The link between unemployment and crime rate fluctuations: An analysis at the county, state, and national levels

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ABSTRACT

Cantor and Land (1985) developed a theoretical model that proposed two pathways through which economic activity – as indexed by the aggregate unemployment rate – could affect the rate of criminal activity. The first is by increasing levels of criminal motivation within the population as deteriorating economic conditions affect social strain and social control; the second is by influencing the availability and vulnerability of criminal targets and thus the number of criminal opportunities. Although much empirical research has applied this theoretical model, few analyses have done so at disaggregated units of analysis. We present the most comprehensive analysis to date by empirically evaluating this model with data on 400 of the largest US counties – and examine the effects of aggregation on results as these county data are combined to the state and national levels – for the years 1978–2005. For seven Index crimes at each of the three levels of analysis, and with or without controls for structural covariates at each level, the directional effects hypothesized by Cantor and Land are found for 78 out of 84 estimated relationships. Even after taking into account the lack of statistical independence of these estimates by drawing on recently developed statistical theory, this is a very unlikely outcome. In accordance with expectations based on theory and prior research, (a) some of these relationships are weak and not statistically significant, and (b) the strongest and most consistent patterns of relationships for both the crime opportunity and crime motivation effects are found for three property crimes: burglary, larceny, and motor vehicle theft. Suggestions for further research on this topic are given.

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1. Introduction

Some 25 years ago, Cantor and Land (1985, p. 317) raised the question: Does aggregate unemployment have a positive, negative, or null effect on levels of crime in capitalist societies? They noted the central importance of answers to this question both to theories of crime and to the formation of social policy. They also observed a lack of consensus of findings from various studies to that date, with some finding a positive unemployment and crime (hereafter U–C) relationship, but others finding a negative or null relationship.

In addressing this question, Cantor and Land (hereafter C&L) developed a theoretical model that proposed two paths through which economic activity – as indexed by the aggregate unemployment rate – could affect the rate of criminal activity. The first is by altering criminal motivation through the impact of changing economic conditions on social strain

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and social control. The second is by influencing the availability and vulnerability of criminal targets and thus the number of criminal opportunities. These effects were hypothesized to be countervailing – a downturn in aggregate economic activity, for example, would increase motivation but decrease opportunity, and the operation of these two opposing effects could account for the relatively weak overall U–C relationships found in most studies. Cantor and Land also posited that the two impacts would likely occur with different timings – changes in opportunity would be coincident with changes in aggregate economic activity, whereas changes in motivation would be delayed and occur after a period of sustained unemployment.

The Cantor and Land (1985) article has been termed a "seminal work" by Arvanities and DeFina (2006, p. 139), because, by showing the complexity of a seemingly simple relationship, it built a foundation for many subsequent empirical studies. The C&L (1985) article used data on crime rates for the United States at the national level, the level of analyses adopted by many subsequent studies. However, with the increased availability of annual data on crime and structural covariates for multiple units of observation such as cities, counties, and states in the US in recent years, researchers have started to apply panel regression models to assess the C&L model. For example, Arvanities and DeFina (2006), noting specifically the benefits to panel analyses at finer units of aggregation (2006, pp. 152–153), used pooled annual data on the fifty US states from 1986 to 2000, to test various features of the C&L model.

In the present paper, we continue this line of investigation by examining the U–C relationship at a still-more disaggregated unit of analysis – the county – between 1978 and 2005. Such an approach has several advantages. First, counties are more homogenous units than states, with less variation in structural covariates within these units over time, and thus biases due to aggregation are mitigated. Second, due to several factors cited below, such as the countervailing effects of the crime opportunity and crime motivation mechanisms through which macroeconomic downturns affect crime rates, the effects of the C&L explanatory variables are not expected to be strong and highly statistically significant. Increasing the number of observations with county-level data enhances statistical power and the ability to detect whether or not the inclusion of these variables produces models that are preferred as compared to models that do not include them. Finally, to our knowledge, no prior work has focused on the original C&L model using county data. Thus, our first objective is to test the original C&L model specification using panel data at the county level.

This approach has another advantage, in that we can aggregate the county-level data into corresponding annual observations on the states in which they are located, as well as up to the national level. Therefore, our second objective is to consider how the process of aggregation affects conclusions regarding the C&L model, and so we also conduct panel regression analyses at the state level and time series analysis at the national level. Our purpose here is not to conduct full analyses at the state and national level (as noted above, past research has done this), but rather to determine the effects of aggregation on our understanding of the C&L model. We use these multiple analyses, all adopting the same model specification, to provide a better and more consistent interpretation of different results found in past research that are based on varying aggregation levels. This juxtaposition of estimates of the C&L model at the three levels of analysis facilitates the most extensive empirical assessment to date.

2. The Cantor–Land model

As noted, a key feature of the C&L model is its distinction of two different mechanisms by which unemployment could affect crime rates. We briefly review this theoretical distinction and the methodological and empirical research it stimulated.

