Document Title: Expanding the Scope of Research on Recent Crime Trends

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Abstract

Statement of Purpose

While there is a burgeoning research literature on crime trends, much of the extant research has adopted a relatively narrow approach, efforts across studies are highly variable, and the overall conclusions that can be drawn are ambiguous. In our judgment, one reason for this state of affairs is that the current data infrastructure that supports crime trends research is incomplete and scattered, yielding redundant efforts and highly inconsistent approaches. The primary purpose of this project was to enhance the data infrastructure by compiling in a centralized location the most commonly referenced datasets and measures. An ancillary objective was to illustrate the utility of the resulting data archive. We do so by considering three substantive research issues: (1) a uniform set of analyses across states, counties, and cities; (2) an assessment of the conditional effects of economic conditions on recent crime trends; and (3) an expanded analysis of the effects of key criminal justice attributes (e.g., the nature of policing, age- and crime-specific imprisonment rates) on recent crime trends that have not been considered extensively in prior research.

Methods

The specific samples, time frames, and measures employed vary somewhat across the three substantive issues addressed, but our general analytical strategy in addressing these issues is to construct when possible from the Crime Trends Data Archive (CTDA) produced in the project a panel database with requisite measures centered on the following time points: 1980, 1985, 1990, 1995, 2000, 2005, and 2010. This approach marshals the strength of a pooled cross-sectional design, while also avoiding the significant data imputation that is needed to support panel analyses of annual time periods for sub-national geographic units. The three sets of empirical analyses reported in the project include models of overall homicide, non-lethal violence (robbery and aggravated assault), and non-violent property crime (burglary, motor vehicle theft, and larceny). We estimate a series of two-way fixed-effects panel models of crime rates that include fixed effects that control for stable unmeasured city attributes and temporal shocks that are shared across cities.

Results

Our uniform empirical analysis across units of analysis revealed that minimalist specifications can yield misleading conclusions. It also revealed that age structure and divorce rates are robust predictors of crime rates, with higher crime in areas with a larger percentage of persons aged 15-29 and where divorce rates are higher. Additionally, the results reaffirm findings shown in other work on non-violent property crime by showing that incarceration rates tend to yield lower crime rates, but at a diminishing rate as incarceration reaches very high levels. Our analysis of conditional economic effects pointed to a tendency of "objective criminal justice risk" to lessen the criminogenic consequences of elevated unemployment rates and depressed wages. Another intriguing pattern that emerged is that the estimated adverse effects of unemployment and wages on non-lethal crime (both violent and property) are weaker in the face of elevated levels of income maintenance payments (i.e., SSI, Snap, family assistance). Finally, our expanded analysis of criminal justice factors showed that, at least for non-lethal violence and non-violent property crime, arrest certainty for these crimes is a robust predictor of lower crime rates. We also found that non-violent

property crime rates are significantly lower in counties with higher imprisonment rates and in counties situated within states that have higher imprisonment rates.

Conclusions

The key product of the grant – the CTDA -- should prove valuable to those involved in or considering the study of contemporary American crime trends. We recommend that the NACJD use the CTDA as the basis of establishing a permanent, distinct archive on crime trends research.

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Executive Summary

Statement of Purpose

This project focused on addressing two general issues, as outlined in the original proposal: (a) enhancing the data infrastructure available to study recent American crime trends; and (b) clarifying and expanding the scope of empirical analysis directed at describing and explaining recent crime trends. Both objectives are motivated by the relatively strong and growing interest among policy makers, the media, criminal justice practitioners, and the general public in the properties and predictors of crime trends across America.

Rationale

Enhancing the Data Infrastructure

Notwithstanding the extraordinarily useful features of the NACJD, which contains many pertinent data elements that will be of interest to researchers who wish to study recent crime trends, the existing data infrastructure is limited in two notable ways: (1) it is incomplete and/or somewhat decentralized; and (2) it contains pieces of the puzzle but little *shared work-product* about how those pieces might be and often are fitted together.

Before elaborating on the first issue, it is important to acknowledge that the NACJD and other data archives bring together an enormous volume of data, much of which is pertinent to research on recent crime trends. Indeed, without the NACJD it would be nearly impossible to access in short-order the various components needed to sufficiently examine crime trends across multiple units, such as states, counties, or cities. Nevertheless, there are several data resources that are relevant to studying crime trends that do not fall within the normal confines of the NACJD. This includes data on social, economic, and demographic attributes from the decennial census and the annual American Community Survey (ACS), data on annual unemployment rates from the Bureau of Labor Statistics (BLS), data on wages and other economic indicators from the Bureau of Economic Analysis (BEA). Other pertinent data sources (e.g., the National Corrections Reporting Program [NCRP]) are included in NACJS, but not in forms that are easily modified to support their use in studies of crime trends. Finally, some of the available resources housed at the NACJD possess notable limitations for studying contemporary crime trends. For example, though the NACJD produced county-level crime and arrest data avoid many of the issues that emerge when researchers estimate county data from NACJD (or FBI) agency-level data (see Maltz and Targonski, 2002, 2004), the current county-level holdings at NACJD apply divergent imputation procedures from 1994 onward, introducing an important break from prior years that can be problematic for studies of crime trends that span before and after this period.

While there is a need to enhance the data infrastructure for studying crime trends by broadening the data that are available in a centralized location, an even more pressing matter is to develop an archive of the substantial data processing and manipulation required to put the available data to work. Studying crime trends is somewhat different than many other research endeavors. Rather than drawing on a single survey or a few major data sources that encompass one or perhaps a small handful of data "waves," a typical study of recent crime trends entails the combination of a very large number of distinct data sources, and often in each case ten, twenty, or perhaps even more "temporal installments" of those sources. The nature of the task at hand means that simply providing an archive of raw data with machine readable "setup" files will help, but this represents a relatively small portion of the overall effort involved in generating the data needed to study crime trends. The point being made here is not that the remainder of the work needed to do a crime trends study should fall on the NACJD, but rather that a highly useful archive would not only house a wide array of data but also would document how such data are combined and analyzed to generate meaningful information about crime trends. This is the general direction in which data archiving has been heading for the past several years within the NACJD, and in the area of crime trends research it should be especially welcomed.

With these points as a backdrop, this project focused in part on assembling in a centralized location the various data resources that might be used in a standard crime trends study to ensure a reasonable, theoretically informed, baseline empirical specification. Many of these sources already are contained within the NACJD, but others were culled from other sources. Importantly, in both of these instances, we include in a centralized directory the raw data, machine readable setup code, and programming syntax used to extract pertinent data and integrate with other sources to generate analysis-ready datasets for states, counties, and cities. This is not to suggest that we have resolved all of the challenging issues that arise in integrating data to study crime trends. There are inherent limitations of data availability with respect to temporal and spatial coverage (e.g., some measures are not available on an annual basis or are not measured for all the pertinent levels of geography that interest crime trends researchers) and some purposeful scope conditions that we imposed to keep the effort manageable (e.g., we do not include metro areas as a distinct unit). Nevertheless, the full data archive assembled for the study includes a substantial amount of information that might be used in a wide variety of ways, and this should facilitate more systematic efforts that focus on some of the more challenging issues just noted.

Clarifying and Expanding the Scope of Empirical Research on Recent Crime Trends

We illustrate the utility of the CTDA with an assessment of three empirical assessments: (1) a uniform set of analyses across states, counties, and cities; (2) an assessment of the conditional effects of economic conditions on recent crime trends; and (3) an expanded analysis of the effects of key criminal justice attributes (e.g., the nature of policing, age- and crime-specific imprisonment rates) on recent crime trends that have not been considered extensively in prior research. We next elaborate briefly on the rationale for each of these analyses.

Uniform empirical specification across states, counties, and cities. An important initial set of analyses conducted in the study encompasses the estimation of parallel empirical models of crime trends across multiple units of analysis, focusing on the most commonly used geographic boundaries employed in the extant research: states, counties, and cities. The basic objective is to "hold constant" differences in model specification to discern potential uniformities in empirical results that may emerge across levels of analysis (or, alternatively, to identify meaningful differences in patterns across different geographies). Though there are many examples of highly sophisticated studies of crime trends, the cumulative body of literature in this area tends to be highly variable and relatively narrow in its application. As Baumer (2008) elaborates, prior research on crime trends often focuses on somewhat different time periods and outcome measures, but it is particularly inconsistent in three ways: (a) the variables included as covariates; (b) the units of analysis used; and (c) the application of different statistical methods to estimate key parameters.

While a diversity of approaches can be a healthy feature of scientific research, it can generate ambiguity if it is not accompanied by some systematic assessments that hold constant key factors that tend to vary across studies. For instance, the conclusions one draws about the role of many factors (e.g., incarceration, police size, and age structure) appear to be highly contingent on the unit of analysis used, and the estimated role of these and other factors (e.g., unemployment) seems highly sensitive to model specification and/or analytical procedure (e.g., Liedka et al., 2006; Defina and Arvanites, 2002; Eck and Maguire, 2006; Spelman, 2005). It could be that crime trend patterns and predictors vary meaningfully across cities, counties, and states. But the current research literature cannot tell us this, because the typical empirical specification adopted is highly variable both within and across studies based on different units of analysis. Studies of crime trends also often apply different methods both within and across units of analysis to estimate key parameters, which may yield different results even when the same data are used.

In summary, while there are no strong reasons at the present time to preference *a priori* a particular unit of analysis or analytical strategy for studying crime trends, it would be useful to know the empirical implications of using different units of analysis and different approaches, something that cannot be deciphered easily from existing research. Building on comparable approaches to cross-sectional crime research (e.g., Land, McCall, and Cohen, 1990), one of the key sets of analysis presented below is directed at advancing the literature by applying a uniform set of empirical specifications and procedures across multiple units of analysis. We specifically address whether identical empirical specifications applied to data for a given time period yields comparable results when applied to American states, counties, and cities. The objective of this portion of our work is modest—does the same specification yield comparable findings across cities, counties, and states?—but we consider an important step in clarifying the existing research on crime trends.

Expanding analyses of economic factors. The project also highlights a few more specific topics, including the potential conditional effects of economic factors. *Specifically, we examine whether two of the most common indicators of economic adversity in crime trends research–high unemployment rates and depressed wages --exhibit effects on crime rates that are contingent on other factors, including prevailing levels of inflation, the extent of unemployment insurance and other income supportive benefits dispensed, police force size, and incarceration rates.*

Adverse economic conditions have been linked to elevated crime rates through a variety of theoretical frameworks, encompassing arguments about cost-benefit assessments, heightened stress and anxiety, and shifting routine activities among others. Drawing on this literature, the accumulated body of evidence on the relationship between crime rates and adverse economic conditions (e.g., rising unemployment and falling wages) suggests that sometimes significant downturns in the economy yield an increase in crime and sometimes they do not (e.g., Bushway, Cook, and Phillips, 2010; Cook and Zarkin, 1985; Chiricos and DeLone, 1992; Smith, Devine and Sheley, 1992). The mixed or ambiguous empirical literature on macro-economic conditions and crime rates sometimes is written-off as a function of empirical misspecification (Greenberg, 2001; Raphael and Winter-Ebmer, 2001). However, another possibility is that adverse economic circumstances yield increases in crime (and good times yield decreases in crime) *only under certain conditions*. In essence, the idea that increasing economic adversity should simply yield a linear increase in crime rates is unlikely to capture the full range of behavioral realities that may be observed. Most prior research has focused on the effects of adverse economic conditions on crime rates, irrespective of the broader context in which those conditions arise or play out. Using the data generated for this NIJ DRP project, we expand prior efforts by evaluating the influence on crime rates of two common indicators of economic adversity – rising unemployment and declining wages. More specifically, we examine both the overall influence of these conditions on crime and the degree to which their effects on crime may differ depending on other factors. As elaborated in the full report, we specifically evaluate: *whether inflation levels moderate the effects on crime of unemployment rates and wages; whether the effects on crime rates of unemployment rates and wages are moderated by levels of spending on unemployment insurance and income maintenance; and whether the effects on crime rates of unemployment rates and wages are conditioned by changes in police force size and incarceration rates.*

Expanding the typical set of criminal justice variables considered. The two factors that perhaps have received the most attention in public discourse on recent crime trends, and especially the 1990s crime decline, are changes in policing and incarceration. Each of these factors, and criminal justice actions more generally, has been linked to crime trends mainly through their theoretical capacity to serve an incapacitation or deterrent function. Prior research on crime trends often includes some indicator of criminal justice activity, but the specific factor(s) included vary across studies. More important from our standpoint, though, is that the extant research tends to approach criminal justice factors from a relatively narrow vantage point. In the context of policing, this narrowness manifests most frequently in a focus on the *quantity of policing* and a parallel neglect in the *quality of policing*. With respect to incarceration, as already noted city- and county-level studies often ignore incarceration rates altogether. But a more general limitation of the extant research is its reliance on *overall incarceration* rates. As elaborated below, a broader consideration of post-arrest criminal justice indicators may prove useful for expanding our understanding of how criminal justice responses affect crime trends. *Accordingly, we extend the typical empirical specifications employed by considering additional criminal justice variables that may be relevant to crime trends, including proactive policing, and age- and crime-specific imprisonment rates per capita.*

As Eck and Maguire (2006) note, most of the studies of crime trends that emphasize the *quantity of policing* do so in a context that ignores the *quality of policing.* A handful of studies have shown that various changes in the nature of policing that occurred in the 1980s and 1990s, and especially policing efforts that target particular types of behaviors thought to facilitate crime, such as levels of public disorder and the prevalence of weapon carrying, can have important implications for crime levels. Early studies of jurisdictional differences in "arrest certainty" (e.g., Yu and Liska, 1993) come to mind here, as does New York City's highly lauded organizational shifts and orchestrated "order maintenance" approach to policing and "reclaiming public spaces" during the first half of the 1990s. This research motivates the need to further assess the role of police force size, but also directs attention to a wider array of policing indicators, including shifts over time and places in "arrest certainty" and the types of activities to which police resources are allocated. The latter has been referred to in the literature in a variety of ways, including "order maintenance policing" (Rosenfeld et al., 2005) and "proactive policing" (e.g., Sampson and Cohen, 1988; Kubrin et al., 2010). The present study builds on existing work by examining whether proactive policing (see also Messner et al., 2007; Rosenfeld et al., 2007), is associated with recent crime trends.

We also expand recent investigations of the role of incarceration in shaping crime trends. Several studies have focused particularly on estimating the effects on crime trends of shifts in levels of incarceration (see Stemen, 2007, for a review). Despite the substantial attention devoted in prior research to the role of incarceration and the possibility of an emerging consensus about the magnitude of its effects on recent crime trends (e.g., Goldberger and Rosenfeld, 2008), several issues warrant additional consideration and are examined in the present study. Specifically, the present study goes beyond prior research by estimating the effect on recent crime trends of age- and crime-specific measures of incarceration rates and by evaluating the role of an alternative indicator, which we label imprisonment-arrest ratio.

Though the standard approach of including overall incarceration rates is a useful beginning point, both of the primary arguments that have been used to link shifts in incarceration to crime trends—incapacitation and deterrence—imply that a more specific focus may be meaningful. In particular, we explore whether age- and crime-specific incarceration rates may yield differential effects on age- and crime-specific offending trends. Analyzing age-specific data seems quite important given the emphasis placed on incapacitation effects in the extant literature. Suffice it to say that analyzing the association between age-specific indicators of imprisonment and crime provide a more direct assessment of such effects than non-disaggregated data. Additionally, though offenders do not tend to specialize in most instances, since a large fraction of the mass imprisonment era has been led by shifts in imprisonment among drug offenders, analyzing overall imprisonment and crime might mask potentially important deterrent and/or incapacitation effects of imprisonment. Crime-specific analyses will enable a closer examination of this possibility.

Methods

The specific samples, time frames, and measures employed vary somewhat across the three substantive issues addressed, but our general analytical strategy in addressing these issues is to construct when possible from the CTDA a panel database with requisite measures centered on the following time points: 1980, 1985, 1990, 1995, 2000, 2005, and 2010. This approach marshals the strength of a pooled cross-sectional design, while also avoiding the significant data imputation that is needed to support panel analyses of annual time periods for sub-national geographic units (see also LaFree, Baumer, and O'Brien, 2010). To elaborate, while annual data are typically available for a small number of requisite measures—namely crime rates, arrest rates, police force size, and incarceration rates—most of the data applied in crime trends studies is available much less frequently, especially for units such as cities. For instance, potentially key predictors such as poverty rates, racial composition, and even population size and density have for most of the contemporary era been available for sub-national units only on a decennial basis. The strategy adopted here limits the assumptions that need to be made in imputing intercensal values for these variables, while also preserving a substantial portion of the observed temporal variation in crime trends over the last three decades.

The three sets of empirical analyses reported in the project include models of overall homicide, non-lethal violence (robbery and aggravated assault), and non-violent property crime (burglary, motor vehicle theft, and larceny). The vast majority of crime trends studies focus on overall homicide, presumably because of the superior validity and reliability of data on homicide across places and over time. While we are sensitive to the potential for systematic measurement errors in studying trends in police-based measures of non-lethal violence and also property crime, we note that spatial and temporal patterns in these crimes tend to parallel those observed for homicide. Additionally, the existing knowledge—admittedly limited--suggests that they exhibit comparable patterns of under-reporting across geographic areas and over time (e.g., Baumer, 2002; Baumer and Lauritsen, 2010). We remain attentive to the potential bias that might be present in assuming, but we include them in the project both because these crimes represent the bulk of criminal activity in America (in comparison with homicide, which is relatively rare) and because they are important theoretically for assessments of conditional economic effects and criminal justice measures.

Though we include a common set of explanatory variables across the three sets of analyses, we also include variables that are unique to each. Thus, we describe the measures in greater detail below under sub-heading that focus explicitly on the three sets of analyses. In contrast, because each analysis draws from the same general design (i.e., a multi-wave panel design, or in other words a pooled cross-sectional design) and encompasses the same outcomes, a common set of statistical issues emerges and we therefore adopt a common analytical strategy. Specifically, given the research issue addressed and the pooled, cross-sectional nature of the data, we apply econometric panel modeling techniques to evaluate the effects on crime rates of the explanatory measures. We specifically estimate a series of two-way fixed-effects panel models of crime rates that include fixed effects that control for stable unmeasured city attributes and temporal shocks that are shared across cities (Raphael and Winter-Ebmer, 2001; Worrall and Pratt, 2004). Consistent with previous research, crime rates across each of the samples examined in the analysis exhibited significant serial autocorrelation, which we account for by specifying first-order autocorrelation within panels. Finally, to minimize the potential bias that can arise from significant cross-sectional correlations among disturbances, we report panel-corrected standard errors, which allow the disturbances to be heteroskedastic and contemporaneously correlated across panels (Wilson and Butler, 2007).

Results

A uniform empirical specification across states, counties, and cities. The results indicate that city, county, and state models of crime trends that apply minimalist empirical specifications are likely to yield misleading results. For instance, the estimated effects of one of the stalwarts of city-level analyses—resource deprivation—is highly sensitive to the model specification employed, and in particular it is greatly attenuated when factors such as state incarceration and temporal and spatial fixed effects are considered. Additionally, in state-level models it is apparent that the estimated effects of stock incarceration rates are sensitive to empirical specification, with evidence of both suppression and attenuation of the anticipated negative effects. Perhaps most important, the uniform empirical analysis across units of analysis reveals some consistent patterns across crime types and units. Most notably, these models suggest that age structure and divorce rates are robust predictors of crime rates, with higher crime in areas with a larger percentage of persons aged 15-29 and where divorce rates are higher. Additionally, the results reaffirm findings shown in other work on non-violent property crime by showing that incarceration rates tend to yield lower crime rates, but at a diminishing rate as incarceration reaches very high levels.

An assessment of conditional economic effects on recent crime trends. The results point to a tendency of "objective criminal justice risk" to lessen the criminogenic consequences of elevated unemployment rates and depressed wages. Another intriguing pattern that emerges is that the estimated adverse effects of unemployment and wages on non-lethal crime (both violent and property) are weaker in the face of elevated levels of income maintenance payments (i.e., SSI, Snap, family assistance). Finally, contrary to expectations, inflation levels do not moderate the effects of wages and unemployment rates in our analysis. Overall, we find moderately strong evidence that the assumed main effects of wages and unemployment rates in most previous studies is questionable. The influence of these economic conditions on contemporary crime trends is contingent on other conditions, and this may be one reason why past research yields highly inconsistent empirical patterns for these attributes.

Expanding the typical set of criminal justice variables considered. Our expanded analysis of criminal justice factors shows that homicide rates appear to be insensitive to the quantity and quality of policing or levels of incarceration. A consistent finding that emerged was that, at least for non-lethal violence and non-violent property crime, arrest certainty for these crimes is a robust predictor of lower crime rates. This implies that prior county-level studies, which typically have not included policing measures, may be misspecified, and it also highlights an important dimension of policing for shaping recent crime trends. In contrast, police size and proactive policing do not yield the anticipated negative associations with crime rates and, in fact, exhibit positive signs in several of the models. With respect to prison measures, the findings for non-lethal violence are not consistent with expectations. County variation in robbery and aggravated assault is generally not responsive to county differences in imprisonment risk. However, non-violent property crime rates are lower in counties with higher imprisonment rates and in counties situated within states that have higher imprisonment rates. The results for the age-specific county imprisonment variables indicate that both yield significant negative associations with non-violent property crime, but imprisonment rates of younger persons (i.e., ages 18-34) is stronger. Finally, consistent with expectations, rates of non-violent property crime are not affected by imprisonment rates for homicide or non-lethal violence, but they are influenced by imprisonment rates for non-violent property crime.

Conclusions

The primary purpose of this project was to enhance the data infrastructure by compiling in a centralized location the most commonly referenced datasets and measures. The key product of the grant -- the Crime Trends Data Archive (CTDA) -- should prove valuable to those involved in or considering the study of contemporary American crime trends (the CTDA is described in greater detail in Appendix A). Thus, while some of the empirical results presented can be read in terms of policy implications, the most important contribution of the present work to policy and practice is in generating a research infrastructure that can facilitate timely and informative research on crime trends and policy issues moving forward. To fully take advantage of the products of this grant, we offer two recommendations. First, it would be a good investment for the appropriate government agency to continue development of the CTDA, including updates as new data become available. Second, the CTDA will be useful to the extent that it is made widely available to other scholars. While the project uses many resources that are already archived, and thus could be retained as separate data collections, the utility of the CTDA lies in its integration of the various components needed to generate meaningful assessments of crime trends in a centralized space. We recommend that the NACJD use the CTDA as the basis of establishing a permanent, distinct archive for studying crime trends.

Technical Report

I. Introduction: Statement of the problem and relation to existing literature

This project focused on addressing two general issues, as outlined in the original proposal: (a) *enhancing the data infrastructure* available to study recent American crime trends; and (b) *clarifying and expanding the scope of empirical analysis* directed at describing and explaining recent crime trends. The rationale for tackling each objective is elaborated below. We begin with a general statement of the problem that motivates these efforts and then elaborate on the specific objectives pursued in the project.

Ia. Enhancing the infrastructure. The substantial shifts in crime observed in the United States since the early 1980s have stimulated a strong and growing interest among policy makers, the media, criminal justice practitioners, and the general public in the properties and predictors of crime trends. Yet, the extant empirical research on recent crime trends has taken an overly narrow empirical approach, yielding significant ambiguity in the conclusions that can be drawn. One apparent reason for this state of affairs is that the underlying data infrastructure that supports current work is incomplete and highly inconsistent across studies. As elaborated below, the literature on crime trends is relatively modest in size; though it has grown in recent years, the work that has been done varies significantly in terms of the measures employed, temporal coverage, and units of analysis. One of the likely major reasons for this is that the data needed to study crime trends tend to be highly decentralized. Even as electronic access to data has increased substantially and highly germane topical archives such as the National Archive of Criminal Justice Data (NACJD) have evolved into invaluable resources for researchers, some of the data elements frequently used to study crime trends are missing or are not easily attainable in available archives, and others are provided in forms that require extensive processing to be ready for analysis. Several scholars have taken the needed steps to assemble the requisite data, but the substantial work product from such efforts typically has not been archived, yielding a very inefficient process in which each crime trends study essentially must start from scratch. Accordingly, one of the primary objectives of the proposed project was to contribute to a comprehensive data infrastructure that would support an ongoing and more systematic research agenda on recent crime trends. Though the resulting, centralized data archive does not contain all of the pertinent pieces that might be relevant to resolving existing crime trends "puzzles," our hope is that it will serve as a launching point to stimulate others to expand and add to the effort on an ongoing basis.

Ib. Clarifying and expanding the scope of empirical analysis. Empirical studies of crime trends tend to be highly variable and relatively narrow in their application. Both of these issues—inconsistency and limited scope—have impeded the accumulation of knowledge on the factors most germane to explaining recent crime trends. These issues are interrelated, and tend to manifest in empirical studies in at least three ways: (a) differences in the variables included as covariates; (b) the use of different units of analysis; and (c) the application of different statistical methods to estimate key parameters. We discuss first the highly variable and somewhat limited empirical specifications employed in the literature on recent crime trends, which also illuminates the disparate approaches often taken in studies that rely on different units of analysis. We then highlight the variety of statistical approaches taken in such studies, many of which are defensible for the task at hand but which nonetheless add a layer of complexity for extracting emergent patterns from the existing research.

