SPECIAL ISSUE ARTICLE
THE IMPACT OF COVID-19 ON CRIME AND JUSTICE

Crime, quarantine, and the U.S. coronavirus pandemic

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Abstract
Research Summary: Prior research has produced varied results regarding the impact of the coronavirus pandemic on crime rates, depending on the offenses and time periods under investigation. The current study of weekly offense rates in large U.S. cities is based on a longer time period, a greater number of offenses than prior research, and a varying number of cities for each offense (max = 28, min = 13, md = 20). We find that weekly property crime and drug offense rates, averaged across the cities, fell during the pandemic. An exception is motor vehicle theft, which trended upward after pandemic-related population restrictions were instituted in March 2020. Robbery rates also declined immediately after the pandemic began. Average weekly homicide, aggravated assault, and gun assault rates did not exhibit statistically significant increases after March. Beginning in June 2020, however, significant increases in these offenses were detected, followed by declines in the late summer and fall. Fixed-effects regression analyses disclose significant decreases in aggravated assault, robbery, and larceny rates associated with reduced residential mobility during the pandemic. These results support the routine activity hypothesis that the dispersion of activity away from households increases crime rates. The results for the other offenses are less supportive.

Policy Implications: Quarantines and lockdowns, although necessary to reduce contagious illness, are not desirable crime-control devices. An object lesson of
the coronavirus pandemic is to redouble effective crime reduction strategies and improve police–community relations without confining people to their homes.

KEYWORDS
crime trends, policy, property crime, violent crime

The global coronavirus pandemic has fueled speculation and research about its impact on crime rates. Some commentators worry that the stress and strain of the pandemic and related population restrictions on individuals and families increased crime, especially domestic violence (Davies et al., 2021). Others point to reported drops in crime, especially property offending, as evidence that the lockdowns and stay-at-home orders have reduced opportunities for criminal activity (MacFarquhar & Kovaleski, 2020). The small but growing research literature on crime changes during the pandemic reports both increases and decreases, depending on the offense types, the places, and the time periods under investigation. There is a pressing need for comprehensive empirical examinations of the impact of the coronavirus pandemic on multiple violent and property offenses, across multiple locales, and beyond the first few weeks or months of the pandemic, to which most prior studies are limited. The current study addresses that need.

Our analysis proceeds in two stages—one largely descriptive and the other explanatory. We first summarize average changes during the pandemic in the rates of 10 different criminal offenses for a sample of large U.S. cities. We use time-series methods to investigate whether the level and trend of the 10 offenses changed significantly after pandemic-related restrictions were instituted across the United States in March 2020. The results are summarized in the text and presented in detail in the Supporting Information S1.

The second stage of the analysis is informed by the key insight of the routine activity perspective in criminology that crime rates are related to population dynamics. Specifically, we evaluate the hypothesis that “the dispersion of activities away from households and families increases the opportunity for crime and thus generates higher crime rates” (Cohen & Felson, 1979, p. 588). Population mobility data are used to measure change in the amount of time persons spent at home during the pandemic. We estimate panel regression models of average weekly city crime rates during 2020 that include this measure of residential duration along with controls for seasonal effects and unmeasured attributes of the sample cities. Consistent with the hypothesis and other research, we find that, net of other influences, the rates of several, but not all, of the 10 offenses declined as people spent more time at home during the pandemic.

1 | BACKGROUND

The surge in the coronavirus pandemic in the spring of 2020 quickly caught the attention of researchers interested in the pandemic’s effect on crime. The global pandemic has been called “the largest criminological experiment in history” (Stickle & Felson, 2020, p. 524). The emerging research literature includes studies of single and multiple offenses carried out in multiple cities during varying time periods. None of the studies under review examined crime data beyond September 2020, and several are based on just a few weeks of data. All of the studies compare crime rates in 2020 with prior years. Many studies focus solely on domestic violence (see Piquero...
et al., 2021 for a review). Despite the heterogeneity in research designs, the research literature has produced some generally consistent results.

In most cases, research based on multiple cities has found that violent crime rates were not statistically different from prior years or decreased during the early weeks of the pandemic. Abrams (2021) found that assaults, including domestic violence, decreased and homicides and shootings exhibited no significant change during the 4 weeks after the imposition of stay-at-home orders in 19 cities. In an analysis of 16 cities through May 10, 2020, Ashby (2020) found no change from prior years in weekly serious assault rates. Nivette et al. (2020) examined daily crime counts in 25 cities across 21 different countries. With some variation across the cities, on average crime decreased after the issuance of the stay-at-home orders (see, also, Eisner & Nivette, 2020; Langton et al., 2021). The crime drop did not last long, however, and crime rates generally returned to normal levels within a few weeks. Two studies found that weekly homicide rates significantly increased in June 2020 compared to prior years (Meyer et al., 2020; Rosenfeld et al., 2021). Domestic violence has been the focus of many pandemic-related studies. In a systematic review and meta-analysis of 18 studies, researchers found that domestic violence increased by 8.1% in the United States after the issuance of stay-at-home orders (Piquero et al., 2021).

Multiple-city studies of property crime yield somewhat less consistent results. The most consistent finding is for larceny, which decreased during the first months of the pandemic (Abrams, 2021; Ashby, 2020; Meyer et al., 2020). Results for robbery and burglary, both residential and non-residential, differ depending on the sample and time period under investigation. Ashby (2020) found inconsistent trends in vehicle theft through the first part of May 2020, whereas Meyer et al. (2020) found that vehicle thefts increased from June to September. Abrams (2021) did not find an increase in vehicle theft. Two studies found decreases in drug offenses during the pandemic (Abrams, 2021; Rosenfeld & Lopez, 2020).

Several studies have focused on crime changes in individual locales during the pandemic. Payne et al. (2020) found that assaults and sexual violence declined with increases in social distancing regulations in Queensland, Australia during March and April 2020. An analysis of calls for service showed that burglary, robbery, and aggravated assault decreased and vehicle theft increased after issuance of a stay-at-home order in Los Angeles (Mohler et al., 2020). Another study of Los Angeles reported similar results for burglary, robbery, and aggravated assault, but found no significant change in motor vehicle theft and a significant decrease in simple assaults (Campedelli et al., 2020). Burglary decreased and robbery, assault, and vehicle theft did not significantly change after a stay-at-home order in Indianapolis (Mohler et al., 2020). Kim and Phillips (2021) found a gradual and sustained increase in both fatal and nonfatal shootings in Buffalo. Felson et al. (2020) reported that burglaries increased during March 2020 in areas of Detroit characterized by mixed use, but not in residential areas. Within-city trend differences were also found in Chicago, with most neighborhoods experiencing decreases in crime early in the pandemic (Campedelli et al., 2020).

