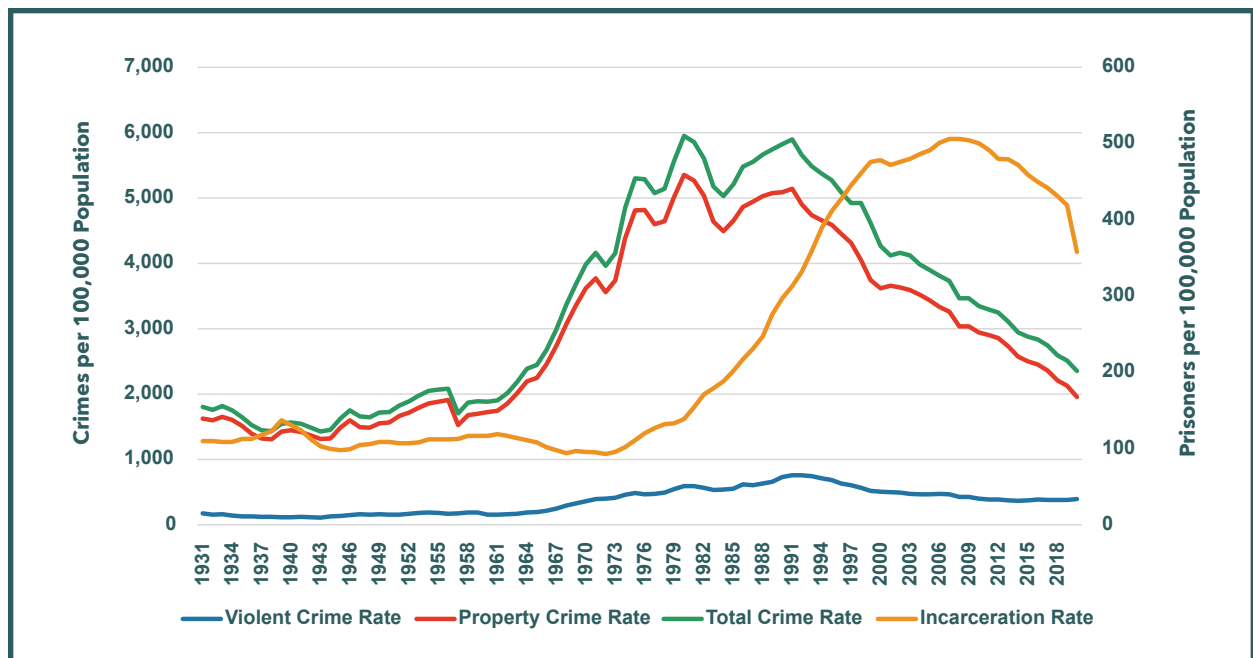
Sources: Crime rates, FBI's Uniform Crime Reports; imprisonment, US Bureau of Justice Statistics.

Figure 3 adds the state and federal imprisonment rate to the UCR crime trends. If imprisonment has a strong deterrent effect on crime, we should see falling crime rates at least roughly associated with rising imprisonment rates. But that is not what we see. If anything, increasing crime rates appear to correspond with increasing rates of imprisonment until about 2008, after which imprisonment begins to fall as crime rates are declining. To properly assess the effect (if any) of imprisonment rates on crime rates, however, other factors affecting crime must be investigated at the same time.

Modeling Crime Rates

In our 2020 report, we presented a statistical model based on national-level data to explain historical trends in UCR violent and property crime rates since 1980 and to project future crime rates to 2021. In this follow-up, we update the models with current data to develop crime rate forecasts to 2025.

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 national 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 very 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 (Rosenfeld 2011; Rosenfeld and Levin 2016). 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 (discussed below). 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.

Forecasting Crime Rates

Crime forecasts have never been widespread in criminology, but they have all but disappeared in recent years.[2] The current unpopularity of crime forecasting is likely attributable to the wildly inaccurate forecasts by criminologists of an impending crime boom just as crime rates were beginning their historic drop in the early 1990s. James Alan Fox, a distinguished criminologist and dean of the Northeastern University College of Criminal Justice, wrote: "The worst is yet to come. I believe we are on the verge of a crime wave that will last into the next century" (quoted in Schuster 1995). Princeton University political scientist and criminologist John DiIullio (1995) coined the term "superpredator" to describe the morally impoverished youth who would fuel the looming crime boom (see also Haberman 2014). This was not criminology's finest hour.