2.1. Criminal motivation

Cantor and Land (1985, p. 319) noted that many classical criminological theories, such as strain, rational choice-utilitarian, and conflict theories, focus on the identification and explanation of forces that drive individuals toward criminal acts. Each of these theories leads to the expectation of a positive U–C relationship, although C&L observed that none of these theories posits a deterministic U–C relationship. Rather, C&L hypothesized that an increase in the unemployment rate shifts the density distribution of the population along a continuum of low to high motivation to commit crime towards its higher end and thus, the central tendency (mean, median) of the motivation density shifts upward. Assuming that the level of crime experienced by the population is an increasing function of the level of the central tendency of this density distribution, the crime rate should subsequently increase.

Cantor and Land (1985, p. 319, 2001, p. 331) emphasized that this formulation does not assert that the upward shift in the density distribution is due solely to changes in motivational levels of individuals who become unemployed. Rather, some fraction of the density shift may be due to individuals who, while not becoming unemployed themselves, are nonetheless adversely impacted by an economic downturn. In the language of multilevel or hierarchical models, C&L:

"... postulated both a *direct effect* of an increase in the aggregate unemployment rate on the criminal motivation of the specific individuals who become unemployed and a *contextual effect* on the criminal motivation of others in the population. It is the combination of these two that, other things equal, produces an increase in crime rates. Based on the heritage of much criminological theory and empirical research, it almost surely is the case that a substantial amount of this total effect would be carried through an increase in the criminogenic motivation of some of the specific persons who [become] unemployed. But it would not necessarily be limited to them..." (Cantor and Land, 2001, p. 331).

In brief, using the unemployment rate as a coincident indicator of the aggregate level of system activity in a society, and based on a heritage of criminological theory and research, the C&L model posited a positive U–C linkage.

2.2. Criminal opportunity

In addition to their effect on criminal motivation, C&L posited that aggregate economic conditions could alter the opportunity to commit crimes. Building on routine activities theory (Cohen and Felson, 1979; Land and Felson, 1976; Cohen et al., 1980, 1981; Felson, 1994), C&L cited pathways by which economic conditions can affect the number and value of crime targets and the extent to which the targets are protected.[1] For instance, aggregate economic conditions can affect the frequency with which individuals are around the home as opposed to at work, in a public place or in transit between home and work. A deteriorating economy means fewer jobs, fewer hours worked, and less time spent in job-related and leisure travel, which in turn decreases suitable targets and increases guardianship. This depresses target vulnerability and is consistent with crime data showing that most personal property crimes occur when individuals are away from their residences. Conversely, a strengthening economy produces higher incomes and greater consumption of high value items, which increases the attractiveness of targets. The circulation of individuals and their valuable property are also increased, and thus the likelihood of concurrence in space and time of offender and targets in the absence of guardians.

C&L emphasized the countervailing effects of these two mechanisms by which changes in aggregate economic activity, as indexed by the unemployment rate, can affect crime rates.[2] This, they argued, helps to account for the often weak and contradictory findings in empirical studies. C&L also noted that direct measurements generally are not available on the intervening variables through which the two mechanisms operate, namely criminal motivation and criminal opportunity. Therefore, empirical studies typically estimate regression relationships either for the effect of unemployment levels or unemployment fluctuations on crime rates or for both simultaneously. At best, C&L stated, these are semi-reduced or reduced form equations from which the identification of the distinct structural processes and coefficients is impossible.

2.3. The postulated structure of effects

C&L also emphasized the difficulties in identifying the two counteracting mechanisms and to move towards identification, they argued that the two mechanisms work on different time schedules. The criminal opportunity effect will be relatively immediate, but increases in strain and decreased social control will develop more slowly as support structures deteriorate. Thus, increases in criminal motivation will take time to develop and be more prominent during a period of sustained or rising unemployment.

While the motivational effects of unemployment build up gradually, C&L argued that they also are of relatively short duration, as many individuals who suffer financial stress during a business downturn will be rehired or otherwise recover economically within 2 years after a recession begins. They then state (Cantor and Land, 1985, p. 322):

> "To operationalize these motivational impacts, the level of unemployment in one year can be compared with that in the previous year. If the former is higher than the latter, and if this change in the level of employment results in a positive motivational impact on crime, then this should produce upward fluctuations in crime rates. Similarly, economic recoveries and the associated declines in the unemployment rate should produce downward perturbations in crime rates."

This specific hypothesis is the basis of the C&L specification of regression models relating changes in aggregate economic activity to changes in crime rates, that is, models that include as regressors both the unemployment rate and its first differences.

This hypothesized structure of the timing of effects led Cantor and Land (1985, 2001) to time series dynamic regression models specified in the following form:

$$DC_t = \alpha - \beta_1 U_t + \beta_2 DU_t + \varepsilon_t, \tag{1}$$

where DC_t denotes a first- or second-differenced Index crime rate annual time series for the United States for a period of years over which the models is estimated,[3] U_t denotes the annual US aggregate unemployment time rate series for the same

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[1] Subsequently, Wilcox et al. (2003, pp. 62–65) defined "environmental level opportunity" to include both "aggregate target suitability" (attractive targets) as well as "aggregate capable guardianship."