Several U.S. and international studies have used Google mobility data to gauge the impact of confinement to the home on crime during the pandemic. With a few exceptions, this research has found that home confinement is associated with lower rates of both property and violent crime (Cheung & Gunby, 2021; Halford et al., 2020; Mohler et al., 2020; Nivette et al., 2020). Abrams (2021) examined the relationship between residential mobility and stay-at-home orders and found that people spent more time in their homes after stay-at-home orders were adopted.

The availability of Google data on population mobility patterns has provided a unique opportunity to test the routine activity theory of crime. Most research implicitly or explicitly invokes routine activity and opportunity perspectives to explain crime changes during the pandemic (see, especially, Felson et al., 2020; Stickle & Felson, 2020). The reasoning is straightforward: In addition to motivated offenders, crime requires suitable targets. When persons remain in their homes and
the streets are emptied, both violent and nonviolent street crimes should decrease, although violence in the home may increase. When businesses are closed, shoplifting and pilfering decrease, reducing overall levels of larceny. We apply these propositions derived from routine activity theory in an investigation of weekly crime changes during the pandemic that builds on the promising leads of prior research and is based on a larger number of offenses, a larger sample than most studies, and a longer time frame.

Finally, we do not argue that alterations in population mobility were the only reason crime rates may have changed during the pandemic. Other factors probably were involved, as we point out. Rather, we carry out multivariate time-series analyses to determine whether crime rates were associated with changes in population mobility net of other influences, which could mean that crime increases that occurred during the pandemic might have been even greater were it not for crime-suppressing changes in routine activities.

2 DATA AND METHODS

The current study is based on city-level weekly data between January 2017 and December 2020 for 10 offenses: homicide, aggravated assault, gun assault, domestic violence, robbery, residential burglary, nonresidential burglary, larceny, motor vehicle theft, and drug offenses. Most of the latter resulted from an arrest on a drug or other charge, rather than a citizen complaint. Unlike the other offenses, therefore, drug offenses largely reflect police-initiated activity.

The crime data were obtained from the online data portals of the police departments in large U.S. cities (~250,000 or more inhabitants) meeting the inclusion criteria (see Appendix A). The FBI’s final Uniform Crime Reporting (UCR) data were not available for yearend 2020 as of this writing. The FBI disseminated quarterly UCR data through December 2020 for about two thirds of the law enforcement agencies typically included in the yearend final data published in the Crime in the United States series.1 The 2020 quarterly reports, however, do not include the weekly crime data needed for this study.

The departmental crime data are subject to revision, and offense classifications varied somewhat across the cities. In addition, not all of the cities reported data needed for the study for each of the offenses or for each week. For instance, domestic violence offenses in Atlanta were not available for the entirety of 2020, and the data for San Francisco erroneously indicated there were no homicides in 2017. A total of 31 cities had data available for at least one of the offenses, a maximum of 28 cities for robbery and a minimum of 13 for domestic violence. Appendix B displays the sample cities for each of the 10 offenses. We could obtain 2017–2020 weekly data for all 10 offenses for just two cities, Chicago and St. Louis. Data were available for more than five of the offenses in 21 additional cities.2

We checked the validity of the offense data by comparing the city-specific 2019 offense rates obtained from the city police department’s website with those from the 2019 UCR for each of the 31 cities. These comparisons excluded gun assaults, domestic violence, drug offenses, and separate tallies for residential and commercial burglary for which city-level UCR data were unavailable. We omitted cities from any offense category where the two counts differed by more than 25%. For example, Appendix B shows that we retained robbery data for 28 of the 31 cities. Three cities were dropped from the robbery sample, in other words, because they exceeded the 25% difference criterion. We had to balance two objectives in this process, data accuracy and sample size. A more restrictive criterion would have improved data accuracy, but it would also have reduced the number of cases available for analysis. We believe the 25% threshold satisfies both objectives.
2.1 | Explanatory variables

We used county-level \(^3\) cellphone location data available from the Google Community Mobility Reports (https://www.google.com/covid19/mobility/) to measure the weekly change in time spent at home during the pandemic. This measure represents the percentage change in the number of hours spent in places of residence from the median time spent between January 3 and February 6, 2020, the baseline in the Google data.\(^4\) We evaluated the validity of the residential duration measure by comparing it with another Google mobility measure, the weekly change from the January 3–February 6 baseline in the percentage of persons who visited a workplace. A very strong negative correlation exists between the two measures \((r = –0.93)\). We also compared the residential duration measure with the change from a January 13, 2020, baseline in nationwide direction requests to Apple Maps (https://covid19.apple.com/mobility). The two measures are negatively correlated \((r = –0.90)\). As people spent more time at home, direction requests declined.

Finally, for each city we obtained the date quarantine or “lockdown” orders went into effect (Moreland et al., 2020). Most cities imposed these orders in mid- to late March 2020 (mean = March 24). The lockdown dates ranged from March 11 in Kings County (Brooklyn), New York, to April 1 in St. Petersburg, Florida. As shown below, residential duration had begun rising before March 24 and climbed to a peak in April 2020.

2.2 | Methods

We present two sets of results from our analyses of crime changes during the pandemic. We first summarize the results of an interrupted time-series analysis of average weekly rates of the 10 offenses between 2017 and 2020. The analysis estimates the change in the level and slope of the crime series that occurs after an intervention, such as the pandemic, which is assumed to “interrupt” the time series. The full results are available in the Supporting Information S1.

We then present panel regression estimates of the association between residential duration and the weekly rates of the 10 offenses during 2020. The estimates are from fixed-effects panel regressions, which model variation within panel units over time, with each unit in effect serving as its own control (Allison, 2009). The regression models include weekly dummy variables to capture period effects common across the cities on the offense rates and a 1-year lag in the weekly offense rates to adjust the estimates for seasonal effects. The models estimate the association between the crime rates and residential mobility during the pandemic, specifically from February to December 2020. As noted, the Google mobility data are not available for prior years. We assess the robustness of the regression results in a series of tests for alterations in sample composition and model specification.