The problem with the inaccurate crime forecasts of the 1990s was not that they were inaccurate. The problem was that they were not based on a verifiable model of crime trends, or any model at all, other than projections based only on the size of the adolescent population. The mistakes of thirty years ago need not be repeated and should not deter renewed efforts at crime forecasting. If the study of crime trends is to have policy relevance, it will come mainly from forecasting. Policymakers have an interest in past crime rates mainly insofar as they portend future changes. 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, a theory's statistical 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

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2 Recent interest in areal predictive policing is something of an exception, but it is limited to short-run (time of day, days, weeks) forecasts in crime hot spots and other small urban spaces. Predictive policing algorithms focused on individuals have been criticized for lack of methodological transparency, racial bias, and ineffectiveness in reducing crime (Lau 2020).

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 the model predicts these out-of-sample observations. We perform such a validation exercise in our forecasts of US violent and property crime through 2025.

Forecast Methods

We present two methods for forecasting national crime rates. The first, a qualitative method, assesses the probable impact of a large number of crime-related conditions on future crime rates. The second method is based on a formal statistical forecasting model.

Qualitative Method

One way to estimate the influence on crime rates of a large number of economic, demographic, and criminal justice correlates of crime rates is to use an additive point scale that indicates the separate and combined direction of each over time. This qualitative approach, which was used by criminologists as early as the 1920s in developing individual risk instruments, can also be employed to gauge the direction of aggregate crime rates in response to expected changes in the factors that influence crime.[3]

Table 1 shows twelve major correlates of crime rates and the expected direction of each. The twelve factors are grouped into four sectors: demographic, household, economic, and criminal justice. For example, it is expected that the percentage of the population aged fifty-five and over will continue to increase over the next few years, which, all else equal, would dampen future crime rates. Likewise, assuming inflation either increases or remains at its current high levels, we would expect it to increase crime rates.

Each variable has been assigned a value of -1, 0, or +1, representing its expected direction of change, if any, and thus its effect on crime rates. A value of +1 indicates that the variable will put upward pressure on crime, -1 indicates a negative (crime-reducing) impact, and 0 indicates no appreciable impact. A total score is calculated for each sector. The sum of these scores—with

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3 More recently, additive point scales have been used in studies of selective incapacitation (Greenwood and Abrahamson 1982) and a variety of other pretrial and parole board risk assessment systems (see Desmarais, Zottola, Duhart Clarke, and Lowder 2021).

a range of potential scores from -12 to +12—indicates the aggregate direction and degree of change in crime predicted by these factors. This method forecasts the impact of multiple factors on the *total* crime rate (i.e., the sum of the rates of violent and property crime). In this case, the overall score is -2, which suggests a slightly lower future crime rate.[4]

TABLE 1. PROJECTED DIRECTION OF CRIME RATE FACTORS

Sector	Projected Direction	Effect	Sector Score
A. Demographic Sector			**-2**
1. % of Population 15–24	Lower	-1	
2. % of Population 55+	Higher	-1	
3. Fertility Rate	Unchanged	0	
4. Teenage Birth Rate	Unchanged	0	
B. Household Sector			**0**
5. Households with People Under 18	Unchanged	0	
6. Total Household Size	Unchanged	0	
C. Economic Sector			**0**
7. Inflation Rate	Higher	+1	
8. Long-Term Interest Rate	Higher	+1	
9. Median Household Income	Lower	-1	
10. % In Poverty	Lower	-1	
D. Criminal Justice Sector			**0**
11. Total Corrections Population (Prison, Jails, Probation, and Parole	Lower	+1	
12. Juvenile Arrests	Lower	-1	
Total Score			**-2**

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4 In the criminal justice sector, reductions in the correctional population due to the pandemic are projected to remain in place, thus exerting modest upward pressure on crime rates. The decline in juvenile arrests is projected to reduce crime, as the declining number of juveniles entering adulthood with an arrest history portends fewer people involved in crime as adults.

Quantitative Method

The second approach to crime forecasting is to derive the forecasts from a formal statistical model. The sample data for the national forecasts span the period 1960 to 2015. Two out-of-sample forecast periods are examined. The first is the period between 2016 and 2020. 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 1960–2015 data. The second out-of-sample period is 2021 to 2025, for which we forecast crime rates. The crime rates for this period were unknown when these analyses were carried out.[5] 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 confirmed that the violent and property crime rates in the 1960–2015 period 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., $Y_t - Y_{t-1}$). Second- and higher-order differencing can be applied if first-differencing does not produce stationarity. First-differencing was sufficient to produce stationarity in the violent and property crime series.