[2] The focus of C&L on the unemployment rate as an index of aggregate economic activity was motivated first by the prior research literature on the relationship of crime rates to the unemployment rate. Secondly, as articulated in the text above, the unemployment rate fairly directly taps into the crime motivation and opportunity mechanisms on which C&L focused. Third, in studies of business cycles in the US, the unemployment rate has been characterized as a "roughly coincident" indicator (Bober, 1968, p. 48; Stock and Watson, 1999), and the Federal Reserve Bank of Philadelphia uses the unemployment rate as one of four monthly state-level indicators in a composite index that summarizes the current economic conditions at the state level in one statistic (http://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/).

[3] Cantor and Land (1985, p. 325) noted that the choice of first- or second-differences in a crime rate time series depends on the extent to which the series exhibits a linear or higher-order time trend. Similarly, they indicated that a log transformation may be necessary to produce a stationary time series of fluctuations in a crime rate with homoscedastic error terms in models of the form of Eq. (1). Generally, time series can be made stationary either by differencing in the case of stochastic trends or by, say, including linear or quadratic time trends in the case of deterministic trends (Yaffee, 2000, pp. 46–47). Time series with stochastic trends due to random shifts in levels or to the cumulative effect of forces, such as macroeconomic conditions, that can be detrended by differencing are termed difference stationary series, while time series that can be detrended by extracting a time trend are termed trend stationary (Yaffee, 2000, p. 49). In the empirical analyses reported below, the crime rate time series are difference stationary.

period, DU_t denotes the first-differenced unemployment rate time series, α, β_1, and β_2 are constants to be estimated, and ε_t denotes a stochastic error term. In Eq. (1), the C&L conceptual model leads to an expected negative sign for β_1 (representing the expected relatively contemporaneous effect of a change in the level of aggregate economic activity on fluctuations in Index crime rates) and an expected positive sign for β_2 (representing the expected positive effect of sustained unemployment (measured by the difference in unemployment rates from 1 year to the next) on fluctuations in Index crime rates).

Estimates of Eq. (1) for US national level data over the post-World War II years 1946–1982 by Cantor and Land (1985) and the years 1946–1990 by Land et al. (1995) generally are consistent with these directional expectations for the four Index crimes with property components: robbery, burglary, larceny, and motor vehicle theft. However, for motor vehicle theft, as for murder, only the estimated contemporaneous β_1 coefficient is statistically significant).[4] For rape and aggravated assault, the estimated coefficients for both the contemporaneous and differenced unemployment rate are negative, thus implying a downturn in these crime rates during a recessionary period, but are statistically insignificant. Given that rape and aggravated assault are crimes less closely associated with economic hardship and downturn, the presence of only opportunity effects of unemployment on rape and aggravated assault rates is to be expected.

2.4. Methodological critiques

The articulation of the two counterbalancing mechanisms by which changes in the economy, as indexed by the unemployment rate and its rates of change, could affect changes in crime rates and the postulated lag structure has produced two major methodological critiques, the first by Hale and Sabbagh (1991) and the second by Greenberg (2001), with responses and analyses by Cantor and Land (1991, 2001) and Land et al. (1995). One focus of these critiques concerned the time series properties of model (1) and of the annual aggregate US unemployment and crime rate time series used in its estimation. A second focus of critiques has been the use of a differenced unemployment rate as a way to capture a lagged effect of criminal motivation (Greenberg, 2001). These points and the discussions they have stimulated have merit (see, e.g., O'Brien, 2001; Paternoster and Bushway, 2001), but they are not the focus of the present study.[5]

3. Previous empirical work at national and state levels of analysis

Extant cross-sectional studies, almost regardless of the unit of analysis from the smallest to the largest – census tracts, cities, metropolitan areas, counties, or states – are more likely than time-series studies to find a positive relationship between contemporaneous unemployment rates and crime rates (see, e.g., Chiricos, 1987). That is, the higher the unemployment rate in a particular cross-sectional unit, the higher the crime rate. This positive significant relationship is more likely to be found for property crimes and smaller units of analysis, such as intra-city studies using neighborhood- or census tract-level data. Even among property crimes, however, there is variability, with the U–C effect more likely to be positive for burglary and larceny than for motor vehicle theft.[6]

Conclusions regarding the U–C relationship from time-series research designs are more mixed, in part due to varying levels of analysis and model specifications. Smith et al. (1992), studying first differences in US arrest rates for homicide, robbery, and burglary between 1959 and 1987, applied the C&L model specification faithfully and found support for the model, with the level of unemployment negatively related to arrest fluctuations for the three offenses (consistent with an opportunity effect) and changes in levels of unemployment positively related (consistent with a motivation effect). Similarly, Britt (1997), examining the effect of age-specific unemployment rates on first differences in US arrest rates between 1958 and 1995, reported a positive impact of the change in unemployment on arrest rates for homicide (ages 18–19), robbery (ages 20–24), and burglary (ages 20–24), but found that levels of unemployment rates for youth (ages 16–17) and young adults (ages 18–24) were negatively related to arrests for homicide and aggravated assault. On the other hand, the unemployment rates for youths were positively related to larceny rates.