3 | RESULTS

Table 1 presents descriptive statistics for the offense rates, the measure of residential duration, and the population in the city sample. Recall that not all cities reported the weekly offense data for each crime type, and the residential duration data are limited to 2020. The 2015–2019 population of the cities varied between 245 thousand (Norfolk) and 8.4 million (New York) residents (https://www.census.gov/programs-surveys/acs). The total population of the sample was 28.6 million. We see that the variability in the homicide rate over time is about equal to that between the cities.
| Time varying          | Mean | SD_{between} | SD_{within} | Min  | Max  | Cities | N   |
|-----------------------|------|--------------|-------------|------|------|--------|-----|
| Homicide              | 0.363| 0.342        | 0.326       | 0.000| 5.516| 25     | 5200|
| Aggravated Assault    | 9.710| 6.505        | 3.326       | 0.000| 74.309| 19     | 3946|
| Gun Assault           | 3.106| 3.870        | 1.908       | 0.000| 44.455| 17     | 3503|
| Domestic Violence     | 13.664| 11.038     | 3.164       | 0.000| 53.073| 13     | 2542|
| Robbery               | 5.108| 3.030        | 1.755       | 0.000| 29.227| 28     | 5817|
| Res. Burglary         | 7.353| 3.788        | 2.351       | 0.000| 34.513| 18     | 3712|
| Nonres. Burglary      | 13.120| 39.773      | 6.246       | 0.000| 220.112| 18   | 3712|
| Larceny               | 51.925| 17.661      | 10.790      | 1.985| 148.918| 25   | 5200|
| Motor Vehicle Theft   | 11.377| 4.705       | 3.253       | 0.396| 45.323| 27    | 5610|
| Drug Offense          | 11.167| 8.464       | 4.568       | 0.000| 81.581| 20    | 4153|
| Res. Duration         | 11.500| 2.833       | 5.163       | –    | 31.714| 31    | 1425|
| Population            | 1,042,931| 1,577,621 | –          | 244,601| 8,419,316| 31 | 6441|

\(a\) 2017–2020.  
\(b\) Weekly measures except population. Res. Duration is for 2020.  

Variable definitions: Homicide, Homicides per 100,000 population; Aggravated Assault, Aggravated assaults per 100,000 population; Gun Assault, Aggravated assaults committed with a firearm per 100,000 population; Domestic Violence, Domestic violence incidents per 100,000 population; Robbery, Robberies per 100,000; Res. Burglary, Residential burglaries per 100,000 population; Nonres. Burglary, Nonresidential burglaries per 100,000 population; Larceny, Larcenies per 100,000 population; Motor Vehicle Theft, Motor vehicle thefts per 100,000 population; Drug Offense, Drug offenses per 100,000 population; Res. Duration, Percent change in time spent in residential areas compared to the median time spent January 3 to February 6, 2020; Population, City population (2015–2019).

For the other offenses, the between-city variability exceeds the temporal variability within cites, in many cases by a factor of two or more.

By contrast, the within-city variability in residential duration (SD = 5.163) is greater than the variability between cities (SD = 2.833). As shown in Figure 1, the cities followed a very similar trajectory in residential duration during 2020. All of them experienced a marked rise in residential duration from the January 3–February 6 baseline to a peak in April, followed by a decline through the remainder of the year. At the peak, time spent at home increased by 15%–25% over the baseline in most cities. An apparent outlier is San Francisco, where time spent at home increased by more than 30% over the baseline at the April peak and did not drop below 19% during the rest of the year. In an evaluation of the impact of sample composition on the robustness of the regression results for the association between residential duration and crime rates (discussed below), each city is removed from the sample one at a time and the regression models are re-estimated on the revised samples.

### 3.1 Crime rates before and during the pandemic

With a couple of exceptions, violent crime rates rose and property crime rates fell during the pandemic, compared with prepandemic trends. We summarize those changes here, based on the interrupted time-series analyses reported in the Supporting Information S1.
3.1.1 Violent offenses

The average weekly homicide rate for the 25 cities with available data was essentially trendless before population restrictions related to the pandemic were imposed in March 2020, fluctuating between 0.2 and 0.4 homicides per 100,000 city population in 2018 and 2019. After quarantines and business closings took hold in March 2020, the homicide rate began to increase and reached a peak during July and August, after which it decreased through the end of the year. The time-series results, however, indicate that the changes in the homicide level and slope after the March intervention were not statistically significant ($p = 0.217$ and $p = 0.609$, respectively).

The increase in the city homicide rate was particularly abrupt beginning in June 2020, a finding consistent with previous research (Rosenfeld & Lopez, 2020). The growth in the level of homicide was statistically significant ($p < 0.000$) and was followed by a significant decrease in slope ($p = 0.002$). In other words, homicide rose to a peak in mid-summer 2020 and then began to decline.

The homicide rise coincided with the emergence of mass protests against police violence after George Floyd was murdered in Minneapolis on May 25. The temporal correspondence between the widespread demonstrations and the homicide increase has prompted speculation and debate about a possible causal connection. A similar debate arose about 6 years ago over the causes of the homicide increase that followed police killings in Ferguson, Missouri, Chicago, and other cities (Rosenfeld & Wallman, 2019; Rosenfeld et al., 2017). The issues in this dispute extend beyond the scope of the current study, but they do highlight the difficulty in distinguishing the role of the pandemic from cooccurring conditions associated with the homicide rise during the spring and summer of 2020.

The results for aggravated assault and gun assault are similar to those for homicide. Both aggravated assault and gun assault rates increased after March 2020, peaked during the summer, and then dropped through the end of the year. These changes correspond with expected seasonal fluctuations and are not statistically significant ($p = 0.505$ and $p = 0.767$ for the changes in level and
slope in aggravated assault and $p = 0.128$ and $p = 0.987$ for the changes in gun assault). Similar to the changes in homicide, however, they become statistically significant when the interruption to the time series is set in June ($p < 0.000$ for the changes in the level and slope of both offenses). These results for homicide, aggravated assault, and gun assault should be considered exploratory because we did not specify beforehand that significant changes in these offenses would occur in June.\(^5\)

The story for domestic violence is more complicated. The average domestic assault rate was highly cyclical and trendless prior to the pandemic, with no significant change in level or trend after pandemic-related restrictions were enacted in March 2020 ($p = 0.188$ and $p = 0.687$). These results should be treated with caution. They are based on just 13 of the 31 cities, and reports of domestic violence to the police or others probably fell, even while incidents rose, when victims were sequestered in their homes with their abusers (Evans et al., 2020). Finally, the level of robbery decreased significantly immediately after March 2020 ($p < 0.000$). Robbery rates quickly recovered and exhibited no significant change in slope through the remainder of the year ($p = 0.582$).