Though there are plenty of sophisticated and useful empirical studies of crime trends, many are focused on a small subset of potential factors. Often, studies focus on a single factor, such as police force size, economic adversity, drug involvement, or incarceration, and they do so in a context of not fully considering many other potentially pertinent predictors. For instance, many city-and county-level studies of recent crime trends (e.g., Levitt, 1997; Baumer, 1998; Lott, 1998; Gallup-Black, 2005; Ousey and Lee, 2002; Phillips, 2006) have focused largely on policing, age structure, and drug involvement, while rarely incorporating *any* indicators of incarceration, which have emerged as central in many other studies. Similarly, state-level studies of recent crime trends routinely include indicators of overall incarceration rates (e.g., Marvell and Moody, 1994; 1997; Levitt, 1996; Liedka, Piehl, and Useem, 2006), but they have not considered age- or crime-specific incarceration rates, average sentence length, time served, or other potentially important criminal justice variables, such as conviction probabilities. Few of the existing studies of recent crime trends (at any level of aggregation) have included indicators of recent immigration flows (for an exception, see Stowell et al., 2009) and, surprisingly, just a few have incorporated direct indicators of changes in the *nature* of policing (MacDonald, 2002; Messner et al., 2007; Rosenfeld, Fornango, and Rengifo, 2007; Kubrin et al., 2010). A similar story is evident for many economic conditions emphasized as potentially important in the theoretical literature on recent crime trends. Although the occasional study examines wages, consumer sentiment, or overall economic output (e.g., Gould, Weinberg, and Mustard, 2002; Rosenfeld and Fornango, 2007), most studies do not consider these factors despite evidence suggesting that they may be important. In short, a common theme in the extant research on recent crime trends is that most studies have a relatively limited scope, focusing on a few select factors and ignoring many other potentially important ones.

More generally, even studies that focus on the same substantive issue rarely employ parallel empirical approaches. To the contrary, there is little uniformity in studies of crime trends. As just noted, studies employ widely varying sets of covariates, but they also frequently adopt different units of analysis and statistical methods to estimate key parameters. While uniformity, per se, is not always desirable, the very high level of variability across crime trends studies in these data and methodological elements has impeded efforts to pin down generalizations in observed empirical patterns. Research on recent crime trends has been conducted across multiple units of analysis, most often states, counties, and cities, but also neighborhoods and police precincts. It is not necessarily important that a particular unit of analysis be identified, *a priori*, as superior for studying crime trends, for the reality is that there are important tradeoffs in the choice of unit (e.g., larger units, such as states and counties, are fairly heterogeneous but they yield the necessary annual data on many of the factors thought to be important for shaping crime trends, while smaller units, such as neighborhoods or police precincts are more homogenous but rarely yield time-varying indicators of most of the relevant factors). Nonetheless, it would be useful to know the empirical implications of using different units of analysis, something that cannot be deciphered easily from existing research. There is usually some overlap, but the models typically estimated using different units (e.g., states vs. counties vs. cities) incorporate quite different sets of explanatory variables (c.f., Ousey and Lee, 2002; Moody and Marvell, 2005; Kovandzic and Vieraitis, 2006). There is also a lack of uniformity across studies of recent crime trends based on the same unit of analysis (c.f., Gould et al., 2002; Phillips, 2006; also, c.f. Donohue and Levitt, 2001; Liedka et al., 2006).

Studies of crime trends also tend to apply different methods to estimate key parameters. Although some studies have used procedures geared toward identifying classes of crime "trajectories" (e.g., Weisburd et al., 2004), perhaps because a central interest in this area of research is in *explaining* recent crime trends, most studies have applied different versions of two suitable analytical strategies: pooled time-series cross-sectional panel models (e.g., Donohue and Levitt, 2001; Gould et al., 2002; Phillips, 2006) and multilevel growth curve models (e.g., Baumer et al., 1998; Kubrin and Herting, 2003; Ousey and Lee, 2004; Rosenfeld et al., 2007). The specific choice between these approaches is not very important, for they can be made to be equivalent with proper modifications, but it is critical to recognize that the two approaches typically are implemented in ways that are likely to generate different findings and conclusions even when applied to the same data (Phillips and Greenberg, 2008). Overall, though we have learned much from existing studies of crime trends, the relatively low degree of uniformity in model specification and statistical methods within and across units of analysis makes it difficult to detect general emergent patterns from the extant research and to draw definitive conclusions about the relevance of given factors.

In light of the noted ambiguities of extant research on recent crime trends, in addition to the data infrastructure component of the project, three sets of analysis were conducted in the project with an aim toward illuminating the utility of the data product generated in the project and for clarifying and expanding the scope of research on recent crime trends: (1) the estimation of a parallel series of "baseline" empirical models of recent crime trends using different units of analysis, focusing on state, counties, and cities[1]; (2) an expanded analysis of the effects of key criminal justice attributes (e.g., the nature of policing, age- and crime-specific imprisonment rates) on recent crime trends that have not been considered extensively in prior research; and (3) an assessment of the conditional effects of economic conditions on recent crime trends. The first of these was explicitly described in the original proposal. The second two were implied but not detailed in the proposal, in large measure because the proposal focused on data infrastructure enhancement and was relatively vague in terms of the specific substantive analyses to be considered. Nonetheless, during the course of the project these issues emerged as logical and particularly fruitful substantive applications of the overarching focal point of the study (i.e., to clarify and expand the scope of crime trends research). Expanding the criminal justice attributes typically considered seems useful both because it focuses on central policy variables and because it draws on several existing NACJD sources, which is the essence of the NIJ Data Resources Program (DRP) under which the project falls. Further, the detailed assessment of conditional economic effects on crime trends is timely in light of the major recession that hit the nation during the latter part of the 2000s, which has occurred largely without notable increases in crime. Not surprisingly, this has stimulated renewed calls for research to explore the conditions under which adverse economic circumstances are or are not likely to yield significant rises in crime rates.

II. Rationale for the research

The main objectives of this project were to *enhance the data infrastructure for studying crime trends*, and to *clarify and expand the scope of existing research on crime trends*. As noted above, the latter effort was focused on three sets of analyses (i.e., analysis of a parallel baseline model across multiple units of analysis; an expanded analysis of criminal justice attributes; and an assessment of conditional economic effects on crime trends). The rationale for considering these issues is described in more detail below in this section, and the data, methods, and results related to them are discussed in subsequent sections. Before turning to these substantive issues, however, we discuss some pertinent issues regarding the backdrop for pursuing the first stated objective. Enhancing the data infrastructure for studying crime trends entailed a major effort directed toward centralizing the somewhat scattered data sources that often are used in studies of crime trends, adding data that are not routinely considered, and producing an integrated set of data files and data manipulation files

[1]As noted in the original research proposal, we also considered the possibility of using Metropolitan Statistical Areas (MSAs) as a distinct geographic unit in this project. Though we concur with others that MSAs can serve as a useful level of geographic and social aggregation (Stowell et al., 2009), we steered away from generating distinct data sources because of its overlap with the state- and county-level components of our research, and because of two unique complications that arise when studying MSA crime trends. First, MSAs represent county-group areas that have changed considerably in composition over time, and though some MSA crime data are routinely published by the FBI, it is not possible to impose from published sources a comparable set of MSA definitions across the three decades considered in our study. Second, while MSA crime estimates could be derived in a consistent manner across time by aggregating county-level crime data with careful attention to shifting MSA boundaries, doing so compounds the general problems that have been documented about aggregating crime data (Maltz and Targonski, 2004).

that could facilitate in a more efficient manner research in this area of inquiry. We next describe the data resource produced in the project, which also serves as the "results" of this effort.

IIa. Enhancing the data infrastructure

Notwithstanding the extraordinarily useful features of the NACJD, which contains many pertinent data elements that will be of interest to researchers who wish to study recent crime trends, the existing data infrastructure is limited in two notable ways: (1) it is incomplete and/or somewhat decentralized; and (2) it contains pieces of the puzzle but little *shared work-product* about how those pieces might be and often are fitted together.

Before elaborating on the first issue, it is important to acknowledge that the NACJD and other data archives bring together an enormous volume of data, much of which is pertinent to research on recent crime trends. Indeed, without the NACJD it would be nearly impossible to access in short-order the various components needed to sufficiently examine crime trends across multiple units, such as states, counties, or cities. Nevertheless, there are several data resources that are relevant to studying crime trends that do not fall within the normal confines of the NACJD. This includes data on social, economic, and demographic attributes from the decennial census and the annual American Community Survey (ACS), data on annual unemployment rates from the Bureau of Labor Statistics (BLS), data on wages and other economic indicators from the Bureau of Economic Analysis (BEA). Other pertinent data sources (e.g., the National Corrections Reporting Program [NCRP]) are included in NACJS, but not in forms that are easily modified to support their use in studies of crime trends. Finally, some of the available resources housed at the NACJD possess notable limitations for studying contemporary crime trends. For example, though the NACJD produced county-level crime and arrest data avoid many of the issues that emerge when researchers estimate county data from NACJD (or FBI) agency-level data (see Maltz and Targonski, 2002, 2004), the current county-level holdings at NACJD apply divergent imputation procedures from 1994 onward, introducing an important break from prior years that can be problematic for studies of crime trends that span before and after this period.

While there is a need to enhance the data infrastructure for studying crime trends by broadening the data that are available in a centralized location, an even more pressing matter is to develop an archive of the substantial data processing and manipulation required to put the available data to work. Studying crime trends is somewhat different than many other research endeavors. Rather than drawing on a single survey or a few major data sources that encompass one or perhaps a small handful of data "waves," a typical study of recent crime trends entails the combination of a very large number of distinct data sources, and often in each case ten, twenty, or perhaps even more "temporal installments" of those sources. The nature of the task at hand means that simply providing an archive of raw data with machine readable "setup" files will help, but this represents a relatively small portion of the overall effort involved in generating the data needed to study crime trends. The point being made here is not that the remainder of the work needed to do a crime trends study should fall on the NACJD, but rather that a highly useful archive would not only house a wide array of data but also would document how such data are combined and analyzed to generate meaningful information about crime trends. This is the general direction in which data archiving has been heading for the past several years within the NACJD, and in the area of crime trends research it should be especially welcomed.

With these points as a backdrop, this project focused in part on assembling in a centralized location the various data resources that might be used in a standard crime trends study to ensure a reasonable, theoretically informed, baseline empirical specification. Many of these sources already are contained within the NACJD, but others were culled from other sources. Importantly, in both of these instances, we include in a centralized directory the raw data, machine readable setup code, and programming syntax used to extract pertinent data and integrate with other sources to generate analysis-ready datasets for states, counties, and cities. This is not to suggest that we have resolved all of the challenging issues that arise in integrating data to study crime trends. There are inherent limitations of data availability with respect to temporal and spatial coverage (e.g., some measures are not available on an annual basis or are not measured for all the pertinent levels of geography that interest crime trends researchers) and some purposeful scope conditions that we imposed to keep the effort manageable (e.g., we do not include metro areas as a distinct unit). Nevertheless, the full data archive assembled for the study includes a substantial amount of information that might be used in a wide variety of ways, and this should facilitate more systematic efforts that focus on some of the more challenging issues just noted. The "final" files used in our substantive analyses were generated from the archived data assembled for the project and are based on a small subset of the available elements, designed to facilitate a uniform set of analyses across states, counties, and cities and to expand existing analyses of selected issues (e.g., to consider additional criminal justice variables and neglected specifications for the effects of economic adversity). The full data archive is described here, and the analysis-ready files are described in detail in the next section.

<u>Crime Trends Data Archive (CTDA)</u>

As outlined in the proposal, this project integrated data from a wide variety of sources with an eye toward enhancing the data infrastructure available to study recent crime trends. In Appendix A, we present a codebook for the data assembled for the project. The codebook details the sources from which we gathered information, the specific files included, and the data elements generated from these files. Other pieces of information that are vital to the effort are documented in the codebook as well. Though the temporal and spatial coverage varies somewhat across the data elements and units of analysis, the general period encompasses 1980-2010 and many of the sources permit estimation for states, counties, and cities. Where available, the CTDA generally encompasses annualized data.

Collectively, the data archive brings together data from more than 150 unique yearly and composite data files encompassed within a variety of sources, including the Uniform Crime Reporting Program (UCR), the Supplemental Homicide Reports (SHR), police employee (LEOKA) data, the National Prisoner Statistics (NPS), the National Corrections Reporting Program (NCRP), the U.S. decennial census and the American Community Survey (ACS), the Bureau of Labor Statistics (BLS), and the Bureau of Economic Analysis (BEA). A good deal of the data we assembled for the crime trends archive currently is encompassed within the National Archive of Criminal Justice Data (NACJD), but for many of the requisite files users typically would have to *start from scratch* when generating databases that pull from these sources. This typically involves not only pulling a large number of annual files from a single source and creating standard measures, but also integrating across various datasets. From our experience with this project, this is a very time consuming process that need not be repeated each time somebody launches a crime trends study. Additionally, a major portion of the data we assembled for the project has yet to be incorporated in a central repository that might stimulate a vibrant, comprehensive, and systematic research agenda on recent crime trends. To that end, we include the raw data and machine readable code used to generate databases suitable for statistical analysis, but also programming code that can be used to extract key measures and integrate variables across files. Additionally, we include in the archive the integrated databases upon which our three sets of substantive analyses (reported below) are based.

We summarize in Appendix A the data archive produced under the project, which we have titled the "Crime Trends Data Archive" (CTDA). There are five major domains covered in the CTDA, including: (1) crime; (2) criminal justice data (i.e., data on arrests, police, and prisons); (3) data on demographic and social conditions; (4) economic data; and (5) data on geographic linking. Appendix A describes the original raw data included in the archive, the SPSS/Stata "systems" files generated from the raw data, and the program files that create the latter. The CTDA can be used for a wide variety of types of analyses that vary with respect to geographic coverage, temporal periods, and substantive focus. We limit our description of the CTDA here to a few of the most pertinent issues of data integration and estimation that are relevant to many common approaches to studying crime trends, including the strategy adopted in the analyses reported below.

Crime Data. The CTDA provides UCR city, county, and state crime estimates that are, in our judgment, preferable in many respects to existing resources. There are several possible sources from which one might obtain estimated UCR crime counts, including annual agency-level and county-level estimates housed in the NACJD. Research on crime trends have drawn from a wide variety of these sources, and sometimes it is not clear where exactly the data used in a given study were obtained. The agency-level NACJD data are useful for estimating city crime totals, but for reasons outlined in detail by Maltz and Targonski (2004), they pose problems for generating valid county-level estimates. Among the more problematic issues are that the available agency-level files—even when linked to geographic cross-walk files that identify the counties in which agencies fall--do not provide a straightforward means by which to apportion data from agencies that serve multiple counties and are prone to yielding double counting of both crime counts and population counts of the areas represented. Additionally, the agency-level data for a given year include only the jurisdictions that report crimes to the FBI during the period, which may be limiting if researchers are interested in estimating total county crime volume that adjusts for non-reporting agencies.

In part as a response to the limitations of the standard agency-level UCR files just noted, the NACJD also produces an annual county-level crime dataset. As Maltz and Targonski (2002) note, these NACJD county-level files differ from the county-level data one can generate independently from publicly available agency-level files in two very important ways. One is that NACJD use as their starting point internally produced FBI files commonly referred to as "Crime by County" files. These are agency-level (i.e., ORI) files that are organized by counties as defined by the FBI, and they are superior to standard agency-level files one can access from NACJD because they explicitly apportion agency-level data to the counties in which they fall (up to a maximum of three) and they properly identify "zero-population agencies" that report crime but do not represent populations that are distinct from other agencies in a county. Another important feature of the NACJD county-level files is that they yield estimates that explicitly account for underreporting and non-reporting at the agency level. Unfortunately, though, the procedures used by NACJD to impute missing or incomplete data have changed significantly over time, yielding in particular a major a break in the available county series in 1994 (see Maltz and Targonski, 2002, Table III). On its face, the imputation procedures used by NACJD since 1994 are an improvement over the method used before that point, but to our knowledge the validity and reliability of the different procedures have not been assessed systematically. Further, the series break imposed by the shift in imputation procedures in 1994 makes the NACJD county crime data quite limited for purposes of studying trends during a period that is often of significant interest to crime trends scholars (e.g., the 1980s and 1990s).

Two nice features of the CTDA are that it includes the "raw" agency-level FBI "Crime by County" files annually from 1980-2010, and that it includes agency-level "population" files obtained from the FBI for 1980, 1990, 2000, and 2010 that define all law enforcement agencies that fall within each U.S. county and the population served by these agencies. By integrating these files, it is possible to generate a full series of annual county-level crime estimates using a set of procedures that are comparable to those currently used by the NACJD, but without the break in series in 1994. This component of the CTDA should prove useful for researchers who wish to study longer-term county crime trends and, importantly, it can facilitate detailed evaluations of different imputation methods for generating county crime estimates from agency-level data.

For the purposes of the county-level crime estimation applied for the analyses reported below, we followed these steps. First, we begin with a full listing of local law enforcement agencies as reported in the "Population Files" provided to us by the FBI for 1980, 1990, 2000, and 2010, a file that includes agency ORI identifiers, population counts, and internal FBI county codes. Using these four files as bookmarks, we then used linear interpolation to estimate population for agencies between the periods. We subsequently linked to this file annual agency-level UCR crime data files obtained from the NACJD using a geographic crosswalk that provides a translation table between ORI identifiers, FBI internal county codes, and FIPS county codes (The geographic cross-walk file was obtained from NACJD as well). An important step taken in appending these files was to identify ORIs that spanned multiple counties (up to three, as is the practice used by the FBI) and to estimate the proportion of the population covered by such agencies that falls within each specified county.

As Maltz and Targonski (2002, 2004) note, a considerable number of law enforcement agencies either report less than 12 months of data to the FBI or do not report at all in a given year. Following the practice of NACJD (from 1994 onward), we adjust crime counts for the full period of our data coverage upward for agencies that report between 3-11 months of data by multiplying the reported crime count by the proportion of months reported (i.e., 12/n, where n is the number of months reported). We deviate somewhat from the approach adopted by NACJD to impute data for agencies that report less than 2 months of data in a given year. Specifically, from 1994 onward, the NACJD replaces crime counts for agencies reporting less than two months of data with a value equal to $C_s * P_a/P_s$, where C_s is the crime count and P_s is the population of agencies of similar size *within the same state*, and P_a is the agency population. While this strikes us as a reasonable approach, it ignores the significant heterogeneity within states in crime levels, making the questionable assumption that agencies of the same size in one part of a specified state are comparable to those quite far away (e.g., rural and urban agencies of similar size). Given this, for agencies that report 0-2 months of crime data, we replace the observed value with an estimate that is equivalent to the average crime count of agencies of similar size *within the same county*.[2] When a comparable agency is not available as defined here, we allocate a value for these agencies that is equivalent to the average crime count of similarly sized agencies within the same state. The end result is that we are able to generate crime estimates for the vast majority of agencies that fall within U.S. counties, using a consistent set of procedures that parallel in important respects those applied by the NACJD but with an added layer of drawing information about non-reporting agencies and "low reporting agencies" (i.e., those that report less than 3 months of data) from comparable agencies within the same county. This permits us to aggregate the agency-level data to produce county- and state-level UCR estimates using a consistent set of procedures. Note that we also include in the CTDA state-level crime estimates drawn from the Bureau of Justice Statistics (BJS) UCR Datatool (http://bjs.ojp.usdoj.gov/ucrdata/Search/Crime/State/StateCrime.cfm). These state estimates are generated by BJS by aggregating crime data only from law enforcement agencies that report 12 months of data within a given year. Given the relatively high rates of non-reporting and under-reporting among U.S. law enforcement agencies, this leaves a significant amount of data out of the state-estimates. It is unclear how these estimates compare to those generated from those obtained in other ways (e.g., the imputation procedures currently used by the NACJD), but this is an important issue worthy of exploration.

As Appendix A shows, the CTDA also includes other crime data besides city and county UCR offenses known. For instance, the archive includes agency-level SHR data from 1976-2009, which can readily be used to support city-level analyses of detailed homicide rates. Though we do not do so for the analysis reported below, using the adjustment and imputation procedures described above, it would be relatively straightforward to generate county- and state-level SHR estimates. To facilitate such estimations, we provide all of the needed components in the CTDA, and also the programming code used to generate adjusted agency-level data as described and aggregate to counties.

[2]We used the following population groups for these computations: (a) under 5,000; (b) 5,000 – 15,000; (c) 15,000 – 45,000; and 45,000+.

Criminal Justice Data. The CTDA includes criminal justice attributes that are frequently considered in city-level crime trends research (e.g., arrest data, city police force size) and state-level crime trends studies (e.g., state incarceration rates). The archive assembles these in a centralized location, generates the annual files that might be desired to support a given set of analyses, and also provides geographic linking files that we hope might facilitate the inclusion of such factors more broadly. As we highlighted above, the vast majority of city- and county-level studies omit state incarceration rates, and most county- and state-level studies omit indicators of police strength; in both cases, this standard practice may introduce significant omitted variable bias. We therefore include geographic linking variables in the files that would help to address these instances of data omission.

There are two other noteworthy features of the CTDA with respect to criminal justice data. One is that we include all the currently available agency-level arrest data available through NACJD (1980-2009), with the program files needed to generate select agency arrest counts for the period. We use the agency-level data to produce city estimates of drug arrest rates and arrest certainty used in the analyses reported below, and we also adopt the imputation and aggregation procedures described above for the UCR crime data to generate county- and state-level arrest data. The latter are particularly significant. Though county-level arrest data are currently made available through the NACJD, estimates for the period prior to 1994 were created using procedures that differ significantly from the procedures used from 1994 onwards. Thus, analysts who wish to study longer-term trends in county-level arrest rates (e.g., 1980-present) would have difficulty doing so with available county-level data. We applied a uniform set of imputation and aggregation procedures (described above) to construct estimates of arrest counts for counties and states over the period covered by our project.

In addition to the procedures outlined above, a final step in producing comparable arrest counts across counties is to allocate agency-level totals across counties which an agency spans. Using information contained in the FBI population files, we generate a list of counties whose arrest totals must be split between two or more counties. Specifically, we do this by computing arrest counts weighted by the proportion of an agency's population which falls in a given county, thus generating more than one record for each of these agencies, specific to each county in which they have jurisdiction. To facilitate such estimations, we provide all of the needed components in the CTDA, and also the programming code used to generate adjusted agency-level data as described and aggregate to counties.

A second noteworthy feature of the CTDA with respect to criminal justice variables is that it is not limited to the standard measures of arrest rates, police force size, and state "stock" incarceration rates. In particular, we include in the archive state-level data from the National Prisoners Statistics (NPS) on prison admissions and releases from 1977-2010, and county-level data on prison admissions from the National Corrections Reporting Program (NCRP) from 1983-2003. The latter enable us to estimate age- and crime-specific prison admission and release rates for a large number of U.S. counties over time, which is significant in light of the tendency for county-level studies to omit information on imprisonment rates.

Demographic and Social Data. The CTDA also includes a wide array of city, county, and state-level data on pertinent demographic and social conditions. Drawing from the extant literature (e.g., Land, McCall, and Cohen, 1990; Baumer, 2008) on the aggregate-level conditions that are most frequently considered in studies of crime trends, we include for each of the geographic units highlighted in the project extensive extracts from U.S. census data holdings. This includes city, county, and state-level data from the decennial censuses of 1980, 1990, and 2000, and comparable data from the American Community Survey (ACS) from 2005-2010. For the purposes of the analyses reported below, we use data from these sources to construct indicators of population structure (i.e., population size and density), divorce rates, immigrant concentration (e.g., % Latino and % foreign born), and resource deprivation (e.g., poverty rates, % non-Latino black, % female headed families, median family income). Though census data for states, counties, and cities are available from a variety of sources, including public repositories such as the Inter-University Consortium for Political and Social Research (ICPSR), of which NACJD is a component, in our experience acquiring the various files that are needed can be quite cumbersome in a standard crime trends study that spans several decades. Additionally, some of the most recent census data—most notably the aggregate ACS data—are not yet widely available in an analysis ready format. The CTDA provides extensive data from the ACS and its predecessor (i.e., the decennial census STF files).

Economic Data. The CTDA contains a relatively rich array of data sources on economic conditions. The census-based sources just described include indicators of unemployment and poverty rates, but supplemented such data with annual estimated unemployment rates from the Bureau of Labor Statistics (BLS) for cities, counties, and states from the early 1980s through 2010. Additionally, the CTDA includes from the Bureau of Economic Analysis (BEA) state and county estimates of average wages, levels of unemployment insurance and income maintenance, and state estimates of GDP and GSP. Finally, we incorporate regional indicators of the consumer price index (which enable us to measure inflation across regions and over time, and also adjust wages for inflation) and the Index of Consumer Sentiment (ICS). The latter has been chronicled in several recent papers on trends in violence and property crime (e.g., Rosenfeld and Fornango, 2007; Rosenfeld, 2009).