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 data-generating process in a time series (Hyndman and Athanasopoulos 2018). 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. The imprisonment rate is lagged one year behind the crime rate. Lagging the imprisonment rate helps to mitigate but does not fully eliminate the estimation error associated with the "endogeneity" of imprisonment, i.e., the fact that the imprisonment rate is, in part, a function of the

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5 See Note 1. See also https://cde.ucr.cjis.gov/LATEST/webapp/#/pages/explorer/crime/crime-trend.

crime rate, so that this year's imprisonment rate may be partially caused by this year's crime rate. Lagging the imprisonment rate removes some of this reverse causality.[6]

The forecast models were fit to the first-differenced violent and property crime rates between 1960 and 2015. The years 2016 to 2020 were held back from the models so they could be used to validate the forecasts from the 1960–2015 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 2021 to 2025, when the crime rates are unknown. The forecast results are presented in Figures 4 and 5.

Figure 4 displays the observed and forecasted year-over-year changes in violent crime. The observed changes, denoted by the red line, extend from 1961 to 2020. The in-sample forecasted changes through 2015 are denoted by the solid blue line, and the dashed blue line represents the forecasted changes during the 2016–2020 out-of-sample validation period. The dotted blue line represents the forecasted changes in the violent crime rate between 2021 and 2025.

**FIGURE 4. OBSERVED AND FORECASTED YEAR-OVER-YEAR CHANGE IN VIOLENT CRIME RATES, 1961–2025**
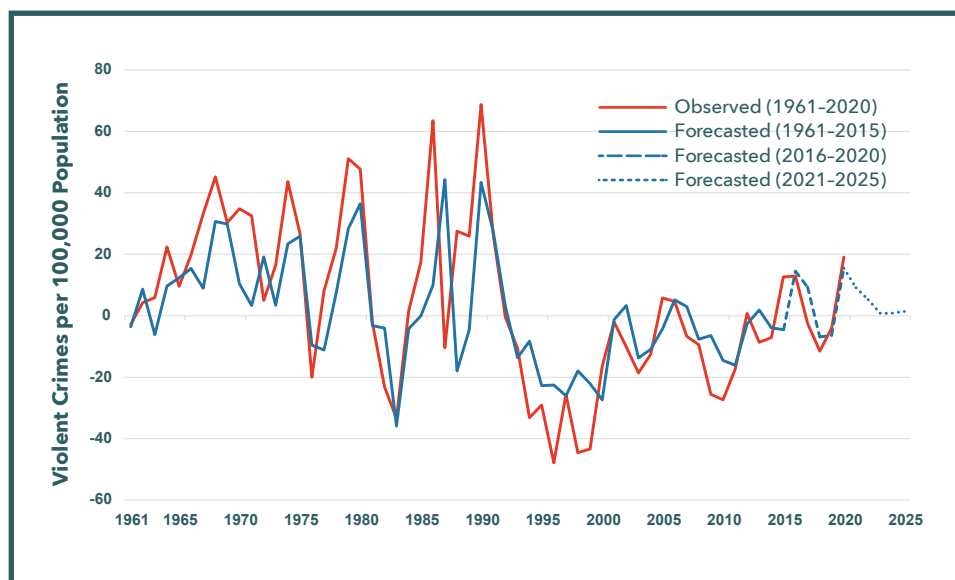
Source: FBI's Uniform Crime Reports.

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6 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 2025 and the income and imprisonment rates for 2022 to 2025 were unknown at the time of this writing. The 2023–2025 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 2022–2025 income and imprisonment values are based on the average yearly rate of change in these measures between 2017 and 2021 (2.7% and -5.4%, respectively). For example, the median household income forecast for 2022 is assumed to be 2.7% greater than median household income in 2021, the forecast for 2023 is 2.7% greater than the 2022 forecast, and so on.

The forecasted yearly changes in violent crime correspond closely to the observed changes, both during the 1961–2015 estimation period and during the 2016–2020 validation period. The results suggest that the violent crime rate will increase slightly in 2021 and 2022 and then flatten through 2025. The observed and forecasted changes in property crime, shown in Figure 5, are also very similar. The largest divergence occurs in 1983, when the observed rate fell by about 395 property crimes per 100,000 population while the forecasted rate decreases by about 130. The results suggest that the property crime rate will decline modestly between 2021 and 2025.