### 3.1.2 Property and drug offenses

While violent crime rates were rising in the spring and summer of 2020, property crime and drug offense rates were not, or not at the same rate or the same time. Residential burglary rates fell for a few weeks after March 2020 and then rose through the summer and fall. Both the change in the level and slope of the residential burglary series are statistically significant ($p < 0.000$ and $p = 0.011$). We find no significant change in the level or slope of nonresidential burglary rates after the pandemic began ($p = 0.566$ and $p = 0.819$), although there is an extreme outlier in the series. The average nonresidential burglary rate rose precipitously during the last week of May 2020.

This increase coincides with the beginning of nationwide protests against police violence after George Floyd was killed. It was just as brief as it was abrupt. By the first week of June, the average nonresidential burglary rate had fallen back to its typical late spring level. Most of the 18 cities for which data were available experienced a marked increase in nonresidential burglary, with large spikes in Atlanta, Chicago, Philadelphia, and Minneapolis. It is very likely that the brief increase in nonresidential burglary resulted from incidents of breaking-and-entering and looting at the beginning of the mass demonstrations against police violence.

Larceny rates decreased immediately after pandemic-related restrictions were adopted. The decrease in the level of larceny is statistically significant ($p < 0.000$). The average weekly larceny rate rose to a plateau during the summer and fall of 2020, but this increase in the slope of the series is not significant ($p = 0.946$). A decrease in larcenies, particularly shoplifting, would be expected when retail businesses are closed.

Motor vehicle theft is the single property crime that trended upward after the pandemic-related restrictions were in place. The level of motor vehicle theft did not change significantly ($p = 0.608$), but the increase in the slope is highly significant ($p = 0.001$). By the end of 2020, the average motor vehicle theft rate in the 27 cities with available data was roughly 50% higher than 3 years before. Motor vehicle thefts may have risen as more people left their vehicles unattended at home rather than in secure parking facilities at work. Motor vehicle theft has also been characterized as a “keystone” crime that facilitates the commission of other offenses, including homicides and assaults (Farrell et al., 2011). As violent crime rates increased during the summer of 2020, motor vehicle thefts may have followed suit.
Finally, drug offense rates fell after March 2020 to levels far lower than at any point since the beginning of 2018. The decrease in the average level of drug offenses is highly significant ($p < 0.000$). Drug offense rates fluctuated with no significant trend through the remainder of the year ($p = 0.829$). The drop in drug offenses could be related to fewer opportunities for street-level drug transactions as more people remained at home. It is also probable that the police prioritized away from drug enforcement as they reduced contact with the public during the pandemic or were redeployed to address protest activity.

In summary, we find that whether crime rates changed significantly after quarantines and business closings were enacted in response to the coronavirus pandemic depends on the type of offense. Increases in homicide, aggravated assault, and gun assault after March 2020 were not statistically significant, although they became significant in June. Robbery rates dropped significantly after the pandemic-related restrictions took hold, as did rates of residential burglary, larceny, and drug offenses. Despite a sharp increase immediately after George Floyd was killed in late May 2020, the average weekly nonresidential burglary rate did not differ significantly from its prepandemic level or slope. We now turn to a more detailed examination of the effect of pandemic-related restrictions, specifically home quarantines, on the change in weekly crime rates during 2020.

### 3.2 Changes in residential duration and crime during the pandemic

As shown in Figure 1, the amount of time persons spent at home increased during the first few months of the pandemic in each of the 31 cities in our sample. From a routine activity perspective, crime rates should decrease with these increases in residential confinement, with the possible exception of domestic violence. Empty streets, occupied households, and closed businesses shrink the volume of suitable targets for both violent and property crime. Figure 2 displays the average monthly percentage change from the January 3–February 6 baseline in hours spent at home.
during 2020, based on the Google mobility data for the 31 sample cities. Average residential duration rose rapidly to a peak in April and then declined during the late spring and summer, presumably because quarantines were lifted or compliance with the stay-at-home orders diminished. Time spent at home increased modestly again near the end of the year.

The average monthly change in residential duration corresponds with fluctuations in the rate of coronavirus deaths. Both rose during the spring of 2020, fell modestly during the summer and early fall, and then increased in the late fall, although the year-end increase in coronavirus deaths was much greater than the increase in residential duration. Monthly change in residential duration also aligns with change in the unemployment rate, which peaked in April 2020 and declined through the remainder of the year. Many persons spent more time at home because they were out of work. The Pearson’s correlation between the Google measure of residential duration and the monthly unemployment rate is 0.79.

We evaluated the effect of residential duration on city offense rates during the pandemic in fixed-effects panel regressions that incorporate weekly period effects and the 52-week lag in the offense rates to condition the estimates on seasonal fluctuations. Some of models are also adjusted for first-order serial correlation in the disturbances. The estimates represent the magnitude and significance of the association between residential duration and the offense rates within the cities over time. The results are presented in Tables 2–4.

Three sets of estimates are presented for each offense. The first is based on the data for the entire period. The second and third are based on the data for February to April, when average time spent at home was increasing sharply, and May to December, when it was decreasing. If home confinement restricts criminal opportunities, as predicted by the routine activity perspective, their relationship should be symmetrical. In other words, we should observe a negative relationship between crime rates and residential duration when home confinement is rising and when it is falling. Finally, the tables show the coefficients of determination ($R^2_{within}$) for the regression models, which indicate the proportion of the variance in the offense rates over time explained by the model.

As shown in Table 2, a significant negative relationship exists between weekly residential duration and the weekly homicide rate between February and December 2020 ($b = -0.020, p < 0.05$). Decreases in homicide correspond with increases in residential duration. This relationship, however, is driven by the association between homicide and time spent at home during the May–December subperiod when time at home was decreasing. We do not find a significant association during the first months of the pandemic when time at home was increasing ($b = -0.007, p = 0.374$). Recall that average homicide rates peaked during the summer of 2020. Although the decrease in home confinement may have helped to push up homicide rates, the earlier increase in time spent at home was not accompanied by a drop in homicide, at least on average. These results provide partial support, at best, for the routine activity hypothesis when applied to homicide.