However, studies that use levels of crime rates as the outcome variable or adopt a lagged rather than differenced measure of economic conditions (i.e. estimate a different model from that specified by C&L) obtain mixed results. Levitt (2001, p. 382) reviewed several cross-section/time-series panel studies and stated that "… a 1% change in the unemployment rate is typically found to increase property crime by 1–2% contemporaneously but often has no impact on violent crime." Using state-

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[4] Using longer national US time series data on first-differenced homicide rates, 1900–1998, and thus with greater statistical power, O'Brien (2001) finds statistically significant effects for both unemployment rates (criminal motivation effects) and first-differenced unemployment rates (criminal opportunity effects).

[5] Some of the debate may be due to semantics – to the C&L use of the term "lagged" to describe the motivation effect associated with sustained unemployment. In fact, Cantor and Land (1985, p. 324, footnote 18) showed the algebraic equivalence of their model to one that incorporates both the contemporaneous and 1-year lagged unemployment rates. Statistically, however, the unemployment rate and the 1-year lagged unemployment rate are much more highly correlated than are the unemployment rate and its first differences. Regression models with regressors that are strongly correlated have a whole array of methodological problems: coefficient estimates are more unstable, coefficient standard errors are larger, reflecting the imprecision of the estimation of the coefficients, thus leading to broader confidence intervals and lower powered hypothesis tests (Fox, 2008, p. 307). Accordingly, models with less correlated regressors generally are preferable to those models with higher levels, which implies that the use of the differenced unemployment rate is a preferable specification.

[6] Motor vehicle theft responds, in part, to the demand for used auto parts, which decreases during an economic downturn (Cantor and Land 1985). This attenuates the positive cross-sectional U–C relationship relative to that for burglary and larceny.

level annual panel data for the years 1950–1990, Levitt (2001) himself found that the contemporaneous unemployment rate has a positive and significant effect on the property crime rate, but not on the violent crime rate, while the *lagged* unemployment rate affects neither rate. This suggests the presence of a crime motivation effect and the absence of a crime opportunity effect; however, Levitt used a lagged unemployment rate rather than a first-differenced rate as specified in the C&L model.

On the other hand, Phillips (2006) reported findings corroborative of the C–L model, using annual US county-level data from 1970 to 1999 on homicide rates and unemployment rates with controls for demographic composition, divorce rates, per capita income, and regional location. Specifically, Phillips found that the within-county contemporaneous unemployment rate effect is significantly negative (consistent with the reduced crime opportunity effect hypothesized in the Cantor–Land model), and the within-county first-differenced unemployment rate effect is significantly positive (consistent with the positive crime motivation effect hypothesized in the Cantor–Land model). Phillips also found that the between-county effect of unemployment is significantly positive, thus implying that counties with higher unemployment rates have relatively high homicide rates.

Finally, the recent state-level panel study by Arvanites and DeFina (2006) sought to test directly the ideas behind the C&L model. With the exception of the 1990–1991 economic recession, this was a historical period of a generally expanding US economy and thus, the C&L theory was put to a strong test. The authors used an alternative index of aggregate economic conditions, namely, the business cycle component of real dollar (inflation-adjusted) gross state product, arguing that this is a more comprehensive index of activity than the unemployment rate and more faithfully reflects the sorts of social processes suggested by the C&L theory. Using a detrending approach, Arvanities and DeFina (2006, p. 139) concluded that "...the strong economy of the 1990s reduced all four index property crimes and robbery by reducing criminal motivation. Business cycle growth produced no significant opportunity effect for any of the crimes studied."

Arvanities and DeFina (2006, p. 159) also estimated models of the form of Eq. (1) with the unemployment rate and its first differences as regressors and concluded that no evidence for opportunity or motivation effects is found for any of the index crimes. However, this conclusion was based on the application of two-tailed *p*-values when the Cantor and Land thesis is predictive of directions of the relationships and thus should be evaluated with one-tailed *p*-values. By the latter criterion, their estimated crime opportunity effects are statistically significant for larceny and motor vehicle theft. And, consistent with findings from prior studies, even in the context of a generally expanding economy of the 1990s, the patterns of algebraic signs estimated for the property crimes in this part of the Arvanites–Defina article are those predicted by C&L – negative for the unemployment rate and positive for its first differences.

In brief, findings on the U–C relationship in prior studies have varied due both to differences in levels of analysis and model specification. In the present study, we commence with analyses of pooled time series data from our lowest level of analysis, large US counties, and then aggregate the data to the state and national levels. Throughout the study, we apply identical model specifications at all levels of analysis. The facilitates comparisons of finding across the levels of analysis and the study of the extent to which the statistical significance of the findings is influenced by the loss of sample sizes and, accordingly, statistical power as the analysis moves from lower to higher levels of aggregation.