FIGURE 5. OBSERVED AND FORECASTED YEAR-OVER-YEAR CHANGE IN PROPERTY CRIME RATES, 1961–2025
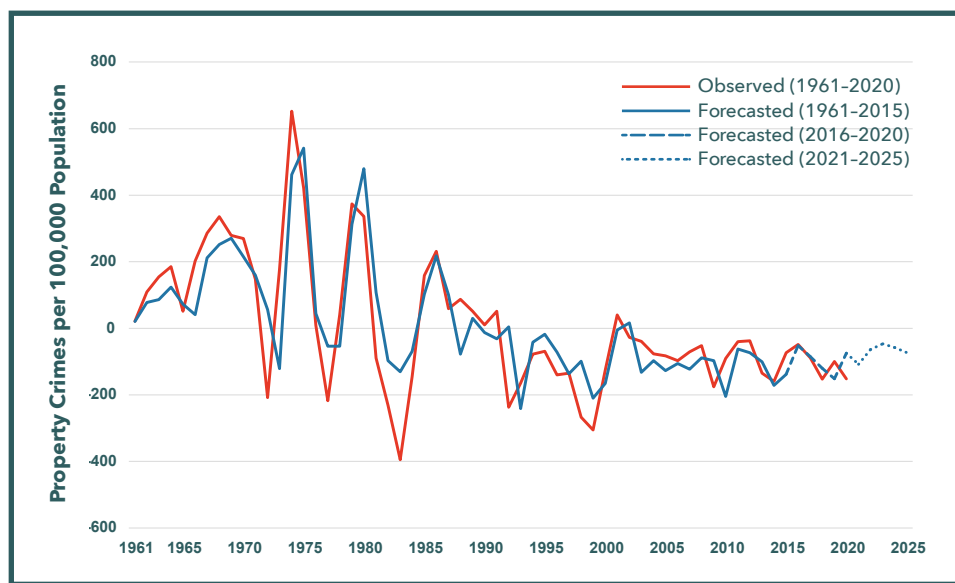
Source: FBI's Uniform Crime Reports.

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 crime rates during the validation period. The rates were computed by adding each year's change in the crime rate to the crime rate of the previous year. The forecast errors—the difference between the observed and forecasted crime

rates during the validation period—are well within the 10% tolerance limits. The largest error for violent crime occurs in 2017, when the forecasted rate exceeds the observed rate by about 3%. The largest error for property crime occurs in 2020, when the forecasted rate exceeds the observed rate by just under 4%. The mean absolute forecast error—the difference between the forecasted and observed crime rate in either direction—during the validation period is under 2% for both violent and property crime.

These tolerance limits for forecast error were arbitrarily drawn, but even if they were cut in half, to 5%, the forecasted violent and property crime rates between 2016 and 2020 would have been accurate and precise enough for both policy and research purposes. In addition, the small size of the forecast errors boosts confidence in the forecasts for the next several years. Finally, the violent and property crime forecasts derived from the ARIMA models align closely with the results of the qualitative forecasting method discussed above. Both methods suggest that US crime rates will not rise appreciably during the next several years.

The Impact on 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. Prison populations can be reduced by altering the sentencing policies that determine prison admissions and the sentencing and parole policies that regulate prison length of stay and releases. But these policy changes inevitably run up against concerns that lowering the prison population will increase crime. Such concerns are not unreasonable. We would not have included the imprisonment rate in our forecasting model 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.

Table 2 provides recent evidence. In 2016, the imprisonment rate was 450 per 100,000 population. By 2020, it had dropped to 358—a 20% decline. The nation's total crime rate, as measured by both the UCR and the NCVS, continued its long-term decline during that five-year period. Property crime declined by 20%, though the UCR violent crime rate showed a small increase in 2020 (and, as mentioned, a very large increase in homicide). As we have noted, the increase in violent crime was coterminous with the onset of the COVID-19 pandemic and its disruptions as well as widespread social unrest in the form of protests against police violence. In summary, the sizeable reduction in imprisonment of recent years was accompanied by a continuation of the long-term decline in property crime and a slight rise in violent crime. Substantially downsizing the prison population did not unleash a crime wave.[7]