The regression results for aggravated assault shown in Table 2 offer stronger support for the routine activity hypothesis. A significant negative association between aggravated assault rates and residential duration exists for the entire period and for the two subperiods. Aggravated assaults increased (decreased) as residential duration decreased (increased). The results for gun assault are closer to those for homicide. The association between gun assault and residential duration is statistically significant only during the months when residential duration was declining ($b = -0.198, p < 0.05$).

The opposite pattern holds for domestic violence. Domestic violence rates are negatively associated with residential duration when time spent at home was increasing in the first months of the pandemic ($b = -0.331, p < 0.05$). We might have expected that domestic violence would increase
|                |          |        |         |         |
|----------------|----------|--------|---------|---------|
| **Homicide**   |          |        |         |         |
| February–December | −0.021*  | 0.092  | 1150    |         |
| (0.008)        |          |        |         |         |
| February–April  | −0.007   | 0.081  | 200     |         |
| (0.008)        |          |        |         |         |
| May–December   | −0.021*  | 0.065  | 950     |         |
| (0.010)        |          |        |         |         |
| **Aggravated assault** |          |        |         |         |
| February–December | −0.570***| 0.334  | 874     |         |
| (0.164)        |          |        |         |         |
| February–April  | −0.243** | 0.142  | 228     |         |
| (0.071)        |          |        |         |         |
| May–December   | −0.548** | 0.265  | 646     |         |
| (0.153)        |          |        |         |         |
| **Gun assault** |          |        |         |         |
| February–December | −0.122   | 0.260  | 755     |         |
| (0.068)        |          |        |         |         |
| February–April  | −0.063   | 0.110  | 204     |         |
| (0.050)        |          |        |         |         |
| May–December   | −0.198*  | 0.244  | 551     |         |
| (0.077)        |          |        |         |         |
| **Domestic violence** |          |        |         |         |
| February–December | −0.158   | 0.202  | 528     |         |
| (0.142)        |          |        |         |         |
| February–April  | −0.331*  | 0.215  | 132     |         |
| (0.159)        |          |        |         |         |
| May–December   | −0.077   | 0.192  | 396     |         |
| (0.190)        |          |        |         |         |

*Standard errors in parentheses. Lagged outcome and period effects not shown.

**AR1 model.

*p < 0.01.

**p < 0.05.

when victims are confined with their abusers. Recall, however, that domestic violence rates did not increase during the pandemic over normal seasonal fluctuations, and that home confinement very likely reduced reports of abuse to the police and other agencies.

The results for robbery and burglary are presented in Table 3. We observe a negative relationship between robbery rates and residential duration during the entire period and both of the subperiods. We expected to find a robust negative relationship between residential burglary and residential duration throughout the entire period because burglars tend to avoid occupied households (Wright & Decker, 1994). Yet this relationship is statistically significant only during the May–December subperiod \( (b = −0.122, p < 0.05) \). Recall that, after dropping at the beginning of the
pandemic, residential burglary rates rose during the summer and fall of 2020. The decline in residential duration after April could have contributed to the increase in burglary. We are left with the question, however, of why a statistically significant association between home burglary rates and residential duration does not exist at the beginning of the pandemic when time spent at home was rising and the greater presence of guardians should have deterred burglaries.

The association between nonresidential burglary and residential duration is negative and significant for the entire period ($b = -0.345$, $p < 0.05$). This relationship stems from a significant association during the May–December subperiod ($b = -0.460$, $p < 0.05$). A significant association does not exist during the initial months of the pandemic when shuttered businesses should have been tempting targets of criminal opportunity. As shown in Table 3, these results are based on offense data that omit the last week in May, an extreme outlier in the nonresidential burglary time series. When that data point is included in the series, we find no significant association between nonresidential burglary and residential duration during the entire time period or the two subperiods.

Table 4 presents the regression results for larceny, motor vehicle theft, and drug offenses. The relationship between larceny and residential duration is negative and significant during the entire period and the two subperiods. No significant relationship exists between motor vehicle theft and

| TABLE 3  | Association between residential duration and city robbery and burglary rates, 2020$^a$ |
|-----------|---------------------------------|-----------------|------------------|
|           | $b$    | $R^2$ (within) | Observations |
| Robbery   |        |                |               |
| February–December | $-0.152^{**}$ | 0.094 | 1231 |
|           | (0.041) |                |               |
| February–April       | $-0.179^{**}$ | 0.106 | 308  |
|           | (0.053) |                |               |
| May–December         | $-0.132^*$ | 0.074 | 923  |
|           | (0.010) |                |               |
| Residential burglary|        |                |               |
| February–December   | $-0.026$  | 0.090 | 766  |
|           | (0.043) |                |               |
| February–April       | $-0.011$  | 0.087 | 198  |
|           | (0.077) |                |               |
| May–December         | $-0.122^*$ | 0.090 | 568  |
|           | (0.050) |                |               |
| Nonresidential burglary$^b$|
| February–December   | $-0.345^*$ | 0.088 | 748  |
|           | (0.147) |                |               |
| February–April       | $-0.209$  | 0.113 | 252  |
|           | (0.223) |                |               |
| May–December         | $-0.460^*$ | 0.096 | 496  |
|           | (0.194) |                |               |

$^a$Standard errors in parentheses. Lagged outcome and period effects not shown. AR(1) models.

$^b$Last week in May omitted.

$^{**}p < 0.01.$

$^*p < 0.05.$
TABLE 4 Association between residential duration and city larceny, motor vehicle theft, and drug offense rates, 2020

|                          | b        | $R^2$ (within) | Observations |
|--------------------------|----------|----------------|--------------|
| **Larceny**              |          |                |              |
| February–December        | $-1.080^{**}$ | 0.116          | 1100         |
|                          | (0.207)  |                |              |
| February–April           | $-1.022^{**}$ | 0.229          | 275          |
|                          | (0.273)  |                |              |
| May–December             | $-1.347^{**}$ | 0.095          | 825          |
|                          | (0.280)  |                |              |
| **Motor vehicle theft**  |          |                |              |
| February–December        | 0.025    | 0.086          | 1188         |
|                          | (0.088)  |                |              |
| February–April           | $-0.016$ | 0.025          | 297          |
|                          | (0.111)  |                |              |
| May–December             | 0.098    | 0.050          | 891          |
|                          | (0.118)  |                |              |
| **Drug offense**         |          |                |              |
| February–December        | $-0.210^*$ | 0.196          | 879          |
|                          | (0.100)  |                |              |
| February–April           | $-0.000$ | 0.259          | 220          |
|                          | (0.164)  |                |              |
| May–December             | $-0.308^*$ | 0.195          | 659          |
|                          | (0.121)  |                |              |

*aStandard errors in parentheses. Lagged outcome and period effects not shown. AR(1) models.