4. Hypotheses

Based on the foregoing review of the C&L model and prior empirical applications thereof, the following hypotheses can be stated:

Hypothesis 1. The level of unemployment (criminal opportunity) is expected to be negatively associated with fluctuations in crime rates while the change in level of unemployment (crime motivation) is anticipated to be positively associated with fluctuations in crime rates. The overall U–C relationship (through the two pathways) posited in the C&L model, as represented in Eq. (1), is not expected to be strong and highly statistically significant due to these countervailing effects of unemployment.

Hypothesis 2. Due to the economic nature of the crime motivation effect identified in the C&L model, stronger effects should be observed for crime rates with a property component than for violent crime rates.

Hypothesis 3. Lower levels of aggregation have greater within-unit homogeneity and higher power, a priori, so it follows that, for effect sizes at the margin, the county and state level analysis will have more statistically significant coefficients than at the national level for any given level of significance.

5. Empirical analysis

5.1. Data

Given the various findings from prior studies that have adopted different levels of analysis and used different research designs and estimated models, the present empirical analysis applies the C&L theoretical framework at three levels of aggre-

gation: counties, states, and the US as a whole. The county-level analysis is based on 400 of the largest (populations greater than 100,000) US counties using annual data for the period 1978–2005. Counties are advantageous for the purposes of this research since they represent fairly small geographic areas (compared to states), annual data for a number of indicators are available, and the boundaries of large counties have not changed over time, unlike those of Metropolitan Statistical Areas (MSAs) or central cities. For comparative purposes and to examine the effects of aggregation, these counties are combined across the states in which they are located to obtain state-level data. For the national-level analysis, the information is summed across all 400 counties for each year of analysis.

5.1.1. Dependent variables

Dependent variables are specific *Index crime rates* in a given year. Following Arvanities and DeFina (2006), the analysis focuses on seven Part I Index crimes (homicide, rape, robbery, assault, burglary, larceny, and motor vehicle theft); arson is excluded as this crime is rare. Information on the numbers of offenses was obtained from the National Archive of Criminal Justice Data (NACJD) county-level data file, available at ICPSR. These data are based on the "Crime by County" data file provided by the FBI's Uniform Crime Reports (UCRs) Program. Data on crimes are not available for the four large counties in Missouri in 1977.

Maltz and Targonski (2002) noted a number of limitations with these data, namely that the reliability, accuracy, consistency and completeness of information received by police departments can be questionable. However, they also observed that these problems are mitigated somewhat with larger counties, such as those used in this analysis. They estimated that almost 15% of data points from counties with populations smaller than 100,000 are in error by 30% or more, compared to only 5% of data points from counties over 100,000 in population. To ensure data quality and minimize measurement error, we focus our analysis only on the 400 largest US counties, within which 70% of the total US resident population lived over the time period. Nonetheless, there are possible problems associated with these data, and results should be interpreted with caution.

The denominator for the crime rates, the total mid-year population of each county in each year, was acquired from the Census Bureau (US Department of Commerce, 1970–2005). The Bureau provides population counts for each county for each census year (1970, 1980, 1990, and 2000) and estimates of county population sizes for intercensal years.[7] The crude rates for all violent crimes were logged to remove skewed data patterns.[8] The distribution of each property crime rate appears approximately normal, and thus no transformation was necessary.

5.1.2. Explanatory variables

The key explanatory variable of interest – aggregate economic conditions – is proxied by *unemployment rates and their first differences*, defined as the percentage of the civilian labor force that is unemployed. Annual unemployment information for counties over the period 1977–2005 was obtained from the Bureau of Labor Statistics (BLS). Unemployment data are missing for the three large counties in Louisiana for the year 2005.

The unit of analysis – county – adopted in this study restricts the economic indicators we can consider. For example, measures of gross state product, used by Arvanities and DeFina (2006) and consumer confidence, adopted by Rosenfeld and Fornango (2007), as alternative proxies for economic conditions are not available at the county level. Details on the estimation methodology employed by the BLS to produce local area unemployment statistics can be found at the following website: http://www.bls.gov/lau/laumthd.htm.

Our choice of controls is guided by prior studies and similar to that of Arvanities and DeFina's (2006) analysis. *Age composition* is captured with a variable indicating the percentage of the county population that is aged 15–24 years in a given year. *Racial composition* is measured by the percentage of the county's population that is nonwhite in a particular year. Both these measures come from the Census Bureau. In addition, an annual measure of changes in rates of removal of offenders from the population, *lagged first differences in the state and federal imprisonment rate*, is also included. Data for this variable were obtained from the *Sourcebook of Criminal Justice Statistics* (Bureau of Justice Statistics). This measure of incarceration excludes inmates housed in local jails and is not available for the District of Columbia for the years 2002–2005.

As noted in Arvanities and DeFina (2006, p. 152), these variables have been shown to have theoretical and empirical importance in affecting crime rates and are the control variables most consistently used in empirical tests of the C&L model. The age and racial composition variables are indicative of the relative prevalence of the sizes of populations from which motivated offenders and/or crime targets are likely to be drawn. Fluctuations in incarceration rates, on the other hand, are indicative of the degree to which offenders are removed from the civilian population, which may have both specific and general deterrence effects.

5.1.3. Descriptive statistics

Table 1 displays descriptive statistics for these variables, showing the mean values as well as temporal and spatial variation in these characteristics across counties. Note that there is considerable variation in these characteristics both across

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[7] Details on the methodology used to obtain the intercensal estimates can be found at the following website: http://www.census.gov/popest/estimates.html.
[8] As there are cases with no particular offenses recorded in a given year (e.g. homicide), a small value (1) was added to all rates so that the log transformation could be performed (see Hamilton, 1992, p. 17).

counties and within counties over time. For example, the percentage unemployed varies quite substantially across counties and over time – a standard deviation of almost two percentage points both across counties and time.

5.2. Methods

5.2.1. County-level and state-level analyses

To assess the impact of unemployment levels and fluctuations therein on fluctuations in crime rates, fixed-effects panel models of the following form were estimated for each Index crime.

$$Dy_{jt} = \alpha + x_{jt}\beta + \nu_j + \lambda_t + \varepsilon_{jt} \tag{2}$$

The dependent variable Dy_{jt}, is the first-differenced Index crime rate for county (state) j at time t. α denotes the model intercept and β represents the estimated set of parameters for x_{jt}, the vector of explanatory variables for each county (state) j and year t. As noted above, following the form of Eq. (1), the explanatory variables in Eq. (2) include unemployment rates and first-differences therein together with controls for deterrence and population structure variables, namely, first differences in incarceration rates; the percentage aged 15–24; and first differences in the percentage non-white. The model also includes a series of county (state) dummy variables (ν_j) and year dummy variables (λ_t). The model residual, ε_{jt}, captures the remaining random variation within counties (states) over time.

Time series panel regression analyses of the form of Eq. (2) require that panel series be stationary, that is, integrated of order 0. We conducted Im–Pesaran–Shin tests in Stata 11 using the xtunitroot commands to determine the stationarity of all the panel series (in levels). In terms of the dependent variables (crime rates) at the county level, tests rejected the null hypothesis of non-stationarity for all panel series except burglary rates, indicating that the fraction of panels that are stationary is non-zero in those cases (Im et al., 2003). After first-differencing county burglary rates, the series was determined to be stationary. At the state level, the crime series were all found to be stationary with the exceptions of burglary and larceny rates. As with county-level data, first-differencing these series rendered them stationary.

With regard to the key independent variable, unemployment rates, the Pesaran tests rejected the null hypothesis of non-stationarity for unemployment levels at both the county and state levels. As first differences of a series stationary in levels are also stationary (Yaffee, 2000, p. 78), the requirement of stationary series in our analyses is met. Among the control variables, Pesaran tests determined that the percentage nonwhite series (in levels) were not stationary at the county and state levels. First-differencing these series made them stationary. In the case of the percentage aged 15–34 and the incarceration rate, the null hypothesis of non-stationarity was rejected at both the county and state units of analysis.

Exploratory analyses revealed that, for all crimes, models allowing for an AR(1) error structure fit better and, hence, all county and state models permit this autocorrelation. An analysis of residual plots indicated that heteroskedasticity does not present a major problem. The caution is added, however, that for most crimes (with the exception of homicide and motor vehicle theft), our models may have limitations at extreme values – for example, for years when a county experiences extremely high or low rates. All county- and state-level models were estimated using PROC MIXED in SAS.

5.2.2. National-level analyses

Auto-Regressive Integrated Moving Average (ARIMA) time-series methods were used to study the properties of our time series and dynamic regression models and to estimate the impact of unemployment levels and fluctuations on fluctuations in crime rates over time at the national level. Box–Cox transformations revealed that all series are variance stationary with the exception of the motor vehicle theft rate, for which a logarithmic transformation was applied to stabilize its variance. Inspection of autocorrelation and partial autocorrelation functions for the undifferenced crime rate time series indicated that first

Table 1
Descriptive statistics for dependent and independent variables.

Variable	Data source	Mean	Between-county Standard deviation	Within-county Standard deviation
Crude violent crime rate per 100,000	Uniform Crime Reports	6.60	6.42	3.26
Crude homicide rate per 100,000	Uniform Crime Reports	35.45	18.32	12.04
Crude rape rate per 100,000	Uniform Crime Reports	163.15	173.78	80.43
Crude robbery rate per 100,000	Uniform Crime Reports	314.32	203.34	120.44
Crude assault rate per 100,000	Uniform Crime Reports	519.52	365.88	176.69
Crude property crime rate per 100,000	Uniform Crime Reports	4563.51	1676.72	1111.23
Crude burglary rate per 100,000	Uniform Crime Reports	1130.74	468.62	411.28
Crude larceny rate per 100,000	Uniform Crime Reports	2983.89	1050.04	701.57
Crude motor vehicle theft rate per 100,000	Uniform Crime Reports	416.57	310.65	184.42
Percent unemployed	Bureau of Labor Statistics	6.07	1.78	1.92
Incarceration rate per 100,000	Bureau of Justice Statistics	283.20	94.83	125.18
Percent aged 15–24	Census Bureau	16.00	2.88	2.14
Percent non-white	Census Bureau	14.60	12.91	2.86

Based on 400 US counties for the 1977–2005 period.

Table 2
Estimated effects across US counties of unemployment levels and fluctuations on index crime rates, 1978–2005.

| | Unemployment rate | | First-differenced unemployment rate | | −2LL | BIC | AR(1) |
	Coeff.	S.E.	Coeff.	S.E.			Coeff.
Violent crimes							
Murder (baseline)					12335.4	14905.8	−0.469[*]
Without controls	−0.006[*]	(0.002)	−0.007	(0.004)	12321.1	14903.5	−0.469[*]
With controls	−0.006[*]	(0.002)	−0.007	(0.004)	12309.3	14909.6	−0.470[*]
Rape (baseline)					12869.5	15440.0	−0.394[*]
Without controls	−0.007[*]	(0.002)	0.011[*]	(0.004)	12856.4	15438.7	−0.395[*]
With controls	−0.007[*]	(0.002)	0.012[*]	(0.004)	12849.8	15450.1	−0.395[*]
Robber (baseline)					13044.0	15614.3	−0.366[*]
Without controls	−0.006[*]	(0.003)	0.005	(0.005)	13037.3	15619.6	−0.366[*]
With controls	−0.006[*]	(0.003)	0.005	(0.005)	13023.9	15624.2	−0.367[*]
Assault (baseline)					13207.7	15778.0	−0.322[*]
Without controls	0.0003	(0.003)	−0.001	(0.005)	13207.0	15789.3	−0.322[*]
With controls	0.0006	(0.003)	−0.001	(0.005)	13202.8	15803.1	−0.322[*]
Property crimes							
Burglary (baseline)					148788.9	151359.2	−0.198[*]
Without controls	−1.097	(1.215)	11.183[*]	(2.046)	148721.4	151303.7	−0.203[*]
With controls	−1.503	(1.219)	11.425[*]	(2.038)	148594.6	151194.9	−0.209[*]
Larceny (baseline)					168253.0	170823.4	−0.271[*]
Without controls	−8.605[*]	(2.749)	26.262[*]	(4.788)	168177.2	170759.6	−0.274[*]
With controls	−8.958[*]	(2.764)	26.779[*]	(4.769)	168029.5	170629.8	−0.277[*]
Vehicle theft (baseline)					134898.7	137469.1	−0.118[*]
Without controls	−4.444[*]	(0.695)	2.379[*]	(1.118)	134813.5	137395.8	−0.121[*]
With controls	−1.490[*]	(0.701)	2.406[*]	(1.117)	134734.0	137334.3	−0.124[*]

N = 11,189 ((400 counties ∗ 28 years) − (11 missing county-years)).
All dependent variables are first-differenced. Violent crime rates are logged to remove non-linearity.
Control variables include logged incarceration rates (lagged by 1 year and first-differenced), percent non-white (first-differenced) and percent aged 15–24.
Baseline model includes year and county dummies and AR(1) coefficient only.
[*] $p \leqslant 0.05$. All tests are two-tailed. Coeff. = regression coefficient and S.E. = standard error. Standard errors are in parentheses.

differencing was sufficient to achieve stationarity, with two exceptions; for assault and motor vehicle theft rates, second differencing was necessary to obtain stationarity. At the national level, differencing was also applied to obtain stationarity for all control variables.

Using model specification criteria (Akaike Information Criterion), a first order autoregressive model (AR(1)) on the error term was specified for the national level crime rates time series. For several violent crime series, the lag one autocorrelation term was not statistically significant and thus was not included in those models. All final dynamic regression models were estimated using the AUTOREG procedure in SAS.

We use two approaches to determine the statistical significance of the unemployment variables. In addition to t-tests, we also consider the log likelihood and Bayesian Information Criterion (BIC) statistics for three models: a baseline model with no covariates, a model including the unemployment variables with no controls, and a final model that includes all covariates (unemployment and controls). We compare these statistics across the models, focusing on the BIC statistic as it introduces a penalty to the conventional likelihood ratio test statistic for the number of free parameters and thus is an appropriate criterion for model selection among nested models with differing numbers of covariates (Raftery, 1995).

6. Results

Table 2 displays results using counties as units of analysis. For all Index crimes except assault and homicide, the patterns of algebraic signs are consistent with those predicted by the C&L model.[9] For rape, larceny, and motor vehicle theft, the contemporaneous and differenced effects are statistically significant, in models with and without controls. For rape and larceny, the positive motivation effect of unemployment on crime appears greater than the negative opportunity effect, while the opposite is true for motor vehicle theft. For example, an increase of one standard deviation in the contemporaneous unemployment rate is associated with a drop of about 8.6 per 100,000 in the motor vehicle theft rate; a rise of one standard deviation in a given year compared to the one prior in the unemployment rate is associated with an average increase of 2.9 per 100,000 in the vehicle theft rate. These estimated coefficients indicate that the decline in the crime opportunity effect during an economic downturn

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[9] In order to focus the discussion on the key explanatory variables in the C&L model, estimates of coefficients for the control variables are not reported in the tables (they are available from the authors on request). Suffice it to state that, among control variables, only the lagged differenced incarceration rate is statistically significant for violent crimes, exhibiting a negative association with fluctuations in both homicide rates and robbery rates. A similar negative effect of fluctuations in the lagged incarceration rate is found for all three property crimes; in addition, the first-differenced percentage of the population that is non-white is negatively associated with fluctuations in burglary and larceny rates.

Table 3
Estimated effects across US States of unemployment levels and fluctuations on index crime rates, 1978–2005.

	Unemployment rate		First-differenced unemployment rate		−2LL	BIC	AR(1)
	Coeff.	S.E.	Coeff.	S.E.			Coeff.
Violent crimes							
Murder (baseline)					272.4	581.5	−0.380[*]
Without controls	−0.014[*]	(0.006)	0.001	(0.010)	266.3	583.2	−0.382[*]
With controls	−0.012[*]	(0.006)	0.002	(0.010)	161.0	485.7	−0.375[*]
Rape (baseline)					1067.2	1376.2	−0.323[*]
Without controls	−0.011	(0.008)	0.006	(0.014)	1065.3	1382.1	−0.324[*]
With controls	−0.002	(0.008)	0.005	(0.014)	951.1	1275.8	−0.324[*]
Robber (baseline)					820.5	1129.6	−0.286[*]
Without controls	−0.010	(0.007)	0.016	(0.013)	817.9	1134.8	−0.287[*]
With controls	−0.005	(0.007)	0.016	(0.012)	614.5	939.2	−0.293[*]
Assault (baseline)					993.5	1302.5	−0.277[*]
Without controls	−0.007	(0.008)	0.001	(0.014)	992.6	1309.5	−0.277[*]
With controls	−0.003	(0.008)	0.001	(0.013)	850.5	1175.2	−0.281[*]
Property crimes							
Burglary (baseline)					17957.6	18266.7	−0.107[*]
Without controls	−11.920[*]	(3.842)	15.682[*]	(6.011)	17945.0	18261.8	−0.115[*]
With controls	−7.081[*,a]	(3.637)	14.222[*]	(5.714)	17036.9	17361.6	−0.150[*]
Larceny (baseline)					20818.1	21127.1	−0.194[*]
Without controls	−29.990[*]	(9.974)	47.793[*]	(16.345)	20804.4	21121.3	−0.202[*]
With controls	−18.915[*]	(9.588)	44.923[*]	(15.669)	19816.3	20141.0	−0.235[*]
Vehicle theft (baseline)					16342.6	16651.7	−0.045
Without controls	−8.404[*]	(2.262)	3.890	(3.414)	16329.1	16645.9	−0.055[*]
With controls	−6.995[*]	(2.317)	3.853	(3.481)	15654.5	15979.2	−0.070[*]

All dependent variables are first-differenced. Violent crime rates are logged to remove non-linearity. Control variables include logged incarceration rates (lagged by 1 year and first-differenced), percent non-white (first-differenced) and percent aged 15–24. Baseline model includes state and year dummies and AR(1) coefficient only.

[*] $p \leqslant 0.05$.
[a] $p = 0.0518$. All tests are two-tailed. Coeff. = regression coefficient and S.E. = standard error. Standard errors are in parentheses.

(due to a lower level of circulation of vehicles and a higher level of guardianship as individuals drive less and are more likely to stay home near their vehicles) is larger than an increase in motivation for vehicle theft.

For robbery, the expected algebraic pattern of negative and positive effects is found, with only the negative contemporaneous effect statistically significant in the model without controls. For burglary, the expected algebraic pattern of effects is found, but only the delayed motivation effect is statistically significant in models with and without controls. For murder, the contemporaneous crime opportunity effect is statistically significant with and without the controls, with the differenced motivation effect showing a small and statistically insignificant negative effect.[10,11]

A comparison of the BIC statistics across the three respective models (baseline, without controls, and with controls) for each crime supports the general conclusion that the C&L model is more applicable to property than to violent crimes. According to model selection guidelines for the interpretation of BIC statistics given by Raftery (1995, p. 139), differences (reductions) in values as one goes from a model with fewer to one with more explanatory variables of 0–2 provide "weak" evidence in favor of the latter model, differences of 2–6 provide "positive" evidence, differences of 6–10 provide "strong" evidence, and differences greater than 10 provide "very strong" evidence. In Table 2, the reductions in the BIC statistics as we transition from the baseline to the other models provide strong evidence in favor of the C&L model for the three property crimes—burglary, larceny, and vehicle theft. For murder and rape, the BIC statistics decrease very modestly in going from the baseline models to the models with the C&L variables (reductions of 2.3 for murder and 1.3 for rape). In the case of assault and robbery, the BICs increase with the addition of these explanatory variables. The implication is that the contributions of the C&L variables to the explanation of fluctuations in the murder rate is very slightly positive (corresponding to the significant negative coefficient for the