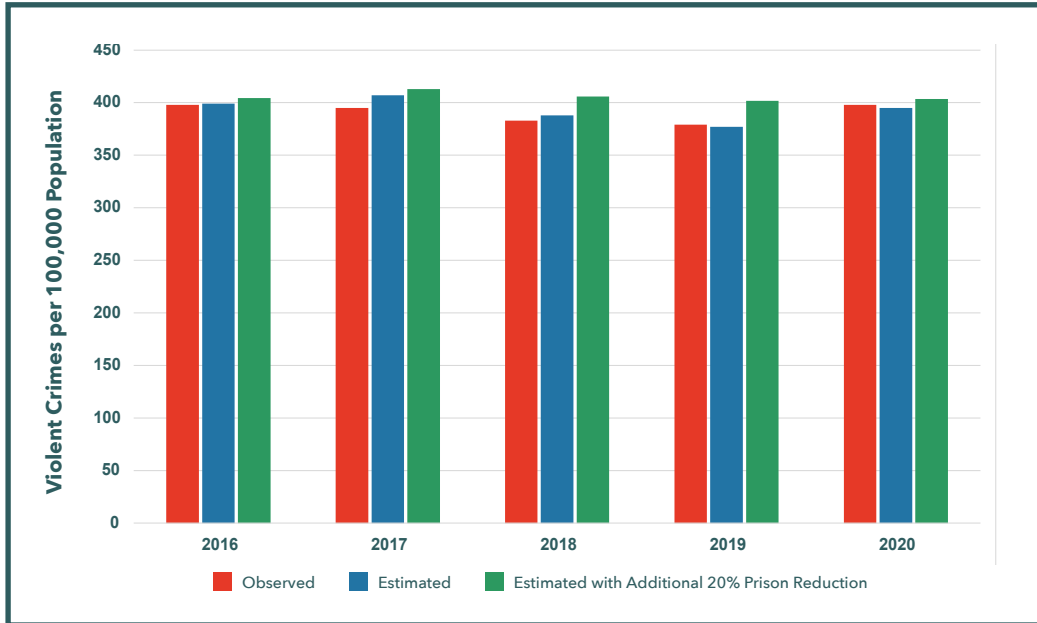**TABLE 2. IMPRISONMENT AND CRIME RATES 2016-2020**

	Imprison-ment	Violent Crime	Property Crime	Total Crime
2016	450	398	2,452	2,850
2017	442	395	2,363	2,758
2018	431	383	2,210	2,593
2019	419	379	2,110	2,489
2020	358	398	1,958	2,356
% Change	**-20%**	**+0%**	**-20%**	**-17%**

Sources: Crime rates, FBI's Uniform Crime Report; imprisonment, US Bureau of Justice Statistics.

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[7] See Kubrin and Bartos (2022) for evidence on the impact of reductions in imprisonment on public safety in California.

Efforts to reduce the prison population have not ended. We can use our crime forecasting model to estimate how an *additional* 20% reduction in the imprisonment rate would have affected the violent and property crime rates. We assume that a reduction of this magnitude would not occur in a single year — for purposes of modeling, we estimate the impact of a five-year, planned decline on violent and property crime rates between 2016 and 2020. The results are shown in Figures 6 and 7.

FIGURE 6. OBSERVED AND ESTIMATED VIOLENT CRIME RATE, 2016–2020

Source: FBI's Uniform Crime Reports.