**$p < 0.01.$

*p $p < 0.05.$

variation in the amount of time spent at home. As with other offenses, drug offenses are negatively associated with residential duration only after April 2020, when average time spent at home was declining.

The fixed-effects regressions offer mixed support for the hypothesis from routine activity theory that the dispersion of activities away from the home increases crime rates. We have interpreted this hypothesis as requiring a symmetrical relationship between crime and residential duration: Crime should increase as a population spends less time at home and decrease with greater time spent at home. The opposite is expected to hold for domestic violence, which should increase when victims are sequestered with their abusers and decline when they able to spend more time away from them. The results for aggravated assault, robbery, and larceny are fully consistent with expectations. Those for homicide, gun assault, burglary, and drug offenses are only partially consistent. The relationship between these offenses and residential duration is statistically significant only during the period between May and December 2020 when average time spent at home was declining. The results for domestic violence are contrary to expectations. Increases (decreases) in domestic violence are significantly associated with decreases (increases) in residential duration, and only during the initial months of the pandemic when average time spent at home was increasing.
We find no significant relationship between motor vehicle theft, which trended upward during the pandemic, and residential duration. The routine activity hypothesis may not hold in this case because opportunities for theft would be expected to increase and not decline as people remain at home and leave their vehicles unattended. The null results for motor vehicle theft, however, may be best explained by the keystone hypothesis, which predicts that vehicle theft will rise with increases in other crimes, apart from changes in residential mobility. The explanatory scope of the routine activity hypothesis clearly does not encompass all forms of property offending, at least during the pandemic.

Caution should be exercised in interpreting the regression results, especially when comparing the findings across offense types. Each offense is based on a different mix of the sample cities, and so differences in the results between the offenses could be confounded with differences between the cities. Even with city and period fixed effects incorporated, most of the variation over time in the offense rates is left unexplained by the models. The results may also be influenced by city or period outliers, as shown for nonresidential burglary, and may be sensitive to reasonable alterations in model specification. The regression results are based on the assumption of a linear relationship between the offense rates and residential duration. It is plausible, however, that the relationship is subject to threshold or ceiling effects. Finally, the regression models are estimated on data restricted to the period of the pandemic. Whether the results hold for the relationship between crime rates and residential mobility during other periods is unknown. It was not possible to address each of these issues, but we carried out several diagnostic tests to evaluate the robustness of the regression results against changes in sample composition and model specification.

3.2.1 Robustness tests

To determine whether the association between the offense rates and residential duration is nonlinear, we included a product term for the measure of residential duration (residential duration × residential duration) in each of the equations. With one exception, the product term is nonsignificant. The exception is the larceny equation, in which the product term is negative and significant \( b = -0.032, p < 0.01 \). This result indicates that the relationship between larceny and residential duration becomes more negative as levels of residential duration increase. The nonlinear bend in the association between larceny and residential duration, however, is quite modest, as shown in Figure 3. It would make little substantive difference whether the association were treated as linear or nonlinear. We conclude that, for all practical purposes, the relationship between weekly larceny rates and time spent at home during the pandemic is approximately linear.

The number of cities with crime data available for analysis in this study is small, ranging from 28 cities with data for robbery to 13 cities with domestic violence data. As a result, small changes in sample composition could influence the regression results. We therefore removed each city from the sample, one at a time, and estimated the regression models on the reconstituted sample. The sample alterations had no significant influence on the results for homicide, aggravated assault, robbery, residential burglary, larceny, and motor vehicle theft. In a few cases, removing a single city from the estimation sample resulted in a nonsignificant coefficient on the measure of residential duration becoming statistically significant. For example, dropping Cincinnati from the gun assault equation results in a significant association with residential duration over the entire period \( b = -0.162, p < 0.05 \), whereas the association with Cincinnati included in the sample is nonsignificant at the 5% level \( b = -0.122, p = 0.092 \). The relationship between domestic violence
and residential duration becomes statistically significant over the entire period with Louisville omitted from the sample ($b = -0.200, p < 0.05$); it is nonsignificant with Louisville included ($b = -0.158, p = 0.264$). In neither instance, however, does the direction of the relationship between domestic violence and residential duration change: As time spent at home increases, domestic violence decreases.

In other cases, a significant association becomes nonsignificant. The association between nonresidential burglary and residential duration is statistically significant when estimated on all 18 cities with available data and is nonsignificant with Chicago dropped from the sample ($b = 0.016, p = 0.789$). The association between drug offenses and residential duration is sensitive to the inclusion of several cities in the sample (Chicago, Denver, Memphis, Norfolk, Philadelphia, St. Paul). Excluding any one of these cities significantly changes the regression results. City differences in policing practices should influence the results for drug offenses, apart from changes in residential duration related to the pandemic.

Finally, although our preferred models contain period effects to capture unmeasured time-varying effects on the crime rates common across the cities, it is instructive to examine their influence on the regression results. Removing the period effects reduces the variance in the crime rates explained by the models. With one exception, however, omitting the period effects does not change the results for the association between the crime rates and residential duration. The exception is homicide. With the period effects removed from the model, the association between homicide and residential duration over the entire period becomes nonsignificant ($b = -0.001, p = 0.459$). It appears that a significant relationship between homicide and residential duration depends on holding other time-varying influences constant. One likely unmeasured influence is the social unrest over police violence during the summer of 2020. Recall that homicide rates rose significantly immediately after George Floyd was killed and protest demonstrations spread across the country, as they did under similar conditions in 2015 (Rosenfeld et al., 2017). Just how social unrest might have affected U.S. homicide rates remains a matter for future research.
DISCUSSION

Building on the results and insights of prior research, the current study examined changes in U.S. city crime rates during the coronavirus pandemic. Controlling for seasonal fluctuations, we found that the weekly rates of some offenses fell and others rose during 2020. With the exception of motor vehicle theft, property crime rates decreased after pandemic-related population restrictions were instituted in March. Drug offense rates also dropped. Homicide, aggravated assault, and gun assault rates rose, but statistically significant increases in these offenses did not begin until June. Violent crime rates peaked during the summer of 2020 and fell through the end of the year. An assessment of the connection between residential mobility and crime changes in 2020 revealed decreases in the rates of serious assault, robbery, and larceny, as people spent more time in their homes during the early months of the pandemic, and increases as residential confinement eased during the summer and fall. These results support the routine activity hypothesis that the dispersion of activity away from households increases crime.