IIb. Clarifying and expanding the scope of empirical analysis

While the data resource just described was a major focus of the project, the overarching motivation for producing this resource was to facilitate meaningful analyses of recent crime trends. The original proposal outlined several possibilities along these lines, with an emphasis on clarifying observed empirical patterns that are often generated from studies that apply different empirical specifications to different units of analysis and on expanding the typical set of criminal justice variables considered. The rationale for these two substantive issues and a third--an assessment of conditional economic effects on recent crime trends—are described in the paragraphs that follow. The data, methods, and results of analyses directed at these issues are presented in subsequent sections of the report.

IIb.1. Uniform empirical specification across states, counties, and cities.

An important initial set of analyses conducted in the study encompasses the estimation of parallel empirical models of crime trends across multiple units of analysis, focusing on the most commonly used geographic boundaries employed in the extant research: states, counties, and cities. The objective is to "hold constant" differences in model specification to discern potential uniformities in empirical results that may emerge across levels of analysis (or, alternatively, to identify meaningful differences in patterns across different geographies).

Though there are many examples of highly sophisticated studies of crime trends, the cumulative body of literature in this area tends to be highly variable and relatively narrow in its application. As Baumer (2008) elaborates, prior research on crime trends often focuses on somewhat different time periods and outcome measures, but it is particularly inconsistent in three ways: (a) the variables included as covariates; (b) the units of analysis used; and (c) the application of different statistical methods to estimate key parameters. While a diversity of approaches can be a healthy feature of scientific research, it can generate ambiguity if it is not accompanied by some systematic assessments that hold constant key factors that tend to vary across studies. For instance, the conclusions one draws about the role of many factors (e.g., incarceration, police size, and age structure) appear to be highly contingent on the unit of analysis used, and the estimated role of these and other factors (e.g., unemployment) seems highly sensitive to model specification and/or analytical procedure (e.g., Liedka et al., 2006; Defina and Arvanites, 2002; Eck and Maguire, 2006; Spelman, 2005). It could be that crime trend patterns and predictors vary meaningfully across cities, counties, and states. But the current research literature cannot tell us this, because the typical empirical specification adopted is highly variable both within and across studies based on different units of analysis.

The lack of systematic research on crime trends across units of analysis may contribute to gaps in knowledge of the factors thought to be most pertinent to shaping contemporary crime trends. For example, shifts in illicit drug use and market activity, and especially crack-cocaine involvement, have received significant attention as explanations for recent changes in crime levels (Blumstein and Wallman, 2006). The arguments presented are compelling, but the empirical research is not as convincing. Some of the studies that represent the primary regression-based evidence for the role of crack cocaine activity on recent crime trends (e.g., Baumer et al., 1998; Ousey and Lee, 2002, 2004) do not include *any* other time-varying indicators other than temporal variability in crack use and market activity, which obviously can contribute to misleading results. Other recent sub-national studies have adopted estimation procedures that control for unmeasured heterogeneity and shared temporal trends across units, which strengthens the faith we can have in estimates obtained for the few factors that are directly measured. However, this strategy divulges little about the role of the unmeasured factors hypothesized to have played a potentially significant part in shaping recent crime trends.

We also see a high degree of inconsistency in model specification for economic factors. State-, and regional-level studies suggest that economic indicators such as GDP, consumer sentiment, and wages are significant predictors of crime trends, but very few city- and county-level studies incorporate time-varying estimates of these factors. Indeed, city-level studies also routinely omit time-varying measures of another economic factor–the unemployment rate—that has been shown to be relevant in other research using larger aggregates (see Levitt, 2001 for a review). Along the same lines, though there is a long history of linking incarceration to crime rates through incapacitation and/or deterrent processes, and there also is a voluminous empirical literature that focuses on estimating the relationship between rates of incarceration and crime (see Spelman, 2006), most city- and county-level studies of crime trends have either omitted incarceration rates altogether or applied state-level incarceration rates uniformly to all places within the same state. Neither approach is ideal. On the one hand, the literature shows fairly consistently that incarceration rates are an important part of the puzzle of recent crime trends, and therefore omitting them may yield biased parameters for the variables that are measured and undermine the validity of results reported in county- and city-level analyses. On the other hand, applying state-level incarceration rates to all places within a state may introduce significant measurement error. There is great variability within states in prison admission rates and, if would-be offenders are affected more by local than by state realities, the estimation of state-level incarceration rates on county or city crime rates may yield highly imprecise estimates.

Finally, studies of crime trends often apply different methods both within and across units of analysis to estimate key parameters. Although some studies have used methods geared toward identifying classes of crime "trajectories" (e.g., Weisburd et al., 2004), perhaps because a central interest in this area of research is in *explaining* recent crime trends, most studies have applied different versions of two suitable analytical strategies: pooled time-series and multilevel growth curve models. Briefly, most applications of growth curve models in the study of crime trends, including prior work by the principal investigator, impose deterministic trend parameters and usually do not account for unmeasured stable characteristics of the spatial units (see, e.g., Baumer et al., 1998; Ousey and Lee, 2002), whereas the typical econometric panel models estimated to study crime trends do not make *a priori* assumptions about how the unit intercepts shift over time and almost always incorporate unit fixed-effects that adjust for time stable unmeasured factors (see, e.g., Donohue and Levitt, 2001; Phillips, 2006). These differences in how the two preferred methods of studying recent crime trends are implemented can have very important implications for the inferences drawn (Wilson and Butler, 2007), and may have contributed significantly to the inconsistency and uncertainty that emerges from the extant research.

In summary, while there are no strong reasons at the present time to preference *a priori* a particular unit of analysis or analytical strategy for studying crime trends, it would be useful to know the empirical implications of using different units of analysis and different approaches, something that cannot be deciphered easily from existing research. There is usually some overlap, but the models typically estimated using different units (e.g., states vs. counties vs. cities) incorporate quite different sets of explanatory variables (c.f., Ousey and Lee, 2002; Moody and Marvell, 2005; Kovandzic and Vieraitis, 2006). There is also a lack of uniformity in empirical specifications across studies of recent crime trends based on the same unit of analysis (c.f., Gould et al., 2002; Phillips, 2006; also, c.f. Donohue and Levitt, 2001; Liedka et al., 2006). Without some uniformity in model specification within and across units of analysis, it is very difficult to detect general emergent patterns from the extant research and to draw definitive conclusions about the relevance of given factors. Similarly, while multiple methods can enhance a research area and the specific method used should be driven by the specific research question under investigation, at present it is difficult to discern whether variation in research findings on contemporary crime trends is due to different units of analysis, different empirical specifications, and/or different analytical techniques.

Building on comparable approaches to cross-sectional crime research (e.g., Land, McCall, and Cohen, 1990), one of the key sets of analysis presented below is directed at advancing the literature by applying a uniform set of empirical specifications and procedures across multiple units of analysis. We specifically address whether the same "base-level" empirical specification applied to data for a given time period yields comparable results when applied to American states, counties, and cities. The objective of this portion of our work is modest—does the same specification yield comparable findings across cities, counties, and states—but we consider an important step in clarifying the existing research on crime trends.

IIb.2. An assessment of conditional economic effects on recent crime trends

The project also highlights a few more specific topics, including the potential conditional effects of economic factors. *Specifically, we examine whether two of the most common indicators of economic adversity in crime trends research—high unemployment rates and depressed wages—exhibit effects on crime rates that are contingent on other factors, including prevailing levels of inflation, the extent of unemployment insurance benefits and income maintenance payments dispensed, police size, and incarceration rates.*

In the wake of significant economic expansion and steeply falling crime rates for much of the 1990s, two notable economic downturns have served as bookmarks for the present decade: a significant contraction of the U.S. economy during the last half of 2001, and a major economic decline that emerged in different sectors in 2006 and 2007 and had by the end of 2009 morphed into one of the most severe economic recessions of the past century (NBER, 2010). The most recent of these economic downturns, dubbed widely as the "Great Recession", has stimulated renewed interest in, and speculation about, a possible link between economic conditions and crime rates. Numerous media reports in the first months of the Great Recession suggested possible links between increased crime rates and the foreclosure crisis, rising unemployment, mass layoffs, and depressed wages. Many accounts speculated that it was just a matter of time before those adverse conditions would yield a significant crime wave. More recently, the popular press has expressed surprise that crime rates did not yet increase significantly during or in the aftermath of the recession, despite an abundance of woeful economic reports and speculation about many possible collateral consequences. These stories often contrast the late 2000s spike in unemployment observed in many

U.S. communities with reports that crime rates appear to have either remained surprisingly stable or have fallen (e.g., Yost, 2010; see FBI, 2010).

What are we to make of evidence that crime rates do not appear to have increased in response to the substantial economic decline that occurred in the late 2000s? More generally, should we expect crime rates to simply rise when economic conditions sour, and to fall when they improve? Or, are the consequences for crime of adverse economic conditions contingent on other prevailing factors, yielding increases in crime in some instances but not others? Economic perspectives point to rational assessments of opportunity costs associated with legitimate vs. illegitimate economic pursuits and imply that a decline in legitimate income-generating opportunities is likely to yield increases in illegitimate income acquisition, such as robbery, burglary, and theft. However, as typically expressed in the research literature, economic perspectives may not be helpful in explaining why significant declines in the legitimate economy do not invariably produce the anticipated rise in instrumental criminal activity. This is a crucial empirical as well as theoretical issue, because the accumulated body of evidence on the relationship between crime rates and adverse economic conditions (e.g., rising unemployment and falling wages), suggests that sometimes significant downturns in the economy yield an increase in crime and sometimes they do not (e.g., Bushway, Cook, and Phillips, 2010; Cook and Zarkin, 1985; Chiricos and DeLone, 1992; Smith, Devine and Sheley, 1992).

The mixed or ambiguous empirical literature on macro-economic conditions and crime rates sometimes is written-off as a function of empirical misspecification (Greenberg, 2001; Raphael and Winter-Ebmer, 2001). However, another possibility is that adverse economic circumstances yield increases in crime (and good times yield decreases in crime) *only under certain conditions*. Cantor and Land (1985) drew attention to this idea, noting that increases in some adverse economic conditions, such as unemployment rates, may yield higher crime rates only to the extent that significant simultaneous or subsequent shifts in routine activities do not limit criminal opportunities. Yet, several other plausible contingencies are also implied in the literature. For example, the criminogenic consequences of the most often studied indicators of growing economic adversity – rising unemployment rates and falling wages – may be conditioned by the presence of other economic conditions such as the level of inflation, or by offsetting income-replacement government transfers, or the potential costs associated with participation in illegitimate activities (e.g., the likelihood of detection by the police or of incarceration once arrested).

In essence, the idea that increasing economic adversity should simply yield a linear increase in crime rates is unlikely to capture the full range of behavioral realities that may be observed. Not all economic downturns occur in the same broader economic or social context. In the U.S., some have happened amidst very high levels of inflation (e.g., the early 1980s recession), while some emerged during historically low inflationary periods (e.g., the two recessions of the 2000s). Some have occurred during periods when the gross probabilities of detection and imprisonment confronted by those contemplating illegal activity were high and rising significantly (i.e., the 1980s and 1990s), while others have progressed in an era of relatively stable incarceration rates and declining police forces (e.g., the most recent recession). Finally, some of the contemporary economic contractions have been accompanied by relatively large and responsive outlays in unemployment insurance benefits (e.g., the most recent recession), while others have occurred during periods when such benefits were reduced dramatically (e.g., the early 1980s).

Most prior research has focused on the effects of adverse economic conditions on crime rates, irrespective of the broader context in which those conditions arise or play out. Using the data generated for this NIJ DRP project, we expand prior efforts by evaluating the influence on crime rates of two common indicators of economic adversity – rising unemployment and declining wages. More specifically, we examine both the overall influence of these conditions on crime and the degree to which their effects on crime may differ depending on rates of inflation, unemployment insurance, incarceration, and the size of the police force. We next describe in more detail the theoretical rationales for this assessment.

Although classic economic arguments about the rational assessment of perceived costs and benefits of legal vs. illegal activities understandably represent the modal framework for linking economic adversity and increasing crime (Becker, 1968; Ehrlich, 1973; see also Bushway et al., 2010), several other perspectives are germane as well. Over time, economic hardships can increase crime and violence by fueling community disorder, reducing collective regulation of public spaces, and discouraging spending on the criminal justice system (Wilson, 1996; Edberg, Yeide, and Rosenfeld, 2010). Deteriorating economic conditions also can push low-income consumers into underground markets for stolen goods and may stimulate property crimes in response to growing demand (Rosenfeld and Fornango, 2007). Both processes have been linked to increases lethal violence (Rosenfeld, 2009). Finally, the stress and frustration associated with job and income loss may lead to crime and violence as coping mechanisms (e.g., Agnew, 1999).

The rich theoretical landscape on possible connections between crime and the economy also reveals several possible contingencies that warrant attention when considering whether growing economic adversity is likely to result in increased rates of crime through one or more of the mechanisms just noted. Consideration of these contingencies has significant implications for the conclusions we draw from prior empirical studies, which almost invariably assume a linear, additive effect of economic conditions on crime rates. One potentially important contingency in the link between changes in crime rates and changes in commonly studied economic conditions, such as unemployment rates and wages, is the level of inflation. Rising prices in legitimate markets may enhance the attractiveness of cheap stolen goods and thereby stimulate an increase in property crimes. They also may fuel violence indirectly by expanding the size and volatility of underground activity. Drawing on such logic, some research has evaluated whether crime rates are responsive to shifts in rates of inflation. The findings are somewhat mixed, but overall the evidence suggests that changes in inflation and crime rates co-vary significantly in the anticipated, positive direction, a pattern found across a variety of national contexts (e.g., Curtis, 1981; Devine, Sheley, and Smith, 1988; Fox, 1978; Gillani, Rehman, and Gill, 2009; Grant and Martínez, 1997; LaFree, Drass, and O'Day, 1992; Land and Felson, 1976; Ralston, 1999; Seals and Nunley, 2007; Tang, 2009; Tang and Lean, 2007). An additional hypothesis worthy of exploration is that high rates of inflation may aggravate the effects on crime of other economic conditions. As unemployment rates rise and wages fall, the standard economic account predicts that growing numbers of individuals on the economic margins may consider illegitimate means to generate income. The economic pressures or incentives to engage in acquisitive criminal activity are likely to be stronger in a context of steep price increases than when prices or stable or falling. Displaced workers and others whose earnings have fallen should be more likely to turn to illegal markets to buy and sell goods during periods of high inflation because of the competitive price structure such markets offer, which may elevate rates of property crime and lethal violence (e.g., Rosenfeld, 2009). *We explore this idea by testing whether inflation levels moderate the effects on crime of unemployment rates and wages.*

Another potentially relevant moderating factor – the extension of unemployment insurance benefits – reflects government fiscal policy regarding how best to respond to economic crises with an emphasis on easing the adversity of those who lose jobs and earnings. In theory, this type of government social spending can help to temper the criminogenic consequences of significant economic contractions by buffering families and individuals from the full brunt of market forces. This proposition is implied by Messner and Rosenfeld's (2007) institutional-anomie theory. The theory locates the genesis of motivations for crime in America's pronounced and universalistic cultural emphasis on the accumulation of wealth in combination with differential access to legitimate economic opportunities (Merton, 1938). According to the authors, social institutions play a vital role in buffering citizens from the pressures that arise when the cultural and social structures are misaligned in this fashion. A key role of the polity is to provide protection, through income replacement and other means, from the full force of the free-market economic system, especially during significant economic downturns. The provision of unemployment insurance benefits is a common way in which the U.S. government has attempted to soften the blow of significant economic contractions. As McMurrer and Chasanov (1995: 30) explain, "The Federal-State unemployment insurance (UI) system, created in 1935, was designed to provide temporary wage replacement for unemployed workers…and to assist in stabilizing the national economy during cyclical economic downturns." Some research has shown that government financial assistance can help to reduce crime rates and reduce the criminogenic effects of high rates of poverty and inequality (e.g., Hannon and DeFronzo, 1998; see Messner and Rosenfeld, 2007, for a review), but we are aware of no prior research on the specific impact of unemployment insurance benefits on crime trends. Significant temporal and spatial variation exists in the provision of unemployment insurance benefits during the past three decades, with historically low levels of support provided during the two recessions of the early 1980s, and a much greater support during the early 1990s and the 2000s (McMurrer and Chasanov, 1995). *We explore the potential implications of this variation in the present research by examining whether the effects on crime rates of unemployment rates and wages are moderated by levels of spending on unemployment insurance and income maintenance payments.*

Finally, an additional consideration germane to a comprehensive assessment of crime trends during the past three decades, and specifically the possible contingent effects of adverse economic conditions, is the punishment risk faced by those who contemplate illicit activities. This is an essential ingredient in both classic economic and sociological theories of crime. Becker (1968) highlights the probability of conviction and punishment in his articulation of the factors that shape decisions to engage in illegal conduct. Also, an often overlooked component of Merton's (1938) anomie theoretical model is that illegitimate responses to significant economic adversity may be conditioned by assessments of the perceived costs of crime. As Merton suggests (1938: 682), when the social structure fails to distribute legitimate economic opportunities in sufficient volume, some persons view illegitimate income-generating pursuits as a viable option, and 'there occurs an approximation of the situation erroneously held by utilitarians to be typical of society generally wherein calculations of advantage and fear of punishment are the sole regulating agencies." This logic suggests that the effects on crime and violence of growing economic adversity may be conditioned by the objective risks to illegitimate actions, such as the probability of being detected by the police and the flow of persons into and out of prisons. *We consider these possibilities in the present research by testing whether the effects on crime rates of unemployment rates and wages are conditioned by changes in police force size and incarceration rates.*

In summary, a broad reading of the literature suggests that anticipating only main effects of economic adversity on crime rates may be overly simplistic. The link between macro-economic conditions and crime rates may instead be highly contingent on the presence or absence of other factors, including levels of inflation, consumer sentiment, unemployment insurance benefits, police presence, and rates of incarceration. Prior research rarely has assessed these possible conditional effects of adverse economic conditions. Instead, with some exceptions the existing research has focused primarily on examining the main effects of economic conditions on crime rates,[3] and it has left a trail of mixed and inconclusive results. There is evidence that property crimes, including violent property crimes such as robbery, tend to rise during economic downturns and fall during periods of recovery (see Blumstein and Rosenfeld, 2008, for a review). Also, some prior research indicates that youth unemployment and wage levels are related to youth crime trends in the same fashion: adverse conditions drive crime rates upward (Gould, Weinberg, and Mustard, 2002; Grogger, 1998, 2006). But other studies yield the opposite conclusion (see Chiricos and DeLone,

[3]One exception is a series of cross-national studies that explore whether levels of social welfare mitigate the criminogenic consequences of income inequality or high rates of poverty (for a review, see Messner and Rosenfeld, 2007). This issue also has been examined in U.S. studies (e.g., Hannon and DeFronzo, 1998).

1992; Baumer, 2008). The ambiguity in findings across studies in the role of adverse economic conditions may reflect differences in model specification or theoretical interpretations (e.g., Cantor and Land, 1985; Greenberg, 2001; Phillips and Greenberg, 2008). Another possibility, though, is that the effects on crime rates of such conditions are highly conditional, an issue we explore in the project.

IIb.3. Expanding the typical set of criminal justice variables considered

There is a long history of theoretical literature linking criminal justice system fucntions to crime rates through incapacitation and/or deterrent processes (e.g., Zimring and Hawkins, 1973) and a relatively large and growing empirical literature. The two factors that perhaps have received the most attention in public discourse on recent crime trends, and especially the 1990s crime decline, are changes in policing and incarceration. Both of these factors, and criminal justice actions more generally, have been linked to crime trends mainly through their capacity to serve an incapacitation or deterrent function. Prior research on crime trends often includes some indicator of criminal justice activity, but the specific factor(s) included vary across studies. More important from our standpoint, though, is that the extant research tends to approach criminal justice factors from a relatively narrow vantage point. In the context of policing, this narrowness manifests most frequently in a focus on the *quantity of policing* and a parallel neglect in the *quality of policing*. With respect to incarceration, as already noted city- and county-level studies often ignore incarceration rates altogether. But a more general limitation of the extant research is its reliance on *overall incarceration* rates. As elaborated below, a broader consideration of post-arrest criminal justice indicators may prove useful for expanding our understanding of how criminal justice responses affect crime trends. *Accordingly, we extend the typical empirical specifications employed by considering additional criminal justice variables that may be relevant to crime trends, including pro-active policing, age- and crime-specific imprisonment rates per capita.* We first discuss some specifics regarding the extant research on policing; we then turn our attention to an elaborated discussion of incarceration.

Policing. Eck and Maguire (2006) provide an excellent treatment of the various changes in the quantity and quality of policing that have occurred in the past several decades, and they summarize a comprehensive body of research relevant to how these changes may be linked to crime, including how they may have shaped recent crime trends (see also Greene, 2000). Although they review numerous shifts in policing, the two elements highlighted by Eck and Maguire that appear to have received the greatest attention with respect to recent crime trends are (1) changes in the number of police officers devoted to helping address crime problems, and (2) the manner by which police agencies have approached their work. The basic idea is that the number of officers on the street has been increased and the police have increasingly used enforcement strategies that are better suited to preventing serious crimes. The presumed effects on crime of these enhancements to the quantity and quality of policing are hypothesized to be negative and to arise through a combination of incapacitation and/or deterrent processes, either directly or indirectly by reducing levels of disorder.

Eck and Maguire's exhaustive review of studies that have examined the general relationship between crime rates and police force size suggest that the relationship is not likely to be large, and perhaps not even substantively or statistically significant. Yet, most of the studies considered in that review are dated, suffer from serious methodological problems, and few actually examine the link between police force size and crime trends in the contemporary era. Further, most of the studies of crime trends that emphasize the *quantity of policing* do so in a context that ignores the *quality of policing*. A handful of studies have shown that various changes in the nature of policing that occurred in the 1980s and 1990s, and especially policing efforts that target particular types of behaviors thought to facilitate crime, such as levels of public disorder and the prevalence of weapon carrying, can have important implications for crime levels. Early studies of jurisdictional differences in "arrest certainty" (e.g., Yu and Liska, 1993) come to mind here, as does New York City's highly lauded organizational shifts and orchestrated "order maintenance" approach to policing and "reclaiming public spaces" during the first half of the 1990s. As Eck and Maguire (2006: 225) note, in New York City the shift in policing focused on increasingly making arrests for minor offenses such as "approaching a vehicle in traffic to wash its windshield (the infamous "squeegee men"), littering, panhandling, prostitution, public intoxication, urinating in public, vandalism, and a variety of other misdemeanor public-order offenses." In New York and elsewhere, there also was a greater emphasis placed on reducing weapon carrying during the past few decades, and especially the 1990s, through a combination of targeted local policing efforts and Federal sentencing enhancements for gun crimes (e.g., Kennedy et al., 2001; Raphael and Ludwig, 2003; Eck and Maguire, 2006). As noted, many studies that assess the role of police force size (i.e., the quantity of policing) do not simultaneously consider the nature or quality of policing, which we consider a significant limitation. This motivates the need to further assess the role of police force size, but also directs attention to a wider array of policing indicators, including shifts over time and places in "arrest certainty" and the types of activities to which police resources are allocated. The latter has been referred to in the literature in a variety of ways, including "order maintenance policing" (Rosenfeld et al., 2005) and "proactive policing" (e.g., Sampson and Cohen, 1988; Kubrin et al., 2010).

Though there is a relatively large body of research that examines the effects of different policing approaches on levels of crime (e.g., Sampson and Cohen, 1988; for a review, see MacDonald, 2002), only a small handful of city-level studies have assessed the role of recent changes in policing on contemporary crime trends (Rosenfeld et al., 2005; Kubrin et al., 2010), and none of the existing county- and state-level studies have done so. Focusing on arguably the two most relevant policing shifts that occurred – the increased focus on order maintenance and weapons interdiction efforts – the conclusions drawn from the existing empirical research range from claims that these factors had either no significant impact (Raphael and Ludwig, 2003; Harcourt and Ludwig, 2006), a modest effect (e.g., Braga et al., 2001; Kennedy et al., 2001; MacDonald, 2002; Piehl et al., 2003; Messner et al. 2007; Rosenfeld et al., 2005; Rosenfeld et al., 2007), or that they accounted for a substantial portion of the observed decline in the 1990s, at least in New York City (Kelling and Sousa, 2001; Zimring, 2006). Although there are exceptions (e.g., Raphael and Ludwig, 2003), overall the extant research suggests that policing efforts that targeted public order violations and weapon carrying had at least a modest effect on crime trends during the 1990s. Evaluations of Boston's Operation Ceasefire, for example, show that the enhanced devotion in that city to reducing firearm possession and use, especially among young persons, was associated with a significant reduction in youth firearm violence (Braga et al., 2001; Kennedy et al., 2001; Piehl et al., 2003). Further, two recent studies suggest a modest contribution of order maintenance policing to crime declines in New York City. Rosenfeld et al. (2007) use misdemeanor and ordinance violation arrest rates to measure the relative focus on order maintenance policing across New York City police precincts between 1988-2001, and they evaluate whether it was significantly associated with crime trends during this period. In a separate study, Messner et al. (2007) use misdemeanor arrest rates to examine the link between order maintenance policing and crime trends across precincts in New York City from 1999-1999. Using slightly different empirical specifications and modeling strategies, both studies report a statistically significant, albeit relatively modest, effect of order maintenance policing efforts on reported crime rates, net of a large number of other relevant variables.

The present study builds on existing work by examining whether a changing police focus toward "proactive policing," as measured by arrest data (see also Messner et al., 2007; Rosenfeld et al., 2007), is associated with recent crime trends, while also considering changes in the probability of arrest more generally.

Incarceration. Several studies have focused particularly on estimating the effects on crime trends of shifts in levels of incarceration (see Stemen, 2007, for a review). The findings from this literature have been notoriously ambiguous, as some studies report no significant association between incarceration rates and crime rates (e.g., Kovandzic and Veiraitis, 2006), and others report a significant relationship between the two variables with elasticities (i.e., the percentage change in crime given a one percent change in rates of incarceration) that range widely across studies, from less than one percent (e.g., Besci, 1999) to more than twenty percent (e.g., Devine, Sheley, and Smith, 1988). Much of the ambiguity in these findings appears to be a function of differences across studies in the units of analysis used, the degree to which other factors are considered simultaneously, and whether or not the generated estimates adjust for the potential simultaneous relationship between incarceration and crime rates (Spelman, 2005; Stemen, 2007). In short, national-level analyses tend to reveal larger incarceration effects than studies based on data from smaller aggregate units, such as states or counties, and the effects tend to be larger in studies that fail to account for simultaneity. Several scholars have suggested that the sub-national estimates of incarceration are more valid and reliable than national-level estimates (e.g., Levitt, 2001; Spelman, 2005), and Stemen's (2007) review of the literature shows that among the few studies that account for simultaneity (Levitt, 1996; Spelman, 2000, 2005; Witt and Witte, 2000), the incarceration rate elasticities tend to be fairly consistent, with a ten percent change in incarceration rates associated with a 2-5 percent change in crime rates (see also Spelman, 2005, 2006). Overall, the most rigorous studies suggest that 10-25% of the 1990s crime decline was due to rising incarceration rates.

Despite the substantial attention devoted in prior research to the role of incarceration and the possibility of an emerging consensus about the magnitude of its effects on recent crime trends, several issues warrant additional consideration and are examined in the present study. Specifically, the present study addresses two issues with respect to the incarceration/crime trends link: (1) the estimation of age- and crime-specific measures of incarceration; and (2) the consideration of an alternative measure of incarceration risk, which we refer to as the imprisonment-arrest ratio.

Age- and crime-specific incarceration. Though the standard approach of including overall incarceration rates is a useful beginning point, both of the primary arguments that have been used to link shifts in incarceration to crime trends—incapacitation and deterrence—imply that a more specific focus may be meaningful. In particular, we explore whether age- and crime-specific incarceration rates may yield differential effects on age- and crime-specific offending trends. Analyzing age-specific data seems quite important given the emphasis placed on incapacitation effects in the extant literature. Suffice it to say that analyzing the association between age-specific indicators of imprisonment and crime provide a more direct assessment of such effects than non-disaggregated data. Additionally, though offenders do not tend to specialize in most instances, since a large fraction of the mass imprisonment era has been led by shifts in imprisonment among drug offenders, analyzing overall imprisonment and crime might mask potentially important deterrent and/or incapacitation effects of imprisonment. Crime-specific analyses will enable a closer examination of this possibility.

III. Methods

As noted above, the primary purpose of this DRP grant was to enhance the infrastructure for conducting research on crime trends. The Crime Trends Data Archive (CTDA) is the primary outcome of that effort. Our hope is that it will stimulate a wide variety of research on crime trends and encourage others to enhance the archive further as new data sources become available or others are uncovered. We also outlined three specific substantive issues that we consider to be worthwhile initial uses of the CTDA. These include a *uniform empirical analysis across states, counties, and cities*, *an assessment of conditional economic effects, and an expansion of the typical set of criminal justice variables considered in studies of crime trends*. The specific samples, time frames, and measures employed vary somewhat across the three substantive issues addressed, but our general analytical strategy in addressing these issues is to construct when possible from the CTDA a panel database with requisite measures centered on the following time points: 1980, 1985, 1990, 1995, 2000, 2005, and 2010. This approach marshals the strength of a pooled cross-sectional design, while also avoiding the significant data imputation that is needed to support panel analyses of annual time periods for sub-national geographic units (see also LaFree, Baumer, and O'Brien, 2010). To elaborate, while annual data are typically available for a small number of requisite measures—namely crime rates, arrest rates, police force size, unemployment rates, and incarceration rates—most of the data applied in crime trends studies is available much less frequently. For instance, potentially key predictors such as poverty rates, racial composition, and even population size and density have for most of the contemporary era been available for sub-national units only on a decennial basis. The strategy adopted here limits the assumptions that need to be made in imputing intercensal values for these variables, while also preserving a substantial portion of the observed temporal variation in crime trends over the last three decades. The point here is not to suggest that this is the only approach that might be adopted, but it strikes us as a reasonable strategy in light of the qualities of the available data and the nature of our research questions.

The first substantive issue addressed—the uniform empirical analysis across states, counties, and cities—is based on models estimated for sampling universes that approximate those employed most frequently in the extant literature: the 50 American states plus the District of Columbia; the 400 largest U.S. counties, and cities with more than 100,000 persons in 1980 (n=173) (e.g., Baumer, 2008; Phillips and Greenberg, 2008; Spelman, 2008). The actual analysis samples diverge somewhat from these benchmarks, however, because of missing data on key measures. Specifically, owing primarily to extensive missing data on crime and arrest measures, our state-level analysis is based on 48 states for which we were able to construct the various measures included in our analysis with minimal missing data (e.g., fewer than three waves of missing data). The analysis excludes Illinois and Florida because of extensive missing data. We also exclude DC given that it is such an atypical "state." Because we wish to impose uniformity as much as possible in the first set of analyses presented, we also exclude Florida, Illinois, and DC from the county- and city-level analyses. As detailed in the analysis programs that accompany the report, we exclude a handful of other counties and cities from the sampling universe due to crossing the threshold of having three or more waves of missing data on the measures included, yielding analysis samples of 353 counties and 147 cities.

We chose to limit the other two sets of analyses—the elaborated assessments of criminal justice factors and the conditional analysis of economic factors--to U.S. counties. We did so because of the significant heterogeneity that exists within American states, which make state-level analyses somewhat crude for the task at hand, and because of data limitations for analyzing city-level crime trends. With respect to the latter, while cities often represent the basic reporting unit for crime data, many other data sources are reported for county government units and are not available (or not reported routinely) for cities. Counties thus offer a reasonable compromise – they are meaningful government units for which significant spatial and temporal variability in crime rates frequently has been observed, and they provide interesting opportunities to explore more nuanced models of economy, criminal justice, and crime.

All three sets of empirical analyses reported in the project include models of overall homicide, non-lethal violence (robbery and aggravated assault), and non-violent property crime (burglary, motor vehicle theft, and larceny). The vast majority of crime trends studies focus on overall homicide, presumably because of the superior validity and reliability of data on homicide across places and over time. While we are sensitive to the potential for systematic measurement errors in studying trends in police-based measures of non-lethal violence and also property crime, we note that spatial and temporal patterns in these crimes tend to parallel those observed for homicide. Additionally, the existing knowledge—admittedly limited--suggests that they exhibit comparable patterns of under-reporting across geographic areas and over time (e.g., Baumer, 2002; Baumer and Lauritsen, 2010). We remain attentive to the potential bias that might be present in assuming constant reporting and recording differences across time and space for non-lethal violence and non-violent property crime. But we include them in the project both because these crimes represent the bulk of criminal activity in America (in comparison with homicide, which is rare in relative terms) and because they are particularly pertinent theoretically for assessments of conditional economic effects and criminal justice measures. All three outcome measures exhibited skewness; for this reason and to conform to the bulk of prior research, we analyze logged rates of homicide, non-lethal violence, and non-violent property crime in the project.

We include a common set of explanatory variables across the three sets of analyses (e.g., population structure, resource deprivation, etc.), but some variables considered are unique to substantive issue under investigation. Thus, we describe the measures in greater detail below under sub-headings that focus explicitly on the three sets of analyses. In contrast, because each analysis draws from the same general design (i.e., a multi-wave panel design, or in other words a pooled cross-sectional design) and encompasses the same outcomes, a common set of statistical issues emerges and we therefore adopt a common analytical strategy. Specifically, given the research issue addressed and the pooled cross-sectional nature of the data, we apply econometric panel modeling techniques to evaluate the effects on crime rates of the explanatory variables considered. Though we initially present results based on "standard specifications" one finds in the extant research for purposes of comparison, and for cities this excludes fixed effects, the core of our analysis is based on two-way fixed-effects panel models of crime rates that include fixed effects that control for stable unmeasured geographic attributes and temporal shocks that are shared across geographic areas (i.e., states, counties, and cities) within the nation (Raphael and Winter-Ebmer, 2001; Worrall and Pratt, 2004). Consistent with previous research, crime rates across each of the samples examined in the analysis exhibited significant serial autocorrelation, which we account for by specifying first-order autocorrelation within panels. Finally, to minimize the potential bias that can arise from significant cross-sectional correlations among disturbances across geographic units[4], the models report panel-corrected standard errors, which allow the disturbances to be heteroskedastic and contemporaneously correlated across panels (Wilson and Butler, 2007).

IIIa. Uniform empirical specification across states, counties, and cities.

As highlighted above, one impediment to drawing more definitive conclusions from extant research on crime trends is the diversity of units, measures, and methods applied across studies. Diversity in approaches, *per se*, is not necessarily a bad thing. Indeed, different research questions might reasonably entail different approaches, and there are good lessons to be learned by tackling the same issue in multiple ways. Yet, diversity in the absence of a relatively standard baseline yields a murky picture of the underlying empirical patterns with respect to crime trends. For instance, conclusions drawn about the role of incarceration tend to differ depending on the unit of analysis that is used. This may tell us something meaningful about how incarceration affects crime, but it also may be an artifact of the tendency for empirical specifications to vary wildly across studies that employ different units. More generally, while states, counties, and cities are each routinely used to study crime trends, the empirical specifications chosen tend to be highly specific to the unit of choice (often driven by data availability) rather than theoretical considerations or accumulated knowledge about potential biases that might arise from omitted variables. This makes it difficult to meaningfully compare results from studies that employ different units of analyses. In light of this, we take a modest step toward clarifying the matter by specifying a parallel model across states, counties, and cities.

We adopt the general methodological strategy outlined above for our assessment of the implications of a uniform empirical specification across states, counties, and cities. Thus, the analysis focuses on seven waves or time points (1980, 1985, 1990, 1995, 2000, 2005, and 2010). For these periods, we construct pooled cross-sectional datasets for states, counties, and cities that include a common set of measures. All of the measures included are described in Table IIIa. As the

[4]We estimated Pesaran's (2004) CD test for cross-sectional dependence in the state, county, and city samples examined in our analysis. In each case, we observed moderate-to-strong cross-sectional dependence, and the test statistic rejected the null hypothesis of independence.

table reveals, we include what are now standard indicators of demographic, economic, and composition (i.e., indices for population size and density, resource deprivation, and immigrant concentration; indicators of age structure and divorce rates). Additionally, we include other economic measures highlighted in some studies (i.e., contemporaneous and first-differenced unemployment rates, average real wages), an indicator of drug involvement (drug arrest rates), and variables meant to capture spatial and temporal variation in the nature of criminal justice efforts (i.e., police force size and state incarceration rates).

Table IIIa about here

Although Table IIIa describes the sources and construction of the various measures considered, a few additional comments are warranted. First, our dependent variables (homicide rate, non-lethal violent crime rate, and non-violent property crime rate) generally reflect two year averages that encompass the seven "waves" upon which we focus (i.e., 1980-81, 1985-86, 1990-91, 1995-96, 2000-01, 2005-06, and 2010). Where possible, we pooled two years of crime data to enhance the stability of the estimated rates and to minimize the possibility of misrepresenting trends based on the selected years. The 2011 data needed to follow suit with this strategy for the last period was not available at the time we conducted the analysis, so we use a single year in this instance (i.e., 2010). Most of the other variables are measured contemporaneously (or at least in an overlapping manner) with the crime data, but two exceptions are state incarceration rates and unemployment rates. Following prior research, we lag the incarceration by one year, and we include both a contemporaneous measure and a first-differenced measure of the unemployment rate (see Phillips and Land, 2012).

We present additional pertinent details about summary statistics and other results below, but two other methodological issues are noteworthy at this point. First, a few of the variables are not measured specifically for cities. For instance, we include rates of incarceration in the analysis of crime variation across each of the geographic units (i.e., states, counties, and cities) even though the figures reflect state-level conditions. We revisit this issue in the second major portion of our analysis, which focuses more squarely on estimating effects of prison admissions and releases at a more localized (i.e., county) level. Wages also are not available for cities, so we merge county-level data to our city sample to capture differences in average wages. Further, while the BLS does provide unemployment data for cities, counties, and states, the coverage for cities during the early 1980s is sparse, so we use census-based city unemployment rate estimates for this period; the city unemployment estimates for other periods are based on BLS data. Second, we include three composite indices in the analysis: population structure (logged population size and density), immigrant concentration (% Latino and % foreign born), and resource deprivation (% non-Latino black, % female headed households with kids, median family income, and the GINI). All are well-grounded in the extant literature, and the latter two revealed strong evidence of reliability (e.g., alpha coefficients above .80 across waves and units of analysis). The population structure index yielded less consistent patterns, with acceptable levels of reliability in the state and county database but weaker evidence of unidimensionality in the city-level database. We therefore estimated supplementary panel regressions of city crime rates with the two components of this index included as separate variables; the results (not shown in tabular form) were substantively similar to what is reported in the tables below.

IIIb. An assessment of conditional economic effects on recent crime trends

Building from the county-level analysis other two sets of analyses described thus far, we also conduct a detailed assessment of conditional economic effects on recent county crime trends. In this instance, our research expectations are quite specific. As elaborated above, the theoretical literature provides evidence that the influence on crime rates of two common indicators of economic adversity – unemployment rates and average wages -- may differ depending on rates of inflation, unemployment insurance and income maintenance, incarceration risk, and the quantity and quality of policing. We focus this analysis on counties as well. While cities and states are also meaningful units of analysis for the research issues at hand, the use of counties maximizes the specification that can be employed while also minimizing some concessions that would need to be made if cities and/or states were used. Specifically, measures of several key economic indicators, such as wages and unemployment insurance, are not available for cities, and several others pertinent indicators are measured only at relatively high levels of aggregation (e.g., region) that may be less relevant for capturing city conditions than county or other larger social aggregates. Additionally, we restrict our attention to county patterns, forgoing an additional state-level analysis, because the two focal variables in this part of our analysis – unemployment rates and wages – tend to exhibit significant heterogeneity across counties within states, largely because in many areas counties closely parallel local labor markets. While state-level analyses can yield meaningful data on the issue at hand, we consider a county-level analysis to be more appropriate conceptually.

Consistent with the more general analysis described in IIIa, the county-level database constructed to support our analysis of the conditional effects of unemployment rates and average wages is based on seven time points spanning from 1980-2010 (i.e., 1980, 1985, 1990, 1995, 2000, 2005, and 2010) and 353 of the largest 400 U.S. counties. We integrate several additional economic variables, however, including state Gross Domestic Product (GDP), regional measures of inflation and consumer sentiment, and county-level indicators of unemployment insurance and income maintenance payments. Table IIIb presents a description of the measures included in the analysis. Most of the measures shown in the table parallel those described above, but note that we also include in the county-level analysis of economic conditions some indicators that are measured only for larger aggregations. For instance, the Index of Consumer Sentiment (ICS) highlighted in recent scholarship (e.g., Rosenfeld, 2009) is not available below the level of regions, and GDP is available only for states.

Table IIIb about here

IIIc. Expanding the typical set of criminal justice variables considered

We build on our initial set of analyses to explore in a more nuanced way the role of specified criminal justice factors. Specifically, we integrate into the county-level database used in the two analyses just described several additional criminal justice measures. These include a measure of proactive policing to further explore the response of crime rates to the nature of policing, and measures of *county-level* rates of prison admissions. The latter are significant both because they replace state-level indicators, but also because we capitalize on the detail available in the NCRP to capture age- and crime-specific measures of imprisonment and release.

The expanded county-level analysis of criminal justice factors draws heavily from the National Corrections Reporting Program (NCRP) to capture county experiences with prison admissions and releases, and thus both the time period and counties included are defined to a large degree by the NCRP sampling frame. Approximately 40 states currently participate in the NCRP, but participation has fluctuated over time and has also been uneven across counties within states. The practical consequence is that only a relatively modest proportion of U.S. counties report in the NCRP in a consistent manner across the full period in which we are interested.

The NCRP data assembled for the project covers 1983-2003; paralleling the multi-wave approach used for the other sets of analyses, we construct for this part of our research a five-wave panel database with requisite measures centered on the following time points: 1985, 1990, 1995, 2000, and 2005. The universe of counties included in this analysis was dictated by three general considerations. One is that since we draw from the 2005-2007 American Community Survey (ACS), we limit the sampling universe to the 1,817 U.S. counties with populations of 20,000 or more persons (the three-year ACS data are censored for counties below 20,000 persons). Two, we limit the analysis to the moderate and large counties in this universe that consistently have participated in the NCRP over the temporal period under investigation. As noted, several U.S. states do not participate in the NCRP, and coverage has varied over time. Imposing the admittedly arbitrary requirements of valid NCRP estimates for at least four of the five waves of data and a minimum of 25 admissions per year led us to retain 429 of these counties in the sampling universe. Third, and lastly, a notable portion of these counties (n=92) had extensive missing data on other measures—most notably arrest rates—for two or more of the five waves covered. The expanded analysis of criminal justice factors is thus based on the 337 counties that were deemed to have sufficient data to support a meaningful assessment of crime trends across time and counties.

As noted, our expanded analysis of criminal justice variables approximates in design the analysis of states, counties, and cities described above, though the available data limit this analysis to five waves (i.e., 1985, 1990, 1995, 2000, and 2005). For these periods, we construct pooled cross-sectional datasets for counties that include a large array of control variables in addition to several key criminal justice explanatory variables. We describe the various measures and identify the sources from which we obtained them in Table IIIc. As with the other analyses described herein, we explore the role of this expanded set of criminal justice factors through a series of two-way fixed-effects panel models of crime rates that include fixed effects that control for stable unmeasured county attributes and temporal shocks that are shared across counties, with inferences based on panel-corrected standard errors. Our analytic focus in this instance is quite general in scope. Rather than assessing specific hypotheses, for instance, we are interested generally in whether the estimated effects of age- and crime-specific rates of prison admissions diverge from estimated effects of overall prison admissions , and also whether proactive policing exhibits significant effects on *county* crime rates (an issue that has not been explored in previous county-level research).

Table IIIc about here

Table IIIa1. Description of variables included in analysis of empirical models of recent crime trends across different units of analysis.

Variable	Variable Definition and Source
Dependent Variables	
Homicide rate (logged)	Homicides per 100,000 residents (UCR; population data from SEER & ACS).
Non-lethal violent crime rate (logged)	Robberies and Aggravated Assaults per 100,000 residents (UCR; population data from SEER & ACS).
Non-violent property crime rate (logged)	Burglaries, Motor Vehicle Thefts, and Larcenies per 100,000 residents (UCR; population data from SEER & ACS).
Explanatory Variables	
Population structure	Standardized additive index that includes logged population size and logged population density (SEER, Census Bureau STF & ACS).
% age 15-29	Percentage of population 15 to 29 (SEER & ACS).
Divorce rate	Percentage of persons 15 and older who are divorced (Census Bureau STF & ACS).
Immigrant concentration	Standardized additive index that include % Latino and % foreign born (Census Bureau STF & ACS).
Resource deprivation	Standardized additive index that includes % families below poverty, GINI, % non-Latino black, % female headed households with kids, and (reverse coded) median family income (Census Bureau STF & ACS).
Unemployment rate	Percentage of civilian labor force unemployed (BLS).
Unemployment rate, first differenced	Percentage of civilian labor force unemployed, first differenced (BLS).
Average wage level	Mean annual real wages across all industries (BEA).
Logged state incarceration rate, once lagged	Persons serving sentences in state or federal prisons, lagged one year, per 100,0000 residents (BJS; population data from SEER & ACS).
Police force size	Police officers per 100,000 residents (LEOKA; population data from SEER & ACS).
Drug arrest rate	Drug arrests per 100,000 residents (UCR; population data from SEER & ACS).

Note: UCR=Uniform Crime Reporting Program, BJS=Bureau of Justice Statistics; BEA=Bureau of Economic Analysis; BLS=Bureau of Labor Statistics; SEER=Surveillance Epidemiology and End Results; Census Bureau STF= Decennial Summary Tape Files for 1980-2000; ACS=American Community Survey; LEOKA=Law Enforcement Officers Killed or Assaulted.

Table IIIb. Description of variables included in analysis of conditional economic effects on recent crime trends.

Variable	Variable Definition and Source
Dependent Variables	
Homicide rate (logged)	Homicides per 100,000 residents (UCR; population data from SEER & ACS).
Non-lethal violent crime rate (logged)	Robberies and Aggravated Assaults per 100,000 residents (UCR; population data from SEER & ACS).
Non-violent property crime rate (logged)	Burglaries, Motor Vehicle Thefts, and Larcenies per 100,000 residents (UCR; population data from SEER & ACS).
Explanatory Variables	
Unemployment rate	Percentage of civilian labor force unemployed (BLS).
Unemployment rate, first differenced	Percentage of civilian labor force unemployed, first differenced (BLS).
Average wage level	Mean annual real wages across all industries (BEA).
Regional inflation rate	Percentage change in regional consumer price index (BEA).
Per capita unemployment insurance	Unemployment insurance compensation in real 2008 dollars (BEA).
Per capita income maintenance	Income maintenance benefits (i.e., SSI, SNAP, Family Assistance) in real 2008 dollars (BEA).
State GDP, once lagged	State-level real Gross Domestic Product (GDP) across all industries, once lagged (BEA).
Regional Index of Consumer Sentiment, once lagged	Summary index of consumer confidence and expectations, once lagged (Reuters-University of Michigan).
Logged state incarceration rate, once lagged	Persons serving sentences in state or federal prisons, lagged one year, per 100,0000 residents (BJS; population data from SEER & ACS).
Police force size	Police officers per 100,000 residents (LEOKA; population data from SEER & ACS).
Control Variables	
Population structure	Standardized additive index that includes logged population size and logged population density (SEER, Census Bureau STF & ACS).
% age 15-29	Percentage of population 15 to 29 (SEER & ACS).
Divorce rate	Percentage of persons 15 and older who are divorced (Census Bureau STF & ACS).
Immigrant concentration	Standardized additive index that include % Latino and % foreign born (Census Bureau STF & ACS).
Resource deprivation	Standardized additive index that includes % families below poverty, GINI, % non-Latino black, % femaile headed households with kids, and (reverse coded) median family income (Census Bureau STF & ACS).
Drug arrest rate	Drug arrests per 100,000 residents (UCR; population data from SEER & ACS).

Note: UCR=Uniform Crime Reporting Program, BJS=Bureau of Justice Statistics; BEA=Bureau of Economic Analysis; BLS=Bureau of Labor Statistics; SEER=Surveillance Epidemiology and End Results; Census Bureau STF= Decennial Summary Tape Files for 1980-2000; ACS=American Community Survey; LEOKA=Law Enforcement Officers Killed or Assaulted.

Table IIIc. Description of variables included in county-level analysis of criminal justice factors and recent crime trends.

Variable	Variable Definition and Source
Dependent Variables	
Homicide rate (logged)	Homicides per 100,000 residents (UCR; population data from SEER & ACS).
Non-lethal violent crime rate (logged)	Robberies and Aggravated Assaults per 100,000 residents (UCR; population data from SEER & ACS).
Non-violent property crime rate (logged)	Burglaries, Motor Vehicle Thefts, and Larcenies per 100,000 residents (UCR; population data from SEER & ACS).
Explanatory Variables	
Logged state incarceration rate, once lagged	Persons serving sentences in state or federal prisons, lagged one year, per 100,0000 residents (BJS; population data from SEER & ACS).
Logged state prison admissions rate, once lagged	Persons admitted to state or federal prisons, lagged one year, per 100,0000 residents (BJS; population data from SEER & ACS).
Logged county prison admissions, once lagged	Persons admitted to prison, lagged one year, per 100,0000 residents (NCRP; population data from SEER).
Logged county prison admissions 18-34, once lagged	Persons 18-34 admitted to prison, lagged one year, per 100,0000 residents (NCRP; population data from SEER).
Logged county prison admissions 35-64, once lagged	Persons 35-64 admitted to prison, lagged one year, per 100,0000 residents (NCRP; population data from SEER).
Logged county homicide prison admissions, once lagged	Persons admitted to prison for homicide, lagged one year, per 100,000 residents (NCRP; population data for SEER).
Logged county non-lethal violence prison admissions, once lagged	Persons admitted to prison for robbery or assault, lagged one year, per 100,000 residents (NCRP; population data for SEER).
Logged county non-violent property crime prison admissions, once lagged	Persons admitted to prison for burglary or larceny, lagged one year, per 100,000 residents (NCRP; population data for SEER).
Police force size	Police officers per 100,000 residents (LEOKA; population data from SEER & ACS).
Logged proactive policing	Ratio of Arrests for DUI and disorderly conduct to the number of police officers (UCR & LEOKA).
Logged homicide arrest certainty	Ratio of arrests for homicide to total homicides known to the police (UCR).
Logged non-lethal violence arrest certainty	Ratio of arrests for non-lethal violence (robbery & aggravated assault) to total non-lethal violent crimes known to the police (UCR).
Logged non-violent property crime arrest certainty	Ratio of arrests for non-violent property crime to total non-violent property crime known to the police (UCR).
Control Variables	
Population structure	Standardized additive index that includes logged population size and logged population density (SEER, Census Bureau STF & ACS).
% age 15-29	Percentage of population 15 to 29 (SEER & ACS).
Divorce rate	Percentage of persons 15 and older who are divorced (Census Bureau STF & ACS).
Immigrant concentration	Standardized additive index that includes % Latino and % foreign born (Census Bureau STF & ACS).
Resource deprivation	Standardized additive index that includes % families below poverty, GINI, % non-Latino black, % femaile headed households with kids, and (reverse coded) median family income (Census Bureau STF & ACS).
Unemployment rate	Percentage of civilian labor force unemployed (BLS).
Unemployment rate, first differenced	Percentage of civilian labor force unemployed, first differenced (BLS).
Average wage level	Mean annual real wages across all industries (BEA).
Drug arrest rate	Drug arrests per 100,000 residents (UCR; population data from SEER & ACS).

Note: UCR=Uniform Crime Reporting Program, BJS=Bureau of Justice Statistics; BEA=Bureau of Economic Analysis; BLS=Bureau of Labor Statistics;
SEER=Surveillance Epidemiology and End Results; Census Bureau STF= Decennial Summary Tape Files for 1980-2000; ACS=American Community Survey;
LEOKA=Law Enforcement Officers Killed or Assaulted.

IV. Results

We report the results of each set of analyses separately, beginning with the assessment of a uniform empirical specification across states, counties, and cities. In each case, we begin by describing some basic features of the samples used in the analyses, followed by a summary of the key results of our panel model estimations.

IVa. *Uniform empirical specification across states, counties, and cities.*

What do parallel empirical specifications of recent crime trends applied across states, counties, and cities reveal? The results displayed in Tables IVa1-IVa4 address this question. The descriptive statistics in Table IVa1 show, as expected, that crime rates are higher in the sample of large cities than in the less urban dominated samples of American states and large counties. Also, crime rates tend to exhibit greater spatial and temporal variability in the county and city samples than in the state sample. Nevertheless, the samples observed for each set of geographic units exhibit substantial variation in crime and the explanatory variables, prompting the question of whether the latter is related to the former similarly across these samples. We explore this issue in a series of panel regression models, the results of which are reported in Tables IVa2-IVa4.

Table IVa1 about here

For illustrative purposes, the starting point for our panel regression models of crime trends across units of analysis is the "typical" model one sees in analyses of cities, counties, and states in the extant research. Based on our perusal of the literature, the modal empirical model employed in city-level crime trends research differs notably from what one usually sees in county-level crime trends studies, and state-level studies often diverge both from city- and county-level studies. In part, the latter occurs because most state-level studies include fixed effects for areas and/or time points, whereas all city-level studies and most county-level research of which we are aware do no not do so. Panel A in the regression tables (Tables IVa2-IVa4) shows the different base-line specifications that, in our judgment, reflect the standard application in previous studies. Table IVa2 displays results for homicide; while the findings for non-lethal violence and non-violent property crime are shown in Tables IVa3 and IVa4, respectively. A row near the bottom of each table indicates the presence or absence of fixed effects in the empirical specification, a designation we flag throughout the tables presented in the report.

Tables IVa2 – IVa4 about here

Some immediate observations to make regarding the "baseline" specification shown in Panel A of these tables is what is missing from each specification. For example, looking at Panel A across the three tables reveals that though immigration has received considerable attention in recent scholarship (e.g., Stowell et al., 2009), it remains largely on the margins of most crime trends research, regardless of the unit of analysis employed. Incarceration rates are almost always present in state-level studies, but rarely included in county- and city-level studies. On the other hand, city-level research on crime trends often focuses resource deprivation, police force size, and drug arrest rates (as in indicator of drug use and involvement in drug markets), but these indicators are routinely excluded from state-level studies (and many county-level studies, too). Perhaps not surprisingly, the baseline results shown in Panel A of the tables yield significant inconsistency across units of analysis. We withhold drawing attention to specific results from Panel A, however, because in each case the empirical specifications are incomplete based on a careful reading of the literature on the factors that may be pertinent to shaping recent crime trends. Additionally, the city- and county-level models do not account for stable unmeasured spatial attributes or temporal shifts that are shared across geographic areas, which may yield biased estimates.

Panel B presents what we refer to as "expanded models." These models essentially "fill in the blanks" that were observed in the baseline models, yielding specifications that are identical across units of analysis and the crime types considered. All of these models include spatial and temporal fixed effects. Panel C takes the modeling an additional few steps, specifically by incorporating insights about the functional form of the specified effects of unemployment rates and incarceration rates (see Liedka et al., 2001; Phillips and Land, 2012). The focal point of this investigation is to illustrate both the sensitivity of inferences for a given unit of analysis to the different specifications that tend to be employed across units, and also to see if any general patterns can be gleaned in the end. There are numerous intriguing patterns revealed across panels, units, and crime types in Tables IVa2-IVa4. We highlight three patterns here.

First, note that the estimated effects of one of the stalwarts of city-level analyses—resource deprivation—is highly sensitive to the model specification employed. In the baseline models (Panel A), the estimated effect is significant for each crime type. But, in each case, the more complete specifications greatly attenuate the magnitude of the estimated resource deprivation effect, and with the exception of homicide it is no longer a significant predictor of city crime trends once other factors and fixed effects are incorporated. Second, in the state models it is apparent that the estimated effects of stock incarceration rates are sensitive to empirical specification, albeit in complex ways. For instance, the more complete specifications reveal significant negative effects of incarceration rates for non-violent property crime rates, where the baseline model did not reveal such a pattern. On the other hand, the baseline model for states indicated a significant inverse association between incarceration and homicide rates, but this effect falls to non-significance in more complete specifications. Third, and most important, if we focus on the most completely specified models (c.f., Panel C in IVa2-IVa4), we see some consistent patterns emerge. Most notably, these models suggest that age structure and divorce rates are robust predictors of crime rates, with higher crime in areas with a larger percentage of persons aged 15-29 and where divorce rates are higher. Additionally, the results in Panel C for non-violent property crime affirm that incarceration rates tend to yield lower crime rates, but there are diminishing returns to this pattern (see also Liedka et al., 2001). For the other crime types, the incarceration effects are more nuanced.

The utility of the empirical models shown in Tables IVa2-IVa4 lies not in the specific results displayed,[5] but rather in prompting the research community to begin thinking in a more targeted fashion about whether the results generated from a particular unit of analysis (the typical research strategy) are sensitive to empirical specification and/or the level of analysis at which the data are measured. The results shown here suggest that findings are likely to be highly sensitive to both issues, at least for the specific samples examined in our study.

[5]Indeed, they could differ if the analyses were applied to a larger universe of cities and counties, and the estimated results of some parameters may vary across temporal eras for a variety of reasons (e.g., McCall, Land, and Parker, 2010). Assessing both of these issues in future research would be informative.

Table IVa1. Summary statistics for variables included in analysis of empirical models of recent crime trends across different units of analysis.

	States (n=48, t=7)			Counties (n=353, t=7)			Cities (n=147, t=7)		
Variable	**Mean**	**Between-Unit SD**	**Within-Unit SD**	**Mean**	**Between-Unit SD**	**Within-Unit SD**	**Mean**	**Between-Unit SD**	**Within-Unit SD**
Dependent Variables									
Homicide rate (logged)	1.662	.573	.299	1.474	.845	.480	2.199	.851	.440
Non-lethal violent crime rate (logged)	5.905	.557	.241	5.916	.660	.323	6.623	.554	.320
Non-violent property crime rate (logged)	8.320	.215	.247	8.345	.359	.272	8.762	.304	.287
Explanatory Variables									
Population structure	-.114	1.663	.128	-.054	1.721	.230	-.057	1.405	.277
% age 15-29	22.927	.981	2.712	23.467	3.259	2.840	25.913	3.353	2.775
Divorce rate	7.110	1.009	1.463	7.062	1.281	1.389	10.285	1.349	3.147
Immigrant concentration	-.098	1.773	.270	-.020	1.809	.311	-.068	1.570	.300
Resource deprivation	2.722	3.595	.767	2.941	4.020	.922	3.245	4.146	1.054
Unemployment rate	5.955	1.123	1.807	6.198	1.700	2.097	6.565	2.017	2.139
Average wage level	14.61	1.822	1.352	14.926	2.222	1.522	16.322	2.365	1.863
Logged state incarceration rate, once lagged	5.458	.424	.494	5.557	.364	.493	5.631	.318	.505
Police force size	208.922	46.775	31.838	22.257	16.880	6.905	279.995	201.046	125.834
Drug arrest rate	265.748	67.891	87.484	256.734	113.884	93.398	166.359	70.149	45.574

Table IVa2. Panel regression models of homicide rates across states, counties, and cities.

A. Baseline Models of Homicide

	Cities	Counties	States
Explanatory Variable	(1)	(2)	(3)
Population structure	.030	-.213**	-.351**
	(.017)	(.043)	(.057)
% age 15-29	-.004	.024	.041**
	(.014)	(.014)	(.012)
Divorce rate	.025	.0005	—
	(.014)	(.024)	—
Immigrant concentration	—	—	—
	—	—	—
Resource deprivation	.153**	—	—
	(.012)	—	—
Unemployment rate	-.018	-.010	-.010
	(.015)	(.007)	(.009)
Average wage level	—	-.011	.028**
	—	(.009)	(.011)
State incarceration rate, once lagged	—	—	-.133*
	—	—	(.057)
Police force size	.0002**	—	—
	(.00006)	—	—
Drug arrest rate	-.00067	—	—
	(.0005)	—	—
Time and Geographic Fixed Effects?	No	No	Yes
N	1010	2466	334
R-Squared	.535	.785	.897

Table IVa2. (Cont.)

B. Expanded Models of Homicide

	Cities	Counties	States
Explanatory Variable	(1)	(2)	(3)
Population structure	-.007	-.219**	-.439**
	(.088)	(.052)	(.089)
% age 15-29	.028**	.030*	.027
	(.007)	(.012)	(.015)
Divorce rate	.016	-.004	.068**
	(.012)	(.024)	(.026)
Immigrant concentration	-.157**	.067**	.176**
	(.045)	(.018)	(.043)
Resource deprivation	.107**	.018	-.028
	(.014)	(.014)	(.015)
Unemployment rate	.002	-.017**	-.007
	(.018)	(.004)	(.011)
Average wage level	-.002	-.005	.018
	(.008)	(.009)	(.015)
Logged state incarceration rate, once lagged	-.450**	-.280**	-.118
	(.101)	(.069)	(.062)
Police force size	.00005	.002	-.001
	(.00006)	(.001)	(.001)
Drug arrest rate	.001	.0004*	-.0001
	(.0006)	(.0002)	(.0002)
Time and Geographic Fixed Effects?	Yes	Yes	Yes
N	1010	2441	331
R-Squared	.834	.797	.918

Table IVa2. (Cont.)

C. More Completely Specified Models of Homicide

Explanatory Variable	Cities (1)	Counties (2)	States (3)
Population structure	.010	-.204**	-.438**
	(.090)	(.049)	(.099)
% age 15-29	.025**	.029*	.027*
	(.006)	(.012)	(.014)
Divorce rate	.023	-.001	.074**
	(.013)	(.022)	(.025)
Immigrant concentration	-.155**	.069**	.184**
	(.043)	(.017)	(.041)
Resource deprivation	.107**	.028	-.021
	(.014)	(.015)	(.017)
Unemployment rate	-.0008	-.026**	-.011
	(.018)	(.004)	(.011)
Unemployment rate, first differenced	.014	.031**	.017
	(.030)	(.009)	(.014)
Average wage level	-.0008	-.009	.018
	(.008)	(.009)	(.015)
State incarceration rate, once lagged	.861*	.420**	.015
	(.364)	(.163)	(.342)
State incarceration rate squared, once lagged	-.119**	-.066**	-.013
	(.032)	(.013)	(.032)
Police force size	.0001	.002	-.0004
	(.00006)	(.001)	(.001)
Drug arrest rate	.0009	.0004*	-.0001
	(.0005)	(.0002)	(.0002)
Time and Geographic Fixed Effects?	Yes	Yes	Yes
N	1009	2441	331
R-Squared	.839	.848	.919

*p < .05

**p < .01

Table IVa3. Panel regression models of non-lethal violence rates across states, counties, and cities.

A. Baseline Models of Non-Lethal Violence

	Cities	Counties	States
Explanatory Variable	(1)	(2)	(3)
Population structure	.073**	-.022	-.153*
	(.025)	(.032)	(.067)
% age 15-29	-.0005	.030**	.043**
	(.009)	(.008)	(.012)
Divorce rate	-.007	.034	—
	(.014)	(.024)	—
Immigrant concentration	—	—	—
	—	—	—
Resource deprivation	.091**	—	—
	(.006)	—	—
Unemployment rate	-.012	-.0005	-.028*
	(.012)	(.007)	(.013)
Average wage level	—	-.020**	-.036*
	—	(.007)	(.017)
State incarceration rate, once lagged	—	—	.045
	—	—	(.114)
Police force size	.0001**	—	—
	(.00004)	—	—
Drug arrest rate	.0004	—	—
	(.0004)	—	—
Time and Geographic Fixed Effects?	No	No	Yes
N	1010	2466	334
R-Squared	.864	.841	.915

Table IVa3. (Cont.)

B. Expanded Models of Non-Lethal Violence

Explanatory Variable	Cities (1)	Counties (2)	States (3)
Population structure	.051	-.017	-.120
	(.036)	(.018)	(.085)
% age 15-29	-.004	.032**	.028*
	(.009)	(.006)	(.014)
Divorce rate	.024**	.029**	.065**
	(.008)	(.009)	(.024)
Immigrant concentration	-.091**	.040**	.111*
	(.035)	(.010)	(.052)
Resource deprivation	.038**	.026**	-.042*
	(.011)	(.005)	(.021)
Unemployment rate	.002	-.005	-.021
	(.011)	(.004)	(.014)
Average wage level	-.003	-.013**	-.054*
	(.010)	(.005)	(.021)
Logged state incarceration rate, once lagged	-.234**	-.134*	.083
	(.067)	(.063)	(.112)
Police force size	-.00007	.001*	.001
	(.00005)	(.0006)	(.001)
Drug arrest rate	.001*	.0004**	-.0001
	(.0005)	(.0001)	(.0002)
Time and Geographic Fixed Effects?	Yes	Yes	Yes
N	1010	2441	331
R-Squared	.853	.848	.920

Table IVa3. (Cont.)

C. More Completely Specified Models of Non-Lethal Violence

Explanatory Variable	Cities (1)	Counties (2)	States (3)
Population structure	.043	-.018	-.103
	(.036)	(.017)	(.109)
% age 15-29	.003	.031**	.029*
	(.009)	(.006)	(.013)
Divorce rate	.021*	.0289**	.065**
	(.009)	(.009)	(.025)
Immigrant concentration	-.091**	.041**	.113*
	(.035)	(.011)	(.056)
Resource deprivation	.040**	.028**	-.042*
	(.010)	(.006)	(.018)
Unemployment rate	.00004	-.007	-.020
	(.012)	(.004)	(.015)
Unemployment rate, first differenced	.008	.006	-.006
	(.023)	(.005)	(.017)
Average wage level	-.003	-.014**	-.055*
	(.010)	(.005)	(.022)
State incarceration rate, once lagged	-.803*	-.151	.222
	(.317)	(.116)	(.601)
State incarceration rate squared, once lagged	.051*	-.001	-.013
	(.025)	(.015)	(.051)
Police force size	-.00009*	.001*	.001
	(.00004)	(.0007)	(.001)
Drug arrest rate	.001*	.0004**	-.0001
	(.0005)	(.0001)	(.0002)
Time and Geographic Fixed Effects?	Yes	Yes	Yes
N	1010	2441	331
R-Squared	.855	.848	.918

*p < .05

**p < .01

Table IVa4. Panel regression models of non-violent property crime rates across states, counties, and cities.

A. Baseline Models of Non-Violent Property Crime

	Cities	Counties	States
Explanatory Variable	(1)	(2)	(3)
Population structure	-.040*	-.049*	-.179*
	(.018)	(.020)	(.082)
% age 15-29	.017	.030**	.023
	(.010)	(.006)	(.016)
Divorce rate	.020	.053**	—
	(.017)	(.014)	—
Immigrant concentration	—	—	—
	—	—	—
Resource deprivation	.038**	—	—
	(.005)	—	—
Unemployment rate	-.026	.005	-.00003
	(.015)	(.005)	(.012)
Average wage level	—	-.023**	-.024*
	—	(.005)	(.012)
State incarceration rate, once lagged	—	—	-.152
	—	—	(.080)
Police force size	.0001**	—	—
	(.00003)	—	—
Drug arrest rate	-.0002	—	—
	(.0003)	—	—
Time and Geographic Fixed Effects?	No	No	Yes
N	1010	2466	334
R-Squared	.955	.923	.968

Table IVa4. (Cont.)

B. Expanded Models of Non-Violent Property Crime

	Cities	Counties	States
Explanatory Variable	(1)	(2)	(3)
Population structure	-.056**	-.033	-.063
	(.015)	(.029)	(.077)
% age 15-29	.008	.034**	.020
	(.005)	(.005)	(.014)
Divorce rate	.025**	.047**	.086*
	(.009)	(.009)	(.036)
Immigrant concentration	-.038*	-.004	.082*
	(.016)	(.016)	(.036)
Resource deprivation	.010	.015*	.002
	(.008)	(.007)	(.014)
Unemployment rate	.007	.002	-.0004
	(.009	(.005)	(.013)
Average wage level	-.010	-.017**	-.022
	(.008)	(.006)	(.015)
Logged state incarceration rate, once lagged	-.247**	-.219**	-.127*
	(.075)	(.073)	(.064)
Police force size	.00004	.002**	.001*
	(.00003)	(.0008)	(.0004)
Drug arrest rate	.0006**	.0003**	.0001
	(.0002)	(.0001)	(.0001)
Time and Geographic Fixed Effects?	Yes	Yes	Yes
N	1010	2441	331
R-Squared	.942	.9232	.974

Table IVa4. (Cont.)

C. More Completely Specified Models of Non-Violent Property Crime

	Cities	Counties	States
Explanatory Variable	(1)	(2)	(3)
Population structure	-.065**	-.055*	-.112
	(.016)	(.021)	(.073)
% age 15-29	.008	.031**	.017
	(.005)	(.005)	(.014)
Divorce rate	.023**	.043**	.087*
	(.008)	(.011)	(.035)
Immigrant concentration	-.037*	-.004	.079*
	(.016)	(.013)	(.037)
Resource deprivation	.012	.015*	.001
	(.007)	(.007)	(.014)
Unemployment rate	.004	-.002	-.003
	(.009)	(.006)	(.014)
Unemployment rate, first differenced	.017	.014	.018
	(.013)	(.007)	(.019)
Average wage level	-.010	-.018**	-.021
	(.007)	(.007)	(.015)
State incarceration rate, once lagged	-.728**	-.992**	-.511**
	(.194)	(.172)	(.187)
State incarceration rate squared, once lagged	.044**	.072**	.037*
	(.016)	(.021)	(.018)
Police force size	.00002	.002*	.001
	(.00002)	(.0009)	(.0004)
Drug arrest rate	.0006**	.0003**	.0001
	(.0002)	(.0001)	(.0001)
Time and Geographic Fixed Effects?	Yes	Yes	Yes
N	1009	2441	331
R-Squared	.943	.928	.977

*p < .05

**p < .01

IVb. ***An assessment of conditional economic effects on recent crime trends***

Are the effects of unemployment rates and wages contingent on other factors? As noted above, prior research has revealed quite variable effects of these conditions across studies. This variability may be a function of differences in time periods, samples, or empirical specifications, but it also could arise because these economic attributes influence crime rates in some contexts but not others. In particular, we outlined above how the potentially criminogenic effects of escalating unemployment and depressed wages may be magnified under conditions of high inflation, while they may be mitigated in contexts of greater spending on unemployment insurance and other sources of income maintenance, and where the objective risk of detection and punishment are higher (e.g., in times and places with larger police forces and higher incarceration rates). We now turn to a set of analyses pertinent to these possibilities, expanding on the county-level analysis reported above.

Table IVb1 displays the summary statistics for the variables included in our assessment of potential conditional effects of unemployment rates and average wages. Most of the measures included in the analysis also were encompassed in the analysis reported above, but we note that we have added several indicators as well: levels of inflation, unemployment insurance, income maintenance, state GDP, and regional consumer sentiment.

Table IVb1 about here

We initiate our assessment by first considering the main effects on crime rates of the explanatory and control variables. Table IVb2 shows the results, with separate models for homicide, non-lethal violence, and non-violent property crime rates. There are several interesting patterns revealed in the models, but we highlight the findings for unemployment and wages given our interest in assessing their conditional effects in subsequent models. Following past research (e.g., Cantor and Land, 1985; Phillips and Land, 2012), we attempt to distinguish between the presumed "opportunity" and "motivational" effects of unemployment. Briefly, as Phillips and Land (2012) most recently convey, extant theory suggests that higher unemployment rates in a given period would be expected to yield lower crime rates in that period because it tends to shift routine activities from the public to private sphere. In contrast, a higher unemployment rate in a given period may yield heightened motivation as time wears on, perhaps because of the stress and frustration associated with prolonged unemployment. Following Phillips and Land (2012), we attempt to capture these two processes by including both contemporaneous (i.e., opportunity-based) and first-differenced (i.e., motivational-based) measures of unemployment; the expectation is for a significant negative effect of the former, and a significant positive effect of the latter. Indeed, we observe precisely this pattern for homicide rates. The patterns observed for the other two crime types diverge from expectations; we find no significant effects of either unemployment measure in the model for non-lethal violence, and we observe a significant effect for only the first-differenced unemployment measure in the non-violent property crime model. In contrast, we find significant negative effects of wages on both non-lethal violence and non-violent property crime rates (see also Gould et al., 2002).

Tables IVb2 about here

Are the effects of unemployment rates and wages on crime trends conditional on other factors? Does their impact on crime rates depend on the prevailing level of inflation, public spending on unemployment insurance and other income supports, or the level of objective sanction risk faced by would-be offenders? We explore these issues by estimating a series of multiplicative panel regressions, the results of which report in Table IVb3. We present results only for the main effects of unemployment rates and mean wages, along with product terms between these indicators and the proposed moderators (i.e., inflation, public benefits, police size, and incarceration rates). To facilitate interpretation, the product terms were formed after mean centering the component terms. The results presented are based on specifications that otherwise parallel those reported in the main effects models, so they include all the control variables along with county and wave fixed effects.

Table IVb3 about here

We present the noted multiplicative models in three panels in Table IVb3: A (homicide), B (non-lethal violence), and C (non-violent property crime rates). For the most part, the results in Panel A indicate that estimated unemployment and wage effects on homicide are not conditioned by other factors. The lone exception is that higher levels of incarceration dampen the positive effect of unemployment on homicide rates (see model 4). This tendency of "objective criminal justice risk" to lessen the criminogenic consequences of elevated unemployment rates and depressed wages emerges as a fairly consistent pattern in the analysis. Indeed, high incarceration rates also weaken the theoretically expected positive effect of the first differenced unemployment rate on non-lethal violence rates (see model 4, panel B), and larger police forces appears to mitigate the adverse effects of low wages on both non-lethal violence and non-violent property crime (see model 5, panels B and C). Another intriguing pattern that emerges in our assessment of conditional economic effects is that the estimated adverse effects of unemployment and wages on non-lethal crime (both violent and property) are weaker in the face of elevated levels of income maintenance payments (i.e., SSI, Snap, family assistance), as shown in model 2 for non-lethal violence and models 2 and 3 for non-violent property crime. Finally, contrary to expectations, inflation levels do not moderate the effects of wages and unemployment rates in our analysis. One possible reason is that the inflation measure, which reflects regional conditions, is too crude to detect theoretically anticipated effects.

Overall, we find moderately strong evidence that the assumed main effects of wages and unemployment rates in most previous studies is questionable. The influence of these economic conditions on contemporary crime trends is contingent on other conditions, and this may be one reason why past research yields highly inconsistent empirical patterns for these attributes.

Table IVb1. Summary statistics for variables included in analysis of conditional economic effects on recent crime trends.

	Counties (n=353, t=7)		
Variable	**Mean**	**Between-Unit SD**	**Within-Unit SD**
Dependent Variables			
Homicide rate (logged)	1.474	0.845	0.480
Non-lethal violent crime rate (logged)	5.916	0.660	0.323
Non-violent property crime rate (logged)	8.345	0.359	0.272
Key Explanatory Variables			
Unemployment rate	6.198	1.700	2.097
Unemployment rate, first differenced	0.082	0.286	1.110
Average wage level	14.926	2.222	1.522
Regional inflation rate	4.808	0.103	3.687
Per capita unemployment insurance	13826.00	5921.51	14250.82
Per capita income maintenance	340.15	152.10	204.75
State GDP, once lagged	27,490.03	3,458.30	11,702.86
Regional Index of Consumer Sentiment, once lagged	87.863	0.735	14.476
Logged state incarceration rate, once lagged	5.557	0.364	0.493
Police force size	22.257	16.880	6.905
Control Variables			
Population structure	-0.054	1.721	0.230
% age 15-29	23.467	3.259	2.840
Divorce rate	7.062	1.281	1.389
Immigrant concentration	-0.020	1.809	0.311
Resource deprivation	2.941	4.020	0.922
Drug arrest rate	256.73	113.88	93.40

Table IVb2. Two-way fixed effects models of the conditional effects of wages and unemployment rates on crime rates across counties (n=353, t=7).

A. Main Effects Models

Explanatory Variable	Homicide	Non-Lethal Violence	Non-Violent Property Crime
Unemployment rate	-.041**	-.007	-.004
	(.007)	(.006)	(.003)
Unemployment rate, first differenced	.032**	.005	.017**
	(.009)	(.005)	(.006)
Average wage level	-.0002	-.013**	-.011
	(.010)	(.005)	(.007)
Regional inflation rate	.035	.017	.018
	(.049)	(.032)	(.026)
Per capita unemployment insurance	.000006**	.0000002	-.000001
	(.000001)	(.000001)	(.000001)
Per capita income maintenance	.0002	.0001	.0002**
	(.0002)	(.0001)	(.0001)
State GDP, once lagged	-.000004*	-.000002	-.00002**
	(.000002)	(.000002)	(.000002)
Regional Index of Consumer Sentiment, once lagged	-.007	.004	.001
	(.004)	(.005)	(.003)
Logged state incarceration rate, once lagged	-.283**	-.133*	-.233**
	(.060)	(.055)	(.062)
Police force size	.002	.001*	.001**
	(.001)	(.0005)	(.0004)
Population structure	-.180**	-.001	-.028
	(.026)	(.015)	(.024)
% age 15-29	.021*	.028**	.030**
	(.009)	(.003)	(.006)
Divorce rate	-.007	.025**	.038**
	(.026)	(.007)	(.006)
Immigrant concentration	.075**	.046**	.01
	(.022)	(.013)	(.012)
Resource deprivation	.023*	.024**	.008
	(.011)	(.003)	(.004)
Drug arrest rate	.0004*	.0004**	.0003**
	(.0002)	(.0001)	(.0001)
Time and Geographic Fixed Effects?	Yes	Yes	Yes
N	2441	2441	2441
R-Squared	.801	.848	.919

*p < .05
*p < .01

Table IVb3. Two-way fixed effects models of the conditional effects of wages and unemployment rates on crime rates across counties (n=353, t=7).

A. Homicide

Explanatory Variable	(1)	(2)	(3)	(4)	(5)
Unemployment rate	-.040**	-.042**	-.041**	-.042**	-.044**
	(.007)	(.006)	(.006)	(.006)	(.006)
Unemployment rate, first differenced	.033**	.031**	.032**	.031**	.032**
	(.010)	(.010)	(.009)	(.008)	(.009)
Average wage level	-.002	.003	-.0002	-.005	-.0009
	(.011)	(.011)	(.010)	(.012)	(.010)
Regional inflation rate	.036	—	—	—	—
	(.046)	—	—	—	—
Unemployment rate X Inflation rate	-.00009	—	—	—	—
	(.001)	—	—	—	—
Average wage X Inflation rate	-.0007	—	—	—	—
	(.002)	—	—	—	—
Per capita unemployment insurance	—	.000009**	—	—	—
	—	(.000002)	—	—	—
Unemployment rate X Unemployment insurance	—	-.000001	—	—	—
	—	(.0000003)	—	—	—
Average wage X Unemployment insurance	—	-.0000005*	—	—	—
	—	(.0000002)	—	—	—
Per capita income maintenance	—	—	.0003	—	—
	—	—	(.0002)	—	—
Unemployment rate X Income maintenance	—	—	-.00002	—	—
	—	—	(.00002)	—	—
Average wage X Income maintenance	—	—	-.000004	—	—
	—	—	(.00002)	—	—
Logged state incarceration rate, once lagged	—	—	—	-.280**	—
	—	—	—	(.058)	—
Unemployment rate X Incarceration rate	—	—	—	-0.01	—
	—	—	—	(.006)	—
Average wage X Incarceration rate	—	—	—	.006	—
	—	—	—	(.011)	—
Police force size	—	—	—	—	.0009
	—	—	—	—	(.0008)
Unemployment rate X Police size	—	—	—	—	-.0006
	—	—	—	—	(.0003)
Average wage X Police size	—	—	—	—	.0002
	—	—	—	—	(.0002)
N	2441	2441	2441	2441	2441
Time and Geographic Fixed Effects?	Yes	Yes	Yes	Yes	Yes
R-Squared	.801	.802	.802	.801	.802

Table IVb3. (Cont.)

B. Non-Lethal Violence

Explanatory Variable	(1)	(2)	(3)	(4)	(5)
Unemployment rate	-.006	-.007	-.007	-.009	-.007
	(.005)	(.006)	(.006)	(.007)	(.005)
Unemployment rate, first differenced	-.002	.004	.004	.003	.004
	(.003)	(.004)	(.004)	(.004)	(.004)
Average wage level	-.013**	-.011*	-.010	-.010	-.013**
	(.005)	(.005)	(.005)	(.008)	(.005)
Regional inflation rate	.009	—	—	—	—
	(.031)	—	—	—	—
Unemployment rate X Inflation rate	.002	—	—	—	—
	(.001)	—	—	—	—
Average wage X Inflation rate	.0008	—	—	—	—
	(.0009)	—	—	—	—
Per capita unemployment insurance	—	0.000003	—	—	—
	—	(.000003)	—	—	—
Unemployment rate X Unemployment insurance	—	-0.000001	—	—	—
	—	(.0000003)	—	—	—
Average wage X Unemployment insurance	—	-0.0000003	—	—	—
	—	(.0000002)	—	—	—
Per capita income maintenance	—	—	.0003	—	—
	—	—	(.0002)	—	—
Unemployment rate X Income maintenance	—	—	-.00002*	—	—
	—	—	(.00001)	—	—
Average wage X Income maintenance	—	—	-.00003**	—	—
	—	—	(.00001)	—	—
Logged state incarceration rate, once lagged	—	—	—	-.137*	—
	—	—	—	(.053)	—
Unemployment rate X Incarceration rate	—	—	—	-.014	—
	—	—	—	(.008)	—
Average wage X Incarceration rate	—	—	—	-.011	—
	—	—	—	(.007)	—
Police force size	—	—	—	—	.001**
	—	—	—	—	(.0006)
Unemployment rate X Police size	—	—	—	—	-.0001
	—	—	—	—	(.0002)
Average wage X Police size	—	—	—	—	-.0002*
	—	—	—	—	(.0001)
N	2441	2441	2441	2441	2441
Time and Geographic Fixed Effects?	Yes	Yes	Yes	Yes	Yes
R-Squared	.848	.849	.848	.848	.848

Table IVb3. (Cont.)

C. Non-Violent Property Crime

Explanatory Variable	(1)	(2)	(3)	(4)	(5)
Unemployment rate	-.003	-.004	-.004	-.005	-.004
	(.003)	(.004)	(.004)	(.004)	(.003)
Unemployment rate, first differenced	.014	.016**	.016*	.017*	.017**
	(.008)	(.006)	(.007)	(.007)	(.006)
Average wage level	-.009	-0.009	-.007	-.011	-.010
	(.008)	(.007)	(.007)	(.007)	(.007)
Regional inflation rate	.013	—	—	—	—
	(.026)	—	—	—	—
Unemployment rate X Inflation rate	.0009	—	—	—	—
	(.0006)	—	—	—	—
Average wage X Inflation rate	.001*	—	—	—	—
	(.0006)	—	—	—	—
Per capita unemployment insurance	—	.000002	—	—	—
	—	(.000002)	—	—	—
Unemployment rate X Unemployment insurance	—	-.000001	—	—	—
	—	(.0000003)	—	—	—
Average wage X Unemployment insurance	—	-.0000003**	—	—	—
	—	(.0000001)	—	—	—
Per capita income maintenance	—	—	.0004**	—	—
	—	—	(.00008)	—	—
Unemployment rate X Income maintenance	—	—	-.00003**	—	—
	—	—	(.000006)	—	—
Average wage X Income maintenance	—	—	-.00004**	—	—
	—	—	(.000004)	—	—
Logged state incarceration rate, once lagged	—	—	—	-.233**	—
	—	—	—	(.062)	—
Unemployment rate X Incarceration rate	—	—	—	-.009	—
	—	—	—	(.006)	—
Average wage X Incarceration rate	—	—	—	-.002	—
	—	—	—	(.005)	—
Police force size	—	—	—	—	.002**
	—	—	—	—	(.0007)
Unemployment rate X Police size	—	—	—	—	-.0001
	—	—	—	—	(.0002)
Average wage X Police size	—	—	—	—	-.0003**
	—	—	—	—	(.00009)
N	2441	2441	2441	2441	2441
Time and Geographic Fixed Effects?	Yes	Yes	Yes	Yes	Yes
R-Squared	.920	.926	.923	.921	.918

IVc. *Expanding the typical set of criminal justice variables considered*

Most county-level studies of crime rates do not consider levels of incarceration, which seems like a major limitation given the empirical evidence pointing to relatively strong effects of incarceration on recent crime trends (Goldberger and Rosenfeld, 2008). Even when county-level studies do include an indicator of incarceration (e.g., Phillips and Greenberg, 2012), the measure employed captures state-level rates of incarceration. While presumably superior than ignoring incarceration rates altogether, simply appending state-level data to counties (as we've done as well in this project, up to this point) ignores the well-known within-state variability in crime rates and imprisonment. Our objective in this final set of analyses is to expand the typical set of criminal justice variables considered, including going beyond the inclusion of state incarceration rates in county-level panel data, incorporating instead indicators of *county-level* imprisonment risk. In addition to defining the geographic scope of imprisonment risk more precisely, though, we also consider age- and crime-specific measures of imprisonment to expand the typical approach.

Policing also has been a common ingredient in models of crime trends, especially among city-level studies. Traditionally, the focus has been on police force size, but increasingly researchers have highlighted the importance of capturing spatial and temporal variation in the nature of policing (e.g., proactive policing and arrest certainty). We include these other dimensions in our expanded assessment of criminal justice factors. It is worth reiterating that most county-level studies omit policing indicators altogether; our analysis will help to shed light on the costs of doing so.

We base our expanded assessment of criminal justice factors on 337 counties, a sample for which we observe crime rates, criminal justice factors, and other attributes for 5 periods (1985, 1990, 1995, 2000, and 2005). Table IVc1 displays the descriptive statistics for the sample.

Table IVc1 about here

We estimated six models for each crime type that explore expanded versions of the typical specification of criminal justice variables in research on crime trends. The results are displayed in Table IVc2, with separate panels for homicide (Panel A), non-lethal violence (Panel B), and non-violent property crime rates (Panel C). In each case, the first model includes only the control variables plus the two criminal justice factors most often considered in research on crime trends (though not typically in county-level studies): police force size and state incarceration rates. We subsequently build on this model by adding two additional indicators of policing—proactive policing (i.e., the ratio of arrests for dui and disorderly conduct to the number of police officers) and arrest certainty (i.e., the ratio of arrest to crimes known, defined specific to each dependent variable)—and substituting state prison admissions rates for the stock incarceration rate. The latter facilitates comparisons with subsequent models. Models 3-6 substitute the state prison admission rate with different variants of county-level prison admissions rates, including an overall measure (model 3), age-specific measures (models 4-5), and crime-specific measures (model 6).

Tables IVc2 about here

One general pattern revealed in Table IVc2 is that homicide rates appear to be insensitive to the quantity and quality of policing or levels of incarceration (Panel A). This is perhaps not unexpected given that homicide is a relatively rare event that often occurs in the heat of the moment, which may render it relatively unresponsive to differences in policing and punishment risk. A second finding we highlight from our expanded assessment of criminal justice factors is that, at least for non-lethal violence and non-violent property crime, arrest certainty for these crimes is a robust predictor of lower crime rates (we were unable to include an indicator of homicide arrest certainty because of the relatively low volume of both homicide arrests and offenses, which yielded a volatile measure). This implied that prior county-level studies, which typically have not included policing measures, may be misspecified, and it also highlights an important dimension of policing for shaping recent crime trends. In contrast, police size and proactive policing do not yield the anticipated negative associations with crime rates and, in fact, exhibit positive signs in several of the models.

With respect to prison measures, the findings for non-lethal violence are not consistent with expectations. County variation in robbery and aggravated assault is generally not responsive to county differences in imprisonment risk, however measured. However, the models for non-violent property crime yield several interesting patterns. Specifically, non-violent property crime is significantly lower in counties with higher imprisonment rates (model 3) and in counties situated within states that have higher imprisonment rates (model 2). The results for the age-specific county imprisonment variables indicate that both yield significant negative associations with non-violent property crime, but imprisonment rates of younger persons (i.e., ages 18-34) is stronger. Finally, consistent with expectations, rates of non-violent property crime are not affected by imprisonment rates for homicide or non-lethal violence, but they are influenced by imprisonment rates for non-violent property crime.

Overall, the results presented in Table IVc2 suggest that a closer examination of expanded models of criminal justice variables is warranted. These county-level models go beyond the typical measures of police force size and state incarceration rates, and they reveal several intriguing patterns, but the analyses highlighted here are illustrative rather than definitive. For instance, it is plausible that the assumed linear functional form in these models is naïve, and it could be that policing and incarceration "work together" (i.e., statistically interact) to influence crime. Finally, integrating county-level imprisonment rates raises "new" questions, such as whether it is reasonable to assume (as these models do) that crime rates in a given county are influenced *only* by the prison admissions rate in that county. The integration of county imprisonment rates reveals the potential for spatial dependencies in imprisonment effects, an issue that warrants close scrutiny in subsequent research.

Table IV.c1. Summary statistics for variables included included in analysis of criminal justice factors and recent crime trends.

	Counties (n=337, t=5)		
Variable	**Mean**	**Between-Unit SD**	**Within-Unit SD**
Dependent Variables			
Homicide rate (logged)	1.36	.973	.853
Non-lethal violent crime rate (logged)	5.85	.678	.322
Non-violent property crime rate (logged)	8.24	.333	.233
Explanatory Variables			
Logged state incarceration rate, once lagged	5.70	.315	.340
Logged state prison admissions rate, once lagged	5.07	.328	.358
Logged county prison admissions, once lagged	5.01	.645	.462
Logged county prison admissions 18-34, once lagged	5.99	.644	.471
Logged county prison admissions 35-64, once lagged	4.74	.725	.640
Logged county homicide prison admissions, once lagged	.340	1.58	1.81
Logged county non-lethal violence prison admissions, once lagged	3.14	.720	.588
Logged county non-violent property crime prison admissions, once lagged	3.84	.688	.422
Police force size	20.41	15.19	2.94
Logged proactive policing	1.22	.751	.370
Logged homicide arrest certainty	—	—	—
Logged non-lethal violence arrest certainty	-.502	.704	.437
Logged non-violent property crime arrest certainty	-1.80	.577	.305
Control Variables			
Population structure	0	1.88	.129
% age 15-29	22.46	3.74	2.20
Divorce rate	6.98	1.22	1.16
Immigrant concentration	.0003	1.90	.222
Resource deprivation	3	4.02	.687
Unemployment rate	5.79	2.18	1.59
Unemployment rate, first differenced	-.256	.446	.944
Average wage level	13.77	2.48	1.19
Drug arrest rate	350.67	162.71	135.70

Table IVc2. Panel regression models of criminal justice effects on

A. Homicide

Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
Police force size	.002	.001	.001	.001	.001	.0002
	(.009)	(.010)	(.010)	(.010)	(.010)	(.0109)
Logged proactive policing	—	-.023	-.025	-.024	-.026	-.026
	—	(.053)	(.053)	(.053)	(.054)	(.049)
Logged arrest certainty	—	—	—	—	—	—
	—	—	—	—	—	—
Logged state incarceration rate, once lagged	.073	—	—	—	—	—
	(.134)	—	—	—	—	—
Logged state prison admissions rate, once lagged	—	.055	—	—	—	—
	—	(.096)	—	—	—	—
Logged county prison admissions, once lagged	—	—	.010	—	—	—
	—	—	(.068)	—	—	—
Logged county prison admissions 18-34, once lagged	—	—	—	.027	—	—
	—	—	—	(.076)	—	—
Logged county prison admissions 35-64, once lagged	—	—	—	—	-.011	—
	—	—	—	—	(.030)	—
Logged county homicide prison admissions, once lagged	—	—	—	—	—	.048**
	—	—	—	—	—	(.018)
Logged county non-lethal violence prison admissions, once lagged	—	—	—	—	—	.048
	—	—	—	—	—	(.029)
Logged county non-violent property crime prison admissions, once lagged	—	—	—	—	—	-.065
	—	—	—	—	—	(.051)
County controls: population structure, % 15-29, divorce rate, immigrant concentration, resource deprivation, unemployment rate, unemployment rate first difference, average wages, drug arrest rate.	Yes	Yes	Yes	Yes	Yes	Yes
Time and Geographic Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
N	1662	1662	1662	1662	1662	1662
R-Squared	.604	.604	.604	.604	.603	.611

Table IVc2. (Cont.)

B. Non-Lethal Violence

Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
Police force size	.012**	.017**	.017**	.017**	.017**	.017**
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Logged proactive policing	—	.230**	.230**	.230**	.231**	.232**
	—	(.032)	(.033)	(.033)	(.032)	(.033)
Logged arrest certainty	—	-.395**	-.394**	-.394**	-.395**	-.395**
	—	(.052)	(.053)	(.053)	(.052)	(.054)
Logged state incarceration rate, once lagged	.280	—	—	—	—	—
	(.168)	—	—	—	—	—
Logged state prison admissions rate, once lagged	—	.072	—	—	—	—
	—	(.047)	—	—	—	—
Logged county prison admissions, once lagged	—	—	.040	—	—	—
	—	—	(.039)	—	—	—
Logged county prison admissions 18-34, once lagged	—	—	—	.043	—	—
	—	—	—	(.040)	—	—
Logged county prison admissions 35-64, once lagged	—	—	—	—	.027	—
	—	—	—	—	(.031)	—
Logged county homicide prison admissions, once lagged	—	—	—	—	—	.013*
	—	—	—	—	—	(.006)
Logged county non-lethal violence prison admissions, once lagged	—	—	—	—	—	.030
	—	—	—	—	—	(.018)
Logged county non-violent property crime prison admissions, once lagged	—	—	—	—	—	.013
	—	—	—	—	—	(.021)
County controls: population structure, % 15-29, divorce rate, immigrant concentration, resource deprivation, unemployment rate, unemployment rate first difference, average wages, drug arrest rate.	Yes	Yes	Yes	Yes	Yes	Yes
Time and Geographic Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
N	1662	1662	1662	1662	1662	1662
R-Squared	.808	.851	.850	.850	.850	.852

Table IVc2. (Cont.)

B. Non-Violent Property Crime

Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
Police force size	.010**	.017**	.017**	.017**	.016**	.017**
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Logged proactive policing	—	.250**	.253**	.253**	.252**	.250**
	—	(.042)	(.04256)	(.043)	(.043)	(.043)
Logged arrest certainty	—	-.442**	-.447**	-.447**	-.447**	-.446**
	—	(.073)	(.075)	(.075)	(.076)	(.076)
Logged state incarceration rate, once lagged	-.154	—	—	—	—	—
	(.106)	—	—	—	—	—
Logged state prison admissions rate, once lagged	—	-.103**	—	—	—	—
	—	(.034)	—	—	—	—
Logged county prison admissions, once lagged	—	—	-.039*	—	—	—
	—	—	(.018)	—	—	—
Logged county prison admissions 18-34, once lagged	—	—	—	-.037*	—	—
	—	—	—	(.017)	—	—
Logged county prison admissions 35-64, once lagged	—	—	—	—	-.030**	—
	—	—	—	—	(.011)	—
Logged county homicide prison admissions, once lagged	—	—	—	—	—	.005**
	—	—	—	—	—	(.001)
Logged county non-lethal violence prison admissions, once lagged	—	—	—	—	—	.021
	—	—	—	—	—	(.020)
Logged county non-violent property crime prison admissions, once lagged	—	—	—	—	—	-.060**
	—	—	—	—	—	(.010)
County controls: population structure, % 15-29, divorce rate, immigrant concentration, resource deprivation, unemployment rate, unemployment rate first difference, average wages, drug arrest rate.	Yes	Yes	Yes	Yes	Yes	Yes
Time and Geographic Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
N	1662	1662	1662	1662	1662	1662
R-Squared	.747	.813	.810	.810	.809	.811

*p < .05
**p < .01

V. Conclusions

This project focused on addressing two general issues, as outlined in the original proposal: (a) enhancing the data infrastructure available to study recent American crime trends; and (b) clarifying and expanding the scope of empirical analysis directed at describing and explaining recent crime trends. While there is a burgeoning research literature on crime trends, much of the extant research has adopted a relatively narrow approach, efforts across studies are highly variable, and the overall conclusions that can be drawn are ambiguous. In our judgment, one reason for this state of affairs is that the current data infrastructure that supports crime trends research is incomplete and scattered, yielding redundant efforts and highly inconsistent approaches. The primary purpose of this project was to enhance the data infrastructure by compiling in a centralized location the most commonly referenced datasets and measures. The key product of the grant -- the Crime Trends Data Archive (CTDA) -- should prove valuable to those involved in or considering the study of contemporary American crime trends. We describe the CTDA in greater detail in Appendix A.

Though the major thrust of the project was to collect, process, and integrate data that might stimulate and facilitate additional research on American crime trends, an ancillary objective was illustrate the utility of the resulting data archive. We did so by considering three substantive research issues: (1) a uniform set of analyses across states, counties, and cities; (2) an assessment of the conditional effects of economic conditions on recent crime trends; and (3) an expanded analysis of the effects of key criminal justice attributes (e.g., the nature of policing, age- and crime-specific imprisonment rates) on recent crime trends that have not been considered extensively in prior research.

Studies of crime trends conducted across different units of analysis (e.g., states, counties, and cities) tend to apply highly variable empirical specifications, yielding an uneven landscape of findings that are difficult to discern. We showed how the typical specification used in state-, county-, and city-level studies diverge, and how this yields disparate empirical findings for the samples considered. Part of this disparity appears to be due to differences in geographic aggregation, since even in the uniform specifications the findings did not yield a uniform set of results. Nevertheless, the analysis highlighted the importance of avoiding minimalist specifications within a given geographic analysis, and it showed some consistent patterns when a parallel specification was applied. Most notably, the results suggest that age structure and divorce rates are robust predictors of crime rates, with higher crime in areas with a larger percentage of persons aged 15-29 and where divorce rates are higher. Additionally, the results in Panel C for non-violent property crime affirm that incarceration rates tend to yield lower crime rates, but there are diminishing returns to this pattern (see also Liedka et al., 2001). Many of the other predictors were inconsistent across levels of analysis and also across different specifications within a single geographic sample unit.

It would be useful to expand these analyses by, for example, assessing the uniformity of expanded models across a larger universe of counties and cities. We focus here on the samples that tend to be most well represented in the literature (i.e., relatively large cities and counties), but expanding the universe of areas covered may shed additional light on the implications of omitting key variables. We also think that it would be worthwhile to further explore the implications of modeling crime across temporal eras. Pooled approaches such as ours assume that the estimated relationships are not conditioned by temporal era, but some research has questioned this assumption on empirical grounds for homicide (McCall et al., 2010). It is unclear whether similar patterns would emerge for other crime types and why temporal variability may arise from a theoretical vantage point, but this strikes us an interesting point of departure for future research.

The findings for our second illustrative analysis indicated that government spending on income maintenance and, to a lesser extent, unemployment insurance plays an important role in muting the adverse consequences for crime of high unemployment and depressed wages. Additionally, two criminal justice measures of objective "risk"—police force size and incarceration rates—also dampen the criminogenic tendencies of elevated unemployment and declining wages.

These patterns reveal two important insights. One is that criminal justice efforts can yield lower crime rates in ways that are not often highlighted, that is by reducing the collateral consequences of a declining economy. Two, such patterns may help to organize the mixed bag of research findings on how economic conditions affect crime rates, and help to address a current puzzle: why, in the midst of two recessions during the 2000s, have crime rates remained relatively stable and, in some locations, on a downward trajectory? Perhaps it is because these recent economic shocks have occurred in a context of high levels of incarceration, and a relatively strong government commitment to provide unemployment insurance benefits.

Our final set of analyses focused on expanding the focus of crime trends research beyond typical criminal justice variables, most notably the application of state incarceration to county-level crime patterns and the narrow conception of policing by focusing on the relative size of police forces. This analysis showed that, at least for non-lethal serious crimes, the degree to which police agencies target particular behaviors matters. We observed significantly lower rates of non-lethal violence and non-violent property crime in counties that exhibit higher probabilities of arrest for non-lethal violence and non-violent property crime, respectively. Additionally, we found that county imprisonment of non-violent property crime offenders significantly reduces non-violent property crime, while imprisonment for homicide and non-lethal violence does not. This reinforces the idea that imprisonment effects operate primarily through incapacitation, rather than deterrence. Also consistent with this idea, we saw that imprisonment rates for young persons exhibited a slightly stronger effect on non-violent property crime rates than did imprisonment rates among older persons.

The findings reported herein should be influential for stimulating additional research. Beyond this, they also have implications for policy and practice. Contemporary crime trends have become central to the public discussion and debate on crime, and policy makers increasingly use data on crime trends while considering policy spending priorities. Legislative hearings on the challenges represented by crime and violence often reference recent crime trends and speculate about factors that might account for them (e.g., Senate Hearing, 2007). Further, the latest Senate Committee on Appropriations report on funding for the Department of Justice (DOJ) makes explicit mention of recent increase in violence in the U.S. that have affected "nearly every region of the country, including large, medium-sized, and small communities", suggests that factors such as illicit drug use, the volume of released prisoners, and strained law enforcement resources may be behind the observed trends, and accordingly recommends enhanced funding to relevant agencies and significant reductions elsewhere (Senate Report 110-124, 2007). Public discussions such as these should not occur in a vacuum, but too often they tend to do so. This project developed a data infrastructure that is poised to provide meaningful input to policymakers who wish to understand why crime trends move in a particular direction and/or how they respond to given policy changes. Thus, while some of the empirical results presented can be read in terms of policy implications, the most important contribution of the present work to policy and practice is in generating a research infrastructure that can facilitate timely and informative research on crime trends and policy issues moving forward.

To fully take advantage of the products of this grant, we offer two recommendations. First, it would be a good investment for the appropriate government agency to continue development of the CTDA, including updates as new data becomes available. Second, the CTDA will be useful only if it is made widely available to other scholars. While the project uses many resources that are already archived, and thus could be retained as separate data collections, the utility of the CTDA lies in its integration of the various components needed to generate meaningful assessments of crime trends in a centralized space. We recommend that the NACJD use the CTDA as the basis of establishing a permanent, distinct archive on crime trends research.

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VII. Dissemination of Research Findings

Publications

Baumer, Eric P., Richard Rosenfeld, and Kevin Wolff (2012). "Are the Criminogenic Consequences of Economic Downturns Conditional? Assessing Potential Moderators of the Link between Adverse Economic Conditions and Crime Rates." In *Macroeconomic Effects on Youth Violence.* New York: New York University Press. (Forthcoming).

Baumer, Eric P. (2011). "Describing and Explaining Crime Trends: An Assessment of Key Issues, Current Knowledge, and Future Directions of Scientific Inquiry." In the *Oxford Handbook on Crime and Criminal Justice*, edited by Michael Tonry. New York: Oxford University Press.

Papers Submitted

Baumer, Eric P., and Kevin T. Wolff. "Evaluating Contemporary Crime Drops in America, New York City, and Many Other Places." Revise & Resubmit at Justice Quarterly.

Wolff, Kevin T., and Eric P. Baumer.
"Military Enlistment and Crime Rates." Revise & Resubmit, Social Science Research.

Presentations

Baumer, Eric P. and Kevin T. Wolff. (2011). "Explanations for Contemporary Crime Drop(s) in America, New York, and Many Other Places." Presented at The Crime Decline Conference, John Jay College of Criminal Justice, New York.

Wolff, Kevin T. and Eric P. Baumer. (2010). "In the Shadow of the Great American Crime Decline: Crime Across U.S. Cities in this Decade." Presented at the American Society of Criminology (ASC) annual meeting, San Francisco, CA.

Baumer, Eric P. (2008). "Crime Rankings in Criminological Research." Presented at the 2008 annual meeting of the American Society of Criminology, St. Louis, Missouri.

Appendix A. Summary of Data Archived under Project on "Expanding the Scope of Research on Recent Crime Trends"

Crime Trends Data Archive (CTDA)

Description: The CTDA provides information on the volume of crime, arrests, and various indicators of demographic, economic, social, and criminal justice factors for American state, counties, and cities. Temporal and geographic coverage varies across indicators and units, but encompasses in many instances 1980 through 2010.

Universe: U.S. states, counties, and cities.

Data Sources, Files, and Notes:

1. Crime counts

Annual estimates of city, county, and state UCR crime counts are an important feature of the CTDA. There are several possible sources from which one might obtain estimated UCR crime counts, including annual agency-level and county-level estimates housed in the NACJD. The agency-level NACJD data are useful for estimating city crime totals, but problematic for generating county estimates for reasons outlined in detail by Maltz and Targonski (2002, 2004). Additionally, because we think it is useful to evaluate crime trends across the full period represented in our study (1980-2010), and because the county-level estimates available from NACJD apply different procedures for allocating missing data before 1994 and from 1994 onward, we decided against relying on the NACJD county data for this archive. Instead, we obtained directly from the FBI the agency-level source data used by the NACJD for county-estimates and used these data to generate annual city- and county-level crime estimates. In our analysis of county crime trends presented in this report, we apply a uniform set of procedures across the full period that mimics in key ways the procedures used by the NACJD for the period beginning in 1994.

The CTDA includes the original text files provided to us by the FBI, along with the SPSS setups used to produce city, county, and state-level UCR estimates. The archive also includes annual state-level crime estimates, which we obtained from the Bureau of Justice Statistics (BJS) on-line UCR Data Tool (Website: http://www.ucrdatatool.gov/). More specifically, the CDTA contains the following crime data files in the designated directory location:

City-level offenses known to the police data, 1978-2010

Parent directory for all files below: DRIVE:\Common_Data\UCR\

- Raw data files:
  - \Crime\FBI_City_County\Raw\YYYY C by C.txt
- Program(s) to read raw data:
  - \Crime\FBI_City_County\FBI_UCR_Agency_Dataprep.sps
  - \FBI_UCR_Crime_Data_Adjustments062212.do
- SPSS/Stata merged database of UCR crime counts:
  - \Crime\FBI_City_County\City_Level\FBI_UCR_City_1974_2010.dta

- Ancillary files needed to generate merged database of UCR crime rates:
  - BJS Agency Crosswalk file:
    - \BJS_Crosswalk_2005.sav

Important user notes:

All raw data was provided by the FBI in for of .txt documents. These files were converted to excel files and then read into SPSSS using the 'FBI_UCR_Agency_Dataprep.sps' program. A file containing data from all agencies for all years in the period was saved out to be open and manipulated in STATA. The program 'FBI_UCR_Crime_Data_Adjustments.do' performs the majority of our data manipulation and produces the final crime files used in the analysis. These procedures are outlined in greater detail in the text of this report.

One of the manipulations was to adjust the agency event counts according to months reported. Specifically, for those agencies who reported between 3-11 months, crime counts were adjusted so that they represent 12 months of data. This does not take into account the seasonality of the months that were reported. For those agencies reporting less than 2 months of data, event counts from an agency of the same population group within the same county were substituted. If there was no data available within the county, data from agencies within the same state were substituted. We used the following population groups for these computations: (a) under 5,000; (b) 5,000 – 15,000; (c) 15,000 – 45,000; and 45,000+.

A second data manipulation that was conducted was to account for the total 'coverage' accounted for by the data included in a given year. City crime totals were adjusted by the proportion of the total population which was represented in the data included so that they represented a proportion equal to 1. Both non-adjusted and adjusted counts were included in the resulting data file.

In order to assign place identifiers, this file was merged to the BLS agency crosswalk file. Totals were produced by summing the number crime events by FIPS place code and a city-level file for 1974-2010 was saved.

County-level offenses known to the police data, 1978-2010

Parent directory for all files below: DRIVE:\Common_Data\UCR\

- Raw data files:
  - \Crime\FBI_City_County\Raw\YYYY C by C.txt
- Program(s) to read raw data:
  - \Crime\FBI_City_County\FBI_UCR_Agency_Dataprep.sps
  - \FBI_UCR_Crime_Data_Adjustments062212.do
- SPSS/Stata merged database of UCR crime counts:
  - \Crime\FBI_City_County\City_Level\FBI_UCR_County_1974_2010.dta
- Ancillary files needed to generate merged database of UCR crime rates:
  - BJS Agency Crosswalk file:
    - \BJS_Crosswalk_2005.sav

Important user notes:

All raw data was provided by the FBI in for of .txt documents. These files were converted to excel files and then read into SPSSS using the 'FBI_UCR_Agency_Dataprep.sps' program. A file containing data from all agencies for all years in the period was saved out to be open and manipulated in STATA. The program 'FBI_UCR_Crime_Data_Adjustments062212.do' performs the majority of our data manipulation and produces the final crime files used in the analysis. These procedures are outlined in greater detail in the text of the project report.

One of the manipulations was to adjust the agency event counts according to months reported. Specifically, for those agencies who reported between 3-11 months, crime counts were adjusted so that they represent 12 months of data. This does not take into account the seasonality of the months that were reported. For those agencies reporting less than 2 months of data, event counts from an agency of the same population group within the same county were substituted. If there was no data available within the county, data from agencies within the same state were substituted. We used the following population groups for these computations: (a) under 5,000; (b) 5,000 – 15,000; (c) 15,000 – 45,000; and 45,000+.

A second data manipulation that was conducted was to account for the total 'coverage' accounted for by the data included in a given year. City crime totals were adjusted by the proportion of the total population which was represented in the data included so that they represented a proportion equal to 1. Both non-adjusted and adjusted counts were included in the resulting data file.

In order to assign place identifiers, this file was merged to the crosswalk file. Totals were produced by summing the number crime events by FIPS code and a county-level file for 1978-2010 was saved out.

State-level offenses known to the police data from UCR, 1978-2010

Parent directory for all files below: DRIVE:\Common_Data\UCR\

Raw data files:

\Crime\FBI_State\Raw\YYYY C by C.txt

Program(s) to read raw data:

\Crime\ FBI_County_City\FBI_UCR_Agency_Dataprep.sps

\FBI_UCR_Crime_Data_Adjustments062212.do

SPSS/Stata merged database of UCR crime counts:

\Crime\ FBI_State\FBI_UCR_State _1974_2010.dta

Ancillary files needed to generate merged database of UCR crime rates:

BJS Agency Crosswalk file:

\BJS_Crosswalk_2005.sav

Important user notes:

All raw data was provided by the FBI in for of .txt documents. These files were converted to excel files and then read into SPSSS using the 'FBI_UCR_Agency_Dataprep.sps' program. A file containing data from all agencies for all years in the period was saved out to be open and manipulated in STATA. The program 'FBI_UCR_Crime_Data_Adjustments062212.do' performs the majority of our data manipulation and produces the final crime files used in the analysis. These procedures are outlined in greater detail in the text of this report.

One of the manipulations was to adjust the agency event counts according to months reported. Specifically, for those agencies who reported between 3-11 months, crime counts were adjusted so that they represent 12 months of data. This does not take into account the seasonality of the months that were reported. For those agencies reporting less than 2 months of data, event counts from an agency of the same population group within the same county were substituted. If there was no data available within the county, data from agencies within the same state were substituted. We used the following population groups for these computations: (a) under 5,000; (b) 5,000 – 15,000; (c) 15,000 – 45,000; and 45,000+.

A second data manipulation that was conducted was to account for the total 'coverage' accounted for by the data included in a given year. City crime totals were adjusted by the proportion of the total population which was represented in the data included so that they represented a proportion equal to 1. Both non-adjusted and adjusted counts were included in the resulting data file.

Totals were produced by summing the number crime events by FIPS code and a state-level file for 1978-2010 was saved.

State-level offenses known to the police data from BJS, 1960-2010

Raw data files:

DRIVE:\Common_Data\UCR\Crime\BJS_State_Level\BJS_UCR_CrimeStatebyState.xls

Program(s) to read raw data:

DRIVE:\Common_Data\UCR\Crime\BJS_State_Level\BJS_State_UCR_1960_2010.sps

SPSS/Stata merged database of UCR crime counts:

DRIVE:\Common_Data\UCR\Crime\BJS_State_Level\BJS_State_UCR_ALL_6010.sav

Ancillary files needed to generate merged database of UCR crime rates:

None needed.

Important user notes:

Data at the state-level were downloaded from BJS (http://www.ucrdatatool.gov/). The excel file provided spans all states for the 1960-2010 period. Individual state files were created from the panel file provided, and then these files were combined to create a state-level file with data for the entire period.

It is important to note that the data included in this file represent only those agencies that reported 12 months of data to the FBI, and therefore will be significantly different from the data described above (which is adjusted for non-reporting and under-reporting). Users of either data set should become familiar with these distinctions and make decisions about data use accordingly.

Other crime data in the CTDA

Supplementary Homicide Reports (SHR)

Detailed data on homicides known to the police, as reported in the Supplementary Homicide Reports (SHR), 1980-2009 (ICPSR studies # 03180, 02906, 03162, 03448, 03722, 03999, 04125, 04465, 04723, 22401, 25103, 27650, 30767).

2. Criminal Justice Data

Arrest Data

Although UCR arrest data exists in the NACJD archive, the individual annual files are particularly cumbersome when preparing data to conduct a time-series analysis. In order to facilitate a vibrant, comprehensive, and systematic research agenda on recent crime trends we combine data from a number of sources in a systematic and meaningful way to be used by researchers. Agency-level arrest data for the years 1980-2009 was extracted from the following ICPSR studies: #23320, 23322, 23324, 23326, 23329, 23330, 23332, 23334, 23336, 23338, 23340, 23342, 23344, 23346, 04562, 04561, 04560, 02742, 02908, 03173, 03443, 03760, 04443, 04285, 04460, 04715, 22404, 25108, 27642, and 30761. Counts of total arrests, as well as arrests for drug related offenses, alcohol offenses, DUI, disorder offenses, homicide, rape assault, larceny, motor vehicle theft and arson were created.

City-level UCR arrest data, 1980-2009

Parent directory for all files below: DRIVE:\Common_Data\UCR\Arrest\

Raw data files:

\Agency_Level\YYYY\ICPSR#-0001-Data.sav

Program(s) to read raw data:

\ICPSR_UCR_Arrest_Agency_Dataprep.sps

\ FBI_UCR_Arrest_Data_Adjustments0622212.do

SPSS/Stata merged database of UCR arrest counts:

\City_Level\City_UCRArrests_8009.dta

Ancillary files needed to generate merged database of UCR Arrest rates:

None

Important user notes:

All raw arrest data in the CTDA were drawn from the ICPSR NACJD. In order to assign place identifiers, the agency-level files were merged to the BLS agency crosswalk file. A file containing data from all agencies for all years in the period was saved out to be open and manipulated in STATA. The program 'FBI_UCR_Arrest_Data_Adjustments062212.do' performs the majority of our data manipulation and produces the final arrest files used in the analysis.

One of the key manipulations was to adjust the agency event counts according to months reported. Specifically, for those agencies who reported between 3-11 months, crime counts were adjusted so that they represent 12 months of data. This does not take into account the seasonality of the months that were reported. For those agencies reporting less than 2 months of data, event counts from an agency of the same population group *within* the same county were substituted. If there was no data available within the county, data from agencies within the same state were substituted. We used the following population groups for these computations: (a) under 5,000; (b) 5,000 – 15,000; (c) 15,000 – 45,000; and 45,000+.

In order to assign place identifiers, this file was merged to the crosswalk file. Totals were produced by summing the number arrest events by FIPS county code. A final data manipulation that was conducted was to account for the total 'coverage' accounted for by the data included in a given year. City-level arrest totals were adjusted by the proportion of the total population which was represented in the data included so that they represented a proportion equal to 1. Both non-adjusted and adjusted counts were included in the resulting city-level data file saved for the 1980-2009 period.

County-level UCR arrest data, 1980-2009

Parent directory for all files below: DRIVE:\Common_Data\UCR\Arrest\

Raw data files:

\Agency_Level\YYYY\ICPSR#-0001-Data.sav

Program(s) to read raw data:

\ICPSR_UCR_Arrest_Agency_Dataprep.sps

\ FBI_UCR_Arrest_Data_Adjustments0622212.do

SPSS/Stata merged database of UCR arrest counts:

\County_Level\County_UCRArrests_8009.sav

Ancillary files needed to generate merged database of UCR crime rates:

\Allocation\FBI_Agency_County_Allocation_1980.sav

\Allocation\FBI_Agency_County_Allocation_1990.sav

\Allocation\FBI_Agency_County_Allocation_2000.sav

Important user notes:

All raw data came from the ICPSR archive. In order to assign place identifiers, the agency-level files were merged to the BLS agency crosswalk file. A file containing data from all agencies for all years in the period was saved out to be open and manipulated in STATA. The program 'FBI_UCR_Arrest_Data_Adjustments062212.do' performs the majority of the data manipulation and produces the final arrest files used in the analysis.

One of the key manipulations was to adjust the agency event counts according to months reported. Specifically, for those agencies who reported between 3-11 months, crime counts were adjusted so that they represent 12 months of data. This does not take into account the seasonality of the months that were reported. For those agencies reporting less than 2 months of data, event counts from an agency of the same population group *within* the same county were substituted. If there was no data available within the county, data from agencies within the same state were substituted. We used the following population groups for these computations: (a) under 5,000; (b) 5,000 – 15,000; (c) 15,000 – 45,000; and 45,000+.

After being adjusted to reflect of full year of reporting, data for those agencies whose jurisdiction spans multiple counties were allocated based on the percentage of the covered population that was allocated to a given county (see additional information below on "allocation of UCR arrest data).

In order to assign place identifiers, this file was merged to the crosswalk file. Totals were produced by summing the number arrest events by FIPS county code. A final data manipulation that was conducted was to account for the total 'coverage' accounted for by the data included in a given year. County-level arrest totals were adjusted by the proportion of the total population which was represented in the data included so that they represented a proportion equal to 1. Both non-adjusted and adjusted counts were included in the resulting county-level data file saved for the 1980-2009 period.

Allocation of UCR Arrest data

Parent directory for all files below: DRIVE:\Common_Data\UCR\Arrest\

Raw data files:

\Allocation\00 pop by c.txt

Program(s) to read raw data:

\Allocation\FBI_Agency_County_Allocation.sps

File allocation file used for adjustments:

\Allocation\FBI_Agency_County_Allocation_1980.sav

\Allocation\FBI_Agency_County_Allocation_1990.sav

\Allocation\FBI_Agency_County_Allocation_2000.sav

Important user notes:

In order to be consistent with the FBI's annual reports *Crime in the United States,* a file designed to allocate agency totals across counties was created. Using information contained in population files obtained from the FBI, a full list of each agency within a county, as well as their covered population was obtained from the FBI. Using these files, variables which represent the percentage of an agency's covered population which resides in a given county were created. These values where then used to adjust the agency's total arrest counts and create separate cases for each county which the agency spans.

State-level UCR arrest data, 1980-2009

Parent directory for all files below: DRIVE:\Common_Data\UCR\Arrest\

Raw data files:

\Agency_Level\YYYY\ICPSR#-0001-Data.sav

Program(s) to read raw data:

\ICPSR_UCR_Arrest_Agency_Dataprep.sps

\ FBI_UCR_Arrest_Data_Adjustments0622212.do

SPSS/Stata merged database of UCR arrest counts:

\State_Level\County_UCRArrests_8009.sav

Ancillary files needed to generate merged database of UCR crime rates:

None needed.

Important user notes:

All raw data were drawn from the ICPSR archive. In order to assign place identifiers, the agency-level files were merged to the BLS agency crosswalk file. A file containing data from all agencies for all years in the period was saved out to be open and manipulated in STATA. The program 'FBI_UCR_Arrest_Data_Adjustments062212.do' performs the majority of our data manipulation and produces the final arrest files used in the analysis.

One of the key manipulations was to adjust the agency event counts according to months reported. Specifically, for those agencies who reported between 3-11 months, crime counts were adjusted so that they represent 12 months of data. This does not take into account the seasonality of the months that were reported. For those agencies reporting less than 2 months of data, event counts from an agency of the same population group *within* the same county were substituted. If there was no data available within the county, data from agencies within the same state were substituted. We used the following population groups for these computations: (a) under 5,000; (b) 5,000 – 15,000; (c) 15,000 – 45,000; and 45,000+.

In order to assign place identifiers, this file was merged to the crosswalk file. Totals were produced by summing the number arrest events by FIPS code. A final data manipulation that was conducted was to account for the total 'coverage' accounted for by the data included in a given year. State-level arrest totals were adjusted by the proportion of the total population which was represented in the data included so that they represented a proportion equal to 1. Both non-adjusted and adjusted counts were included in the resulting data file saved for the 1980-2010 period.

Police Force Size

Police officer counts: The number of police officers in each law enforcement agency for which such data have been reported in the UCR Law Enforcement Officers Killed or Assaulted (LEOKA) data files. For the years 1980 – 1997, LEOKA data were obtained from ICPSR #09028 computer files. The 1998 – 2009 LEOKA data are from ICPSR studies (#02907, 03165, 03445, 03749, 03996, 04269, 04462, 04719, 22402, 25104, 27646, and 30765).

City-level LEOKA police officer data, 1980-2009

Parent directory for all files below: DRIVE:\Common_Data\Police\LEOKA\

Raw data files:

\Data\YYYY_ICSPR_Datafile.sav

Program(s) to read raw data:

\UCR_LEOKA_Dataprep.sps

SPSS/Stata merged database of UCR police force size:

\City\UCR_LEOKA_CITY.sav

Ancillary files needed to generate merged database of police force size:

DRIVE:\Common_Data\Police\BLS_Crosswalk_05\BLS_Crosswalk_2005.sav

Important user notes:

Agency-level data were read into SPSS, and annual, agency-level files were produced. These files were then combined into a single file spanning 1980-2009. In order to obtain officer counts for both cities and counties in our sample, the agency-level file was merged to the BJS Crosswalk file, the number of officers was then summed by FIPS code, resulting in both a city and county-level file which includes the number of sworn officers for the years 1980-2009.

County-level LEOKA police officer data, 1980-2009

Parent directory for all files below: DRIVE:\Common_Data\Police\LEOKA\

Raw data files:

\Data\YYYY_ICSPR_Datafile.sav

Program(s) to read raw data:

\UCR_LEOKA_Dataprep.sps

SPSS/Stata merged database of UCR police force size:

\County\UCR_LEOKA_COUNTY.sav

Ancillary files needed to generate merged database of police force size:

DRIVE:\Common_Data\Police\BLS_Crosswalk_05\BLS_Crosswalk_2005.sav

Important user notes:

Agency-level data were read into SPSS, and annual, agency-level files were produced. These files were then combined into a single file spanning 1980-2009. In order to obtain officer counts for both cities and counties in our sample, the agency-level file was merged to the BJS Crosswalk file, the number of officers was then summed by FIPS code, resulting in both a city and county-level file which includes the number of sworn officers for the years 1980-2009.

State-level UCR LEOKA Data, 1980-2009

State-level data on police force size was created by aggregating from county totals produced as described above.

Incarceration, Imprisonment, and Prison Releases

State-Level Data on Sentenced Prisoners 1977-2010

State-level year-end incarceration counts for prisoners sentenced to more than 1 year were obtained from the Bureau of Justice Statistics for the years 1977 – 2010 (http://www.ojp.usdoj.gov/bjs/dtdata.htm#corrections).

Parent directory for all files below: DRIVE:\Common_Data\Incarceration

Raw data files:

\BJS State Level Sentenced Prisoners\80-04 Sentenced Prisoners.xls

\BJS State Level Sentenced Prisoners\p05t04.xls

p06at06.xls

p07at03.xls

p08at05.xls

p09at04.xls

p10at04.xls

Program(s) to read raw data:

\BJS State Level Sentenced Prisoners\BJS_Sentenced_Prisoners_7710_Dataprep.sps

SPSS/Stata merged database of state incarceration

\BJS State Level Sentenced Prisoners\Incarceration_1977_2010.sav

Ancillary files needed to generate merged database of police force size:

None needed.

Important user notes:

Raw excel data were read into SPSS using the program listed above. Unnecessary information was removed, and variables were labeled. A file covering the entire period (1977-2010) was saved.

State-Level Data on Persons Admitted to and Released from Prison, 1977-2010

State-level counts of prisoners admitted and released were obtained from the Bureau of Justice Statistics for the years 1977 – 2010. The original source data is the National Prisoners Statistics (NPS).

Parent directory for all files below: DRIVE:\Common_Data\Incarceration

Raw data files:

\BJS State Level Admitted and Released Prisoners\Admits 1978-1998.xls
\Admits 1999-2010.xls

Program(s) to read raw data:

\ BJS State Level Admitted and Released Prisoners\State Prison_Admissions_and _Releases_7809.sps

SPSS/Stata merged database of state incarceration

\ BJS State Level Admitted and Released Prisoners\ Prison_Admissions_Releases_7809.dta

Ancillary files needed to generate merged database of police force size:

None needed.

Important user notes:

Raw excel data were read into SPSS using the program listed above. Unnecessary information was removed, and variables were labeled. A file covering the entire period (1977-2010) was saved.

County-Level Data on State Prison Admissions and Releases, 1983-2003

County-level counts of prisoners admitted to and released from state prisons. The raw data were obtained from the NACJD [the original source data is the National Prisoners Statistics (NPS)]. NCRP data report prison admissions and releases for individuals, identifying among other things the demographic attributes of the subjects (e.g. age) and the crime for which he/she was admitted or released, and the county in which the sentence was processed. Using the county geographic codes, the NCRP data were aggregated to produce overall year-specific county counts of prison admissions and releases, and age- and crime-specific counts.

Parent directory for all files below: DRIVE:\Common_Data\Incarceration\NCRP

Raw data files:

\admissions*multiple files
\releases*multiple files

Program(s) to read raw data:

\ncrp part 1 admissions raw data setup.sps
\ncrp part 1 admissions rename and extract.sps
\ncrp part 2 releases raw data setup.sps
\ncrp part 2 releases rename and extract.sps

SPSS/Stata merged database of county prison admissions and releases:

\admissions\ncrp_1983_8363_part1.sav, ncrp_1984_8497_part1.sav, ncrp_1985_8918_part1.sav, ncrp_1986_9276_part1.sav, ncrp_1987_9402_part1.sav, ncrp_1988_9450_part1.sav, ncrp_1989_9849_part1.sav, ncrp_1990_6141_part1.sav, ncrp_1991_6272_part1.sav, ncrp_1992_6400_part1.sav, ncrp_1993_6823_part1.sav, ncrp_1994_6881_part1.sav, ncrp_1995_2194_part1.sav, ncrp_1996_2448_part1.sav, ncrp_1997_2613_part1.sav, ncrp_1998_3029_part1.sav, ncrp_1999_3339_part1.sav, ncrp_2000_3761_part1.sav, ncrp_2001_4052_part1.sav, ncrp_2002_4345_part1.sav, ncrp_2003_20741_part1.sav

\releases\ncrp_1983_8363_part2.sav, ncrp_1984_8497_part2.sav, ncrp_1985_8918_part2.sav, ncrp_1986_9276_part2.sav, ncrp_1987_9402_part2.sav, ncrp_1988_9450_part2.sav, ncrp_1989_9849_part2.sav, ncrp_1990_6141_part2.sav, ncrp_1991_6272_part2.sav, ncrp_1992_6400_part2.sav, ncrp_1993_6823_part2.sav, ncrp_1994_6881_part2.sav, ncrp_1995_2194_part2.sav, ncrp_1996_2448_part2.sav, ncrp_1997_2613_part2.sav, ncrp_1998_3029_part2.sav, ncrp_1999_3339_part2.sav, ncrp_2000_3761_part2.sav, ncrp_2001_4052_part2.sav, ncrp_2002_4345_part2.sav, ncrp_2003_20741_part2.sav

Ancillary files needed to generate merged database of police force size:
None needed.

Important user notes:

The record layout and coding scheme used in the NCRP has changed over time, which is reflected in the "sps" extraction and recoding programs highlighted above.

3. Demographic and Social Conditions

Surveillance Epidemiology and End Results (SEER) Population Data

Parent directory for all files below: DRIVE:\Common_Data\SEER\

Raw data files:
\us.1969_2009.19ages.adjusted.txt
\us.1969_2009.singleages.adjusted

Program(s) to read raw data:
\SEER_Population_Dataprep_051912.do

SPSS/Stata merged population database:
\SEER_County_Population_6909_FINAL.dta
\SEER_State _Population_6909_FINAL.dta

Ancillary files needed to generate population databases:
None needed.

Important user notes:

SEER population data was downloaded from website. All files were opened and processed in STATA using the above program. Final files created in the program were combined and saved out (SEER_County_Population_6909_FINAL.dta).

Decennial Census Data, 1980, 1990, & 2000

Parent directory for all files below: DRIVE:\Common_Data\Census_Data\NHGIS_Census\

Raw data files:
All raw files were downloaded from the National Historical Geographic Information System (NHGIS) website: https://www.nhgis.org/

Program(s) to read raw data:
NHGIS_Census_County_Data_Prep.spss
NHGIS_Census_State_Data_Prep.spss
NHGIS_Census_Place_Data_Prep.spss

SPSS/Stata merged database of population and social conditions:
\state\ nhgis_state_allvars_809000.dta
\county\ nhgis_county_allvars_809000.dta
\place \ nhgis_place _allvars_809000.dta

Ancillary files needed to generate databases:
Census_Place_To_FIPS_Place.sav

Important user notes

All raw data were downloaded from the National Historical Geographic Information System (NHGIS) webpage cited above. All raw data were retained in both text form, and .dat SAS files. Raw .txt files were read into SPSS, variables were labeled, and component files were saved out for each geographic unit. Finally, all components were combined into a single file containing all variables for all years. Additional information about finding and downloading NHGIS census data is available here: https://www.nhgis.org/user-resources/users-guide.

Land Area for places, counties and states 1980, 1990, 2000

Parent directory for all files below: DRIVE:\Common_Data\Land_Area\

Raw data files were downloaded from various websites, as specified below.

(a) http://www2.lib.virginia.edu/ccdb/ (1980, 1990, and 2000 State-Level; 1990 and 2000 County-Level)
(b) http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/9251?archive=ICPSR&q=1988+County+and+City+Data+Book (1980 County- and Place-Level)
(c) http://www.census.gov/population/www/censusdata/places.html (1990 Place-Level)
(d) http://factfinder2.census.gov/ (2000 Place-Level)

Program(s) to read raw data:

1980 Land Area\DS0001\09251-0004-Place.sps
1980 Land Area\DS0001\09251-0001-StateCounty.sps
1980 Land Area\1980State.sps
1990 Land Area\1990Place.sps
1990 Land Area\1990County.sps
1990 Land Area\1990State.sps
2000 Land Area\2000Place .sps
2000 Land Area\2000County.sps
2000 Land Area\2000State.sps

SPSS merged databases for land area for each geography level:

1980_1990_2000_Place.sav
1980_1990_2000_County.sav
1980_1990_2000_State.sav

Ancillary files needed to generate databases:

2000 County FIPS.xls
Census_Place_To_FIPS_Place.sav

Important user notes:

All state data as well as the 1990 and 2000 county data were downloaded from the University of Virginia website listed above. This server limits downloads to approximately 200 locations per request, so the county data was copied into an Excel spreadsheet through multiple requests, and this file is treated in the program files as the raw data. As the raw data did not contain geographic identifiers, FIPS codes were attached to the raw data during processing. For states, this was accomplished with basic “compute” commands in the program files. For counties, the 2000 county FIPS codes (taken from the 2007 County and City Data Book, http://www.census.gov/statab/www/ccdb.html) were attached to the raw data by geography name. Several typographic reconciliations, as documented in the .sps programs, were required to ensure that the names were precisely the same in each file (including punctuation and capitalization). Data for the remaining 1980 geographies, county and place, were taken from the Interuniversity Consortium for Political and Social Research (ICPSR), and the Census_Place_To_FIPS_Place file was needed for the place-level data to convert the census codes into FIPS codes. The 1990 place data was available at the website listed above in HTML format, and in a fashion similar to that used for the 1990 county data, text copied directly from the site was pasted into an Excel file to create usable raw data. Finally, the 2000 place data came from the U.S. Census American Factfinder website and the specific file downloaded was titled "Population, Housing Units, Area, and Density: 2000 - State -- Place and (in selected states) County Subdivision".

Gini Coefficient of Family Income Inequality 1980, 1990, 2000

Parent directory for all files below: DRIVE:\Common_Data\Census_Data\NHGIS_Census

Raw data files:

All raw files were downloaded from NHGIS website: https://www.nhgis.org/

Program(s) to read raw data:

NHGIS_Census_County_Data_Prep.spss
NHGIS_Census_State_Data_Prep.spss
NHGIS_Census_Place_Data_Prep.spss
\gini\ nhgis_gini_calculation.do

SPSS/Stata merged population database:

nhgis_all_county_gini_80.dta
nhgis_all_county_gini_90.dta
nhgis_all_county_gini_00.dta
nhgis_all_state_gini_80.dta
nhgis_all_state_gini_90.dta
nhgis_all_state_gini_00.dta

Ancillary files needed to generate population databases:

None needed.

Important user notes:

The Gini coefficient of income inequality was not available for all census years from NHGIS, therefore it was computed independently using the program above. In order to accommodate this calculation, family income categories were downloaded from NHIS as described above. These 'raw' files opened and saved as STATA files using the NHIGIS programs. Finally, Gini coefficients of family income inequality were calculated using the "nhgis_gini_calculation.do" program. Additionally, parallel estimates were created using the 2005 and 2010 ACS family income data in order to be consistent. Final files are available for cities, counties, and states for 1980, 1990, 2000, 2005 and 2010.

American Community Survey

Parent directory for all files below: DRIVE:\Common_Data\Census_Data\ACS\

Note: in the description below "YYYY" or "YY" represents the year in question, XXX represent the summary-level in question (040-States, 050-Counties, 160-Places).

Raw data files:

All master files for individual years of the ACS were downloaded from FTP site at http://www2.census.gov/

Saved to: \ACSYY\Estimates\

Program(s) to read raw data:

\ACSYY\Programs\
"ACSYYYY_XXX_Variable_Extraction_Rev_05_28_12.do

Final Measures prepared using:

\ACSYY\Programs \
"ACSYYYY_XXX_Variable_Creation_05_28_12.do"

SPSS/Stata merged database of ACS data:

\ACSYY\ ACSYY_SumXXX_AllVars_Final.dta

Important user notes:

The data preparation done for the American Community Survey is extensive. The basic process undertaken for the entire data series is described here. All data for all files were downloaded from the U.S. Census webpage listed above. Data were extracted from the raw estimates text files using the extraction program mentioned above. After extraction from the raw .txt files was completed, these files were processed using the second program mentioned above. There are a lot of files produced and merged together throughout this process; please see the programing files for additional notes and clarification. Final files include all measures created for every area, within given geography, available from the ACS for a given year. This is sample data, so these files do not contain all geographies that a decennial census file would.

4. Economic Data

Bureau of Labor Statistics (BLS) Annual Unemployment Rate

Parent directory for all files below: DRIVE:\Common_Data\BLS_UE\

Raw data files:

All data for years 1990-2010 was downloaded from the BLS FTP site: ftp://ftp.bls.gov/pub/time.series/la>. Historical/Archived Data were provided by BLS for a cost of $75.00.

County-Level Files: E:\Common_Data\BLS_UE\Counties
BLS_LAUS_County_7679.xlsx
BLS_LAUS_County_8083.xlsx
BLS_LAUS_County_8486.xlsx
BLS_LAUS_County_8789.xlsx

City-level Files: E:\Common_Data\BLS_UE\Places\Archived_City_Data
Cities Alabama-Georgia 1976-1989.xlsx
Cities Haw-Marland, 1976-1989.xlsx
Cities Mass-Montana, 1976-1989
Cities Nev-Wyoming 1976-1989

All-Geographies for Recent Era (1990-2010)
Raw data files were downloaded from BLS LAUS FTP site and were renamed as follows: \All_Geo\
La.data.0.CurrentU00-04→ LAUS_0004.txt
La.data.0.CurrentU05-09→ LAUS_0509.txt
La.data.0.CurrentU10-14→ LAUS_1014.txt

State-Level Files: *State data was available for the whole time period via a separate file which was downloaded, opened and renamed as an excel spreadsheet: \States
\la.data.2.AllStatesU.txt→BLS_LAUS_STATE7610.xlsx

Program(s) to read raw data:
\BLS_LAUS_DATA_PREP_010512.sps

Ancillary files needed to generate databases: \Crosswalks
\BLS_LAUS_City_Crosswalk.sav
\BLS_LAUS_County_Crosswalk.sav
\BLS_LAUS_State_Crosswalk.sav

SPSS/Stata merged database of BLS & ACS unemployment data:
City-level
\Places\BLS_LAUS_City_7610.dta
County-level
\Counties\BLS_LAUS_County_7610.dta
State-level
\States\ BLS_LAUS_State_7610.dta

Important user notes:

The prepared syntax file ('BLS_LAUS_DATA_PREP.sps') creates .sav files for each one of the text files, consisting of all of the series for all geographies available from BLS for the specified years. Additionally, it reads in the crosswalk files, provided via personal correspondence from BLS, into similar .sav files in order to be merged with the full files and create geography-specific files for the years 1990-2010.

For counties, for the "historical period" (i.e., 1976-1989) individual-year files were created from each sheet in the excel file, and then combined into a single file for the years 1976-1989. The more recent period (i.e., 1990-2010) was created in the manner described above and then the two files were combined.

For places/cities during the historical period, files were created from each sheet in the excel file, and then combined into a single file for all places. The later period was created in the manner described above and then the two files were combined. Note that there is a large amount of missing data in the early 1980s, and BLS cautions that the historical and contemporary data are not fully compatible. See 'Historical Comparability.doc".

Bureau of Labor Statistics (BLS) Consumer Price Index

Parent directory for all files below: DRIVE:\Common_Data\BLS_CPI

Raw data files: Data downloaded from: < http://data.bls.gov/cgi-bin/dsrv>

Series Downloaded: CUUR0100SA0
CUUR0200SA0
CUUR0300SA0
CUUR0400SA0

Data Saved As: \BLS_CPI_6711csv

Program(s) to read raw data: \ BLS_CPI_Dataprep_052112.do

SPSS/Stata merged database of ACS data: \BLS_CPI_6711.dta

Ancillary files needed to generate databases:

None needed.

Important user notes:

Regional Consumer Price Index data was downloaded from the BLS datatool mentioned above. The downloaded .csv file was processed using the program above, and a final file to be used in the analysis was saved out.

Bureau of Economic Analysis (BEA) Personal Income Data

Personal income is the sum of net earnings by place of residence, property income, and personal current transfer receipts. Property income is rental income of persons, personal dividend income, and personal interest income. Net earnings is earnings by place of work (the sum of wage and salary disbursements, supplements to wages and salaries, and proprietors' income) less contributions for government social insurance, plus an adjustment to convert earnings by place of work to a place-of-residence basis. Data available for states for years (1948-2010) and counties (1969-2010).

Parent directory for all files below: DRIVE:\Common_Data\BEA

Raw data files: Downloaded: <http://www.bea.gov/regional/downloadzip.cfm>

Saved to: \Data\CA30

Program(s) to read raw data:

\BEA_Dataprep_061312.do

SPSS/Stata merged database of ACS data:

State-level

\State\BEA_personal_income_4810_annual.dta

County-level

\County\ BEA_personal_income_6909.dta

Ancillary files needed to generate databases:

None needed.

Important user notes:

All BEA measures are created by same .do file for both levels of geography. This program reads in raw data, produces specific measures and then final files are saved into their respective folders.

Bureau of Economic Analysis, Unemployment Insurance Spending

Unemployment insurance (UI) is a program for the accumulation of funds paid by employers to be used for the payment of unemployment insurance to workers during periods of unemployment which are beyond the workers' control. Unemployment insurance replaces a part of the worker's wage loss if he becomes eligible for payments. UI serves as an economic stabilizer by maintaining an individual's purchasing power when unemployed.

Parent directory for all files below: DRIVE:\Common_Data\BEA
Raw data files: Downloaded: <http://www.bea.gov/regional/downloadzip.cfm>
Saved to: \Data\CA30
Program(s) to read raw data: \ BEA_Dataprep_061312.do
SPSS/Stata merged database of ACS data:
State-level
\State\ BEA_ue_insurance_6909.dta
County-level
\County\ BEA_ue_insurance_6909.dta
Ancillary files needed to generate databases:
None needed.

Important user notes:

All BEA measures are created by same .do file for both levels of geography. This program reads in raw data, produces specific measures and then final files are saved into their respective folders.

Bureau of Economic Analysis, Income Maintenance Payment Data

Income maintenance payments consist largely of supplemental security income payments, family assistance, food stamp payments, and other assistance payments, including general assistance.

Parent directory for all files below: DRIVE:\Common_Data\BEA
Raw data files: Downloaded: <http://www.bea.gov/regional/downloadzip.cfm>
Saved to: \Data\CA30
Program(s) to read raw data: \ BEA_Dataprep_061312.do
SPSS/Stata merged database of ACS data:
State-level
\State\ BEA_inc_maintenance_6909.dta
County-level
\County\ BEA_inc_maintenance_6909.dta
Ancillary files needed to generate databases:
None needed.
Important user notes:
All BEA measures are created by same .do file for both levels of geography. This program reads in raw data, produces specific measures and then final files are saved into their respective folders.

Bureau of Economic Analysis, Average Wage Data

Average earnings per job reflects total earnings divided by the total number employed. The Bureau of Economic Analysis (BEA) employment series for states and local areas comprises estimates of the number of jobs, full-time plus part-time, at the place of work. Full-time and part-time jobs are counted at equal weight. Employees, sole proprietors, and active partners are included, but unpaid family workers and volunteers are not included.

Parent directory for all files below: DRIVE:\Common_Data\BEA
Raw data files: Downloaded: <http://www.bea.gov/regional/downloadzip.cfm>
Saved to: \Data\CA34
Program(s) to read raw data:
\ BEA_Dataprep_061312.do
SPSS/Stata merged database of ACS data:
State-level
\State\BEA_avg_wage_6910.dta
County-level
\County\BEA_avg_wage_6910.dta
Ancillary files needed to generate databases:

None needed.

Important user notes:

All BEA measures are created by same .do file for both levels of geography. This program reads in raw data, produces specific measures and then final files are saved into their respective folders.

Bureau of Economic Analysis, State Gross Domestic Product Data

Gross Domestic Product (GDP) by state is the state counterpart of the Nation's gross domestic product, the Bureau's featured and most comprehensive measure of U.S. economic activity. GDP by state is derived as the sum of the GDP originating in all the industries in a state.

Cautionary note:

There is a discontinuity in the GDP-by-state time series at 1997, where the data change from SIC industry definitions to NAICS industry definitions. This discontinuity results from many sources, including differences in source data and different estimation methodologies. In addition, the NAICS-based GDP-by-state estimates are consistent with U.S. gross domestic product (GDP) while the SIC-based GDP-by-state estimates are consistent with U.S. gross domestic income (GDI). This data discontinuity may affect both the levels and the growth rates of the GDP-by-state estimates. Users of the GDP-by-state estimates are strongly cautioned against appending the two data series in an attempt to construct a single time series of GDP-by-state estimates for 1963 to 2011.

Parent directory for all files below: DRIVE:\Common_Data\BEA

Raw data files: Downloaded: <http://www.bea.gov/regional/downloadzip.cfm>

Saved to: \Data\State\gsp_naics_all_PC\gsp_naics_all_PC.csv

\Data\State\gsp_naics_all_PC \gsp_naics_all_PC.csv

Program(s) to read raw data:

\ BEA_Dataprep_061312.do

SPSS/Stata merged database of ACS data:

State-level

\State\BEA_totalstgdp_GDP_6311.dta

Ancillary files needed to generate databases:

None needed.

Important user notes:

All BEA measures are created by same .do file for both levels of geography. This program reads in raw data, produces specific measures and then final files are saved into their respective folders. Two measures of state GDP were produced, 'real GDP per capita' which has been adjusted for inflation and is represented in 2005 chained dollars, and a second 'total GDP' which has not been adjusted for inflation. The later is the one used in the analysis files, after adjusting it with the measures of inflation discussed below.

Regional Index of Consumer Sentiment (ICS)

Parent directory for all files below: DRIVE:\Common_Data\ICS

Raw data files: Downloaded: < http://www.sca.isr.umich.edu>

Saved to: \ICS_Regions_1970_2011.csv

Program(s) to read raw data:

\ICS_Region_Dataprep.do

SPSS/Stata merged database of ACS data:

\ICS_Regions_1970_2011.dta

Ancillary files needed to generate databases:

None needed.

Important user notes:

The Index of Consumer Sentiment, available from the University of Michigan, was downloaded from the above website. The raw .csv file was opened using the program mentioned above, processed to provide annual measures, variables were labeled and the final file was saved out.

5. Geographic Linking Files

Bureau of Justice Statistics Law Enforcement Agency Identifiers Crosswalk Files

To facilitate the creation of place-level crime and arrest files, the Bureau of Justice Statistics (BJS) and the National Archive of Criminal Justice Data (NACJD) created a Law Enforcement Agency Identifiers Crosswalk files. These files are designed to provide geographic information for each record contained in the FBI's UCR files. Translations between the UCR originating agency identifier number (ORI) and geographic FIPS codes are made possible. The current project utilizes these files in a number of different ways to facilitate the aggregation and combine UCR data with data from a wide variety of sources. These original files are available from NACJD and ICPSR (studies #02876, 04082, 04634).

Parent directory for all files below: DRIVE:\Common_Data\UCR

Raw data files:
\BJS_Crosswalk\ICPSR_02876\02876-0001-Data.txt
\BJS_Crosswalk\ICPSR_04082\04082-0001-Data.txt
\BJS_Crosswalk\ICPSR_04634\04634-0001-Data.txt

Saved to:
\BJS_Crosswalk_1996.sav
\BJS_Crosswalk_2000.sav
\BJS_Crosswalk_2005.sav

Program(s) to read raw data:
\BJS_Crosswalk\ICPSR_02876\02876-0001-Setup.sps
\BJS_Crosswalk\ICPSR_04082\04082-0001-Setup.sps
\BJS_Crosswalk\ICPSR_04634\04634-0001-Setup.sps

SPSS/Stata merged database of ACS data:
\BJS_Crosswalk_2005.dta

Ancillary files needed to generate databases:
None needed.

Important user notes:

Raw crosswalk files were opened in SPSS using NACJD's setup files. Variables were renamed following the naming convention employed in the current project. Unnecessary variables were deleted and final files were saved out for later use in the data prep and analysis programs.

FBI UCR County Code to FIPS County Code Translation File

It was also necessary in the project to create a geographic linking file which links the FBI's county codes (unique within states) to FIPS county codes. In order to create this file 'BJS_UCR_FIPS_Crosswalk' one record from each county contained in the UCR 'C by C.txt' files was retained. From here, the file was merged to the BJS crosswalk file described above in order to obtain the FIPS codes contained within. The resulting files contain a translation between UCR and FIPS county codes (unique within states). Unnecessary variables were deleted and final files were saved out for later use in the data prep and analysis programs.

Parent directory for all files below: DRIVE:\Common_Data\UCR

Raw data files:
\Crime\FBI_City_County\Raw\YYYY C by C.txt

Program(s) to read raw data:
\Crime\FBI_City_County\FBI_UCR_Agency_Dataprep.sps

SPSS/Stata merged database of ACS data:
\BJS_UCR_FIPS_Crosswalk.sav

Ancillary files needed to generate databases:
\BJS_Crosswalk_2005.dta

Important user notes:

Raw crosswalk files were opened in SPSS. Variables were renamed following the naming convention employed in the current project. Unnecessary variables were deleted and file was merged to the BJS crosswalk file. Final files were saved out for later use in the data prep and analysis programs.

Gecorr Mable Geographic Translation Files

It was also necessary in the project to create geographic linking files which link several smaller levels of geography to their larger counterparts so that various data elements could be included. All of these files were downloaded from the Missouri Census Data Center Geographic Correspondence Engine. All files were downloaded as comma delimited text files from their website < http://mcdc2.missouri.edu/websas/geocorr2k.html>.

Parent directory for all files below: E:\Common_Data\Geocorr

Raw data files:

\ Geocorr_Place_to_County.csv

SPSS/Stata merged database of ACS data:

\ Geocorr_Place_to_County.dta

Ancillary files needed to generate databases:

None Needed

Important user notes:

Comma delimited files were downloaded from their website mentioned above. Files were opened in STATA, variables were renamed, unnecessary variables were deleted, and the final files to be used in the analysis were saved out.