FIGURE 7. OBSERVED AND ESTIMATED PROPERTY CRIME RATE, 2016–2020
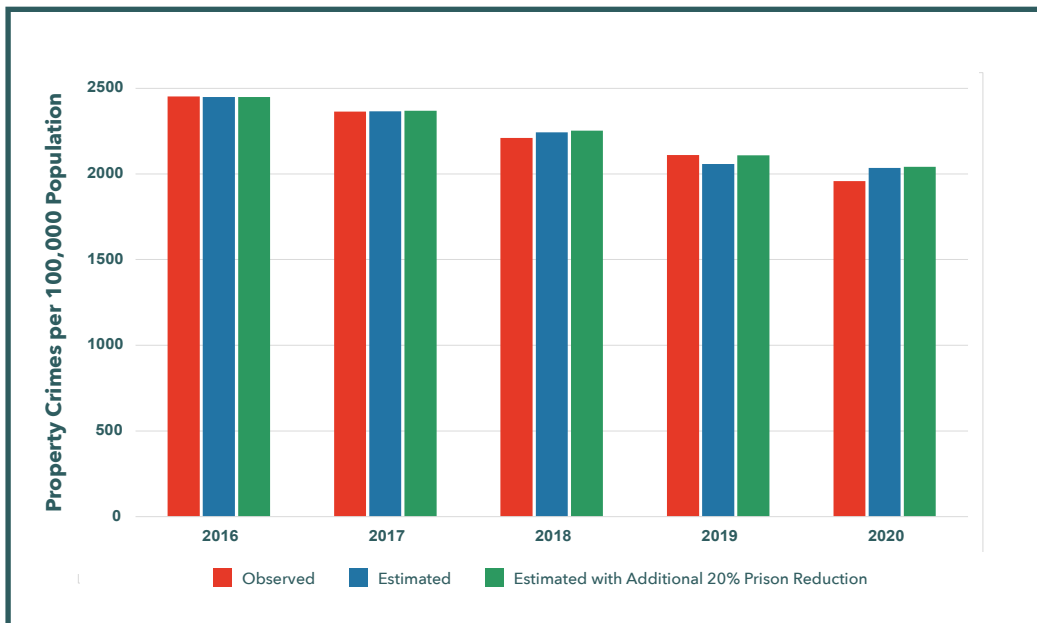
Source: FBI's Uniform Crime Reports.

The figures display the observed crime rates between 2016 and 2020, the estimated rates if imprisonment rates were at their observed values, and the estimated rates given a further 20% reduction in imprisonment. The impact of an additional 20% reduction in imprisonment would be very modest increases in the violent crime rate (see Figure 6). The average increase over the five years is estimated to be just 3.9% over the observed rates. The largest estimated increase is in 2019, when the reduction in the imprisonment rate would have increased the violent crime rate by 6.0% over the observed rate (402 vs. 379 violent crimes per 100,000 population). Any increase in violent crime merits attention, of course, but these results suggest that a sizable reduction in imprisonment, on top of the decreases that were already occurring between 2016 and 2020, could have been accomplished without resulting in a large rise in violent crime.

The results for property crime suggest that a 20% reduction in the imprisonment rate would have had an even smaller impact between 2016 and 2020 (see Figure 7). The average increase over the five years is estimated to be just 1.2%, and the largest increase is in 2020, when the property crime rate is estimated to be 4.2% greater than the observed rate (2041 vs. 1958 property crimes per 100,000 population). These results suggest that reducing imprisonment by an additional 20% would have had a very small impact on property crime between 2016 and 2020.

There are reasons to treat even these small expected crime increases with caution. First, this exercise assumes that the aggregate prison population is reduced by 20%. The policy change, however, would almost certainly be more selective by, for example, limiting early release from prison to older inmates and others at relatively low risk of reoffending.

Second, the prison population is only one component of the overall correctional population, which also includes people on probation and parole and people held in local jails. Probation, parole, and jail systems deal with three to four times as many people as prisons. For example, the jail system, which has millions of people admitted and released each year, touches almost ten times more people annually than prison. Each of these correctional forms has its own impact on crime. The crime prevention effects of probation and parole are often disputed, but officials who run those systems would certainly claim that they place a high priority on public safety.

Our estimates of the effect of the prison population on crime rates, based on our analysis of their relationship in the past, could thus be confounded with the effects of the other correctional populations. That is in fact the case. The prison, probation, parole, and jail population rates are highly correlated. Table 3 presents the annual correlations among the four components of the

correctional control system between 1980 and 2020. Correlations of this magnitude mean that the independent effects on crime of the different components of the correctional population cannot be reliably estimated by our statistical model. Thus what we view as the crime-reduction effect of imprisonment might actually be the effect of the probation, parole, or jail population, or some combination of the three. It is very likely we would reach the same conclusions about the impact of imprisonment on violent and property crime rates whether our estimates were based on the prison population alone or on imprisonment in combination with the other components of the correctional population. This limitation affects not only the current study but nearly all prior research on the impact of imprisonment on crime.

TABLE 3. CORRELATIONS BETWEEN YEARLY IMPRISONMENT, PROBATION, PAROLE, AND JAIL RATES, 1980-2020 (N=41)[A]

	Prison	Probation	Parole	Jail
Prison	–			
Probation	0.925	–		
Parole	0.944	0.896	–	
Jail	0.988	0.915	0.932	–

[A] Rate per 100,000 population
Data source: Bureau of Justice Statistics.