The results for the other offenses are less consistent with routine activity theory. We did not find a significant association between motor vehicle theft and the amount of time persons spent at home. Time at home was negatively related to homicide, gun assault, burglary, and drug offenses only after it began to decrease in the late spring of 2020, and to domestic violence only when residential duration was rapidly increasing in March and April. In addition, the results for some of the offenses are sensitive to small changes in sample composition, and the homicide results are significant only when other time-varying influences are held constant.

The regression results should not be generalized beyond the time period of the pandemic or the cities for which we could obtain the requisite weekly crime data. Caution should be exercised in comparing the results across the 10 offenses, which are based on differing city samples. Whether the results for 2020 can be extended beyond the offense-specific samples will have to be determined after yearend UCR crime statistics are released in the fall of 2021.

The most consistent results from prior research on property crime changes during the first few months of the pandemic are for larceny. Thefts tend to be opportunistic and responsive to target density. The more time people spend at home, the fewer the opportunities for theft in public. The press and researchers have devoted much less attention to how residential confinement may have reduced violence rates. After the first month or two of the pandemic, the big crime story of 2020 was the rise in homicide and shootings and how the pandemic contributed to it. In fact, some public officials attributed the violence increase, not reductions, to more time spent at home. For example, New York’s Mayor de Blasio told a reporter: “It’s clearly related, in part, to the coronavirus and to the fact that people are cooped up” (Corley, 2021). Our result that residential confinement reduced or limited the increase in aggravated assault rates serves as a reminder that not all relevant factors were pushing crime rates in the same direction and of the importance of multivariate research for disclosing their contrasting effects.

A limitation of the current study and nearly all prior research on crime changes during the pandemic is the use of offense data that are not disaggregated by circumstance and victim–offender relationship. It might be expected, for example, that robberies and assaults committed against strangers would decrease with greater social distancing. Perhaps the most important limitation of our study is inherent in its design. We focused on how pandemic-related restrictions on population mobility affected crime rates during the pandemic. We did not include other factors, beyond period effects common across the cities, that almost certainly influenced changes in crime rates during 2020. That omission limits the conclusions to be drawn from this study for violent crime in particular. Many U.S. cities experienced sizable increases in fatal and nonfatal violence over
previous years (Rosenfeld et al., 2021). Those increases coincided with the mass protests against police violence beginning in late May and early June 2020. The increases were far too large to be attributed directly to the protesters, and they have persisted since the demonstrations subsided, but the sources of the rise in violence are subject to debate (see Cassell, 2020; Rosenfeld, 2020). The impact, if any, of the protests against police violence on the troubling increases in violent crime during 2020 is an especially important issue for future research.\(^8\)

Despite these limitations, we conclude that the amount of time persons spent at home had a nontrivial impact on aggravated assault, robbery, and larceny. An unanticipated consequence of residential confinement during the pandemic was, all else equal, to reduce the frequency of these offenses. But all else was not equal during the summer of 2020. Other factors influenced the trajectory of street crime, especially serious assault rates, which did not increase significantly until June, well after pandemic-related restrictions on population mobility went into effect. A comprehensive explanation of crime changes during the coronavirus pandemic must encompass conditions beyond the reduction of criminal opportunities occasioned by home quarantines and business closings, including social unrest over police violence, severe economic dislocations, and the sheer anguish of the pandemic itself. In short, explaining crime during the pandemic requires attention to factors that modify criminal motivations as well as opportunities.

The policy implications of the current study are complicated. It should go without saying that we do not promote quarantines and lockdowns as crime control devices. We do support recommendations to reduce crime by strengthening target hardening and guardianship in public spaces, such as augmenting street lighting, encouraging people to walk in groups while out at night, and increasing the visibility of convenience stores to the street. We also support the more timely and frequent release of official crime data. Waiting until the fall of 2021, a year and-a-half after the pandemic began, for the release of the 2020 UCR data unnecessarily inhibits research, public understanding, and policy response. Reviving a practice that was discontinued in the 1930s, the FBI took an important step by releasing quarterly offense data in 2020. The timely dissemination of nationwide crime data should continue, and the data should be sufficiently granular to permit the kind of empirical analyses carried out in the current study and prior research on crime during the pandemic.

We hesitate to offer policy recommendations that extend beyond the aims and results of the current study. That said, an urgent task in many cities is to quell persisting increases in homicide and other violent crime as the pandemic is brought under control and public activity returns to normal levels. This will require in our view proceeding along two intertwined paths: redoubling proactive crime control strategies of proven effectiveness (e.g., Braga et al., 2019), while at the same time implementing reforms to improve the relationship between the police and the communities they serve. At a minimum, the reforms should include increasing police accountability for proven misconduct and redirecting certain activities the police have assumed, largely by default, to other agencies better equipped to handle them. Were the police freed from frontline responsibility for addressing these problems, they would have more time to devote to their core mission, which currently has to be reducing serious violent crime. The difficult lesson of the coronavirus pandemic for crime control is to augment effective crime-reduction strategies and improving police–community relations without confining people to their homes.

**CONFLICT OF INTEREST**
The authors confirm that they have no conflict of interest to declare.

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ENDNOTES

1 See https://www.fbi.gov/services/cjis/ucr. The quarterly data can be found at https://crime-data-explorer.app.cloud.gov/explorer/national/united-states/prelim-quarter.

2 The weekly data were available for nine of the offenses in Austin and San Francisco; eight in Denver, Memphis, Philadelphia, Phoenix, Pittsburgh, Raleigh, St. Paul, and St. Petersburg; seven in Atlanta, Los Angeles, Louisville, Nashville, and Riverside; and six in Baltimore, Dallas, New York, Omaha, Seattle, and Washington.

3 Several cities in our sample occupy more than one county. The county that contains most of the city’s population is used in the analysis. For New York City, all counties (boroughs) are included.

4 The Google mobility data are not available for prior years.

5 We obtained 2020 monthly unemployment data from the Bureau of Labor Statistics (https://www.bls.gov). The unemployment rate was converted to a weekly measure by assigning each week its corresponding monthly value (i.e., the unemployment rate is constant within months).

6 The nonresidential burglary outlier in the last week in May 2020 is omitted from these estimations.

7 An upcoming special issue of Criminology & Public Policy is devoted to this topic.

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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## APPENDIX A

| City        | Source                                                                 |
|-------------|------------------------------------------------------------------------|
| Atlanta     | https://www.atlantapd.org/i-want-to/crime-data-downloads              |
| Austin      | https://data.austintexas.gov/Public-Safety/Crime-Reports/fdj4-gpfu     |
| Buffalo     | https://data.buffalony.gov/Public-Safety/Crime-Incidents/d6g9-xbgu/data?pane=feed |
| Chandler    | https://data.chandlerpd.com/catalog/general-offenses/                  |
| Chicago     | https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-Present/ijzp-q8t2 |
| Cincinnati  | https://data.cincinnati-oh.gov/Safety/PDI-Police-Data-Initiative-Crime-Incidents/k59e-2pvf |
| Dallas      | https://www.dallasopendata.com/Public-Safety/Police-Incidents/qv6i-rr7  |
| Denver      | https://www.denvergov.org/opendata/dataset/city-and-county-of-denver-crime |
| Detroit     | https://data.detroitmi.gov/datasets/rms-crime-incidents/              |
| Los Angeles | https://data.lacity.org/A-Safe-City/Crime-Data-from-2010-to-2019/63jg-8b9z |
| Louisville  | https://data.louisvilleky.gov/dataset/crime-reports                    |
| Memphis     | https://data.memphistn.gov/Public-Safety/Memphis-Police-Department-Public-Safety-Incidents/ybsi-jur4 |
| Milwaukee   | https://data.memphistn.gov/Public-Safety/Memphis-Police-Department-Public-Safety-Incidents/ybsi-jur4 |
| Minneapolis | http://opendata.minneapolismn.gov/                                   |
| Nashville   | https://data.nashville.gov/Police/Metro-Nashville-Police-Department-Incidents/2u6w-ujjs |
| New York    | https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Current-Year-To-Date-/5uac-w243 |
| Norfolk     | https://data.norfolk.gov/Public-Safety/Police-Incident-Reports/r7bn-2egr |
| Omaha       | https://police.cityofomaha.org/crime-information/incident-data-download |
| Philadelphia| https://www.opendataphilly.org/dataset/crime-incidents                 |
| Phoenix     | https://www.phoenixopendata.com/dataset/crime-data                    |
| Pittsburgh  | https://data.wprdc.org/dataset/police-incident-blotter                |
| Raleigh     | https://data-ral.opendata.arcgis.com/datasets/raleigh-police-incidents-nibrs |
| Riverside   | https://www.riversideca.gov/ transparency/dataset/show/27             |
| Sacramento  | http://data.cityofsacramento.org/search?tags=Public%20Safety           |
| San Francisco| https://data.sfgov.org/Public-Safety/Police-Department-Incident-Reports-2018-to-Present/wg3w-h783 |
| Seattle     | https://data.seattle.gov/Public-Safety/SPD-Crime-Data-2008-Present/tazs-3rd5 |
| St. Louis   | https://www.slmpd.org/Crimereports.shtml                              |
| St. Paul    | https://information.stpaul.gov/Public-Safety/Crime-incident-Report-Dataset/gppbgg9gc |
| St. Petersburg| https://stat.stpete.org/dataset/Police-Calls/2eks-pg5j                |
| Washington  | http://crimemap.dc.gov/Download.aspx                                  |
### APPENDIX B

| City            | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|-----------------|---|---|---|---|---|---|---|---|---|----|
| Atlanta         | x |   | x |   | x |   | x |   |   | x  |
| Austin          | x | x |   | x |   | x | x |   |   | x  |
| Baltimore       | x |   | x |   | x | x |   |   |   | x  |
| Buffalo         |   |   | x |   |   | x |   |   |   | x  |
| Chandler        | x | x |   |   |   |   |   |   |   | x  |
| Chicago         | x | x |   | x | x |   | x | x | x | x  |
| Cincinnati      | x | x | x | x |   |   | x |   |   |    |
| Dallas          |   |   |   | x | x | x | x | x | x | x  |
| Denver          | x |   | x | x |   | x | x | x |   | x  |
| Detroit         |   | x |   |   |   |   |   |   |   |    |
| Los Angeles     | x | x | x |   | x | x |   |   |   | x  |
| Louisville      | x | x |   | x | x | x |   |   |   | x  |
| Memphis         | x |   | x | x |   | x | x | x | x | x  |
| Milwaukee       | x | x |   |   |   |   |   |   |   | x  |
| Minneapolis     |   |   | x |   | x | x |   | x | x | x  |
| Nashville       | x | x |   | x | x |   | x | x |   | x  |
| New York        | x |   | x | x | x | x |   |   |   | x  |
| Norfolk         | x | x |   |   |   |   | x | x | x | x  |
| Omaha           | x | x | x | x | x |   | x |   |   | x  |
| Philadelphia    | x | x | x | x | x | x | x |   | x | x  |
| Phoenix         | x |   | x | x | x | x | x | x |   | x  |
| Pittsburgh      | x | x | x | x | x |   | x | x | x | x  |
| Raleigh         | x | x |   | x | x | x | x | x | x | x  |
| Riverside       | x | x | x | x | x | x | x | x | x | x  |
| Sacramento      |   |   |   |   |   |   |   |   |   | x  |
| San Francisco   | x |   | x | x | x | x | x | x |   | x  |
| Seattle         | x | x |   | x |   |   | x | x | x | x  |
| St. Louis       | x | x | x | x | x | x | x | x | x | x  |
| St. Paul        | x | x | x | x | x | x | x |   |   | x  |
| St. Petersburg  | x | x |   | x | x | x | x | x | x | x  |
| Washington      | x | x | x | x |   | x | x | x |   |    |
| **Number**      | 25| 19| 17| 13| 28| 18| 18| 25| 27| 20 |

**Key**

1. Homicide
2. Aggravated Assault
3. Gun Assault
4. Domestic Violence
5. Robbery
6. Residential Burglary
7. Nonresidential Burglary
8. Larceny
9. Motor Vehicle Theft
10. Drug Offense