In summary, it is very likely we would reach the same conclusions about the impact of imprisonment on violent and property crime rates whether our estimates were based on the prison population alone or on imprisonment in combination with the other components of the correctional population. In either case, the results of our hypothetical policy experiment indicate that a meaningful further reduction in imprisonment would have a very small effect on U.S. crime rates.

The Need for Local-Level Models

The crime rate forecasts we report here are based on the national-level statistical model we have developed, which treats the total prison (or total correctional) population of the United States as the relevant policy unit for understanding the impact of corrections policy on crime. But most criminal justice policy in the US is not promulgated nationally; rather, states and localities are the operational units for crime policy. County and municipal governments enact and implement the policies that determine the number of people in jails and in many places the number of people on probation. About 90% of the prison population is produced by state-level prison policy. While our national-level analyses are useful for illustrative purposes, policy-relevant crime projections would, ideally, be based on data available at the state and local levels.

We produced analyses of crime trends for Illinois and Florida, with crime projections through 2021 (Austin, Rosenfeld, and Clear 2021, 2022). We are currently conducting an analysis of crime and imprisonment trends and projections through 2025 in Los Angeles, Chicago, and New York City.

We believe that developing additional models of the drivers of crime rates for individual jurisdictions would be a substantial policy contribution. Local-level crime forecasts and assessments of corrections policies would be valuable, given the variability across jurisdictions in crime-producing factors, including inflation, income, continuing dislocations from the pandemic, and firearm prevalence. Not only would they help to explain similarities and differences across states and localities in the factors influencing crime but they would provide policymakers with a locally relevant, evidence-based mechanism for evaluating corrections policy. State legislators and corrections officials could forecast trends in crime and then appraise the probable effects of new sentencing and corrections policies on public safety. Local decision makers could do the same with respect to the jail population and, in some places, the probation population. Most important, jurisdiction-specific models would ground the national conversation more realistically at the levels that matter most: state and local criminal justice policy.

Appendix: Forecast Methods and Models

Testing the Crime Series for Stationarity

Two formal tests were conducted to determine whether the 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 both series. US violent and property crime rates between 1960 and 2015 are nonstationary and conform to a random walk. The two series were therefore converted to first differences and the same tests were conducted. The tests revealed that both series 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 first-differenced crime rates. The models that minimized the mean-squared errors and mean absolute errors of the estimates for both the estimation (1960–2015) and validation periods (2016–2020) of the time series were retained. These models were then used to forecast the violent and property crime rates for 2021 to 2025.

In Table A, the year-to-year forecasted changes in US violent and property 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(1,0,2) model, which contains a single autoregressive term and first- and second-order moving average terms in addition to the substantive covariates. The model forecasts violent crime rates between 2016 and 2020 that diverge in either direction from the observed rates by an average of 1.22%. The forecasts through 2025 suggest that violent crime rates will increase slightly in 2021 and 2022 and flatten thereafter.

TABLE A. ARIMA FORECASTS OF U.S. VIOLENT AND PROPERTY CRIME RATES, 2016-2025

	Violent Crime (ARIMA$_{(1,0,2)}$)			Property Crime (ARIMA$_{(2,0,0)}$)		
	Observed Rate	*Forecasted Rate*	*Percentage Error*	*Observed Rate*	*Forecasted Rate*	*Percentage Error*
2016	397.5	399.0	0.38%	2451.6	2448.7	-0.12%
2017	394.9	406.8	3.01%	2362.9	2366.2	0.14%
2018	383.4	388.0	1.20%	2209.8	2242.7	1.49%
2019	379.4	377.0	-0.63%	2109.9	2058.2	-2.45%
2020	398.5	394.9	-0.90%	1958.2	2034.8	3.91%
MAPE[1]			**1.22%**			**1.62%**
2021		404.1			1927.0	
2022		409.3			1862.8	
2023		410.2			1815.8	
2024		411.0			1758.4	
2025		412.4			1684.9	

[1] MAPE = Mean Absolute Percentage Error

The best-fitting forecast model for property crime is an ARIMA(2,0,0) model that contains two autoregressive terms in addition to the substantive covariates. None of the forecasted property crime rates diverge from the observed rates by more than 4% during the validation period, and the average divergence is 1.62%. The forecasts indicate steadily falling property crime rates through 2025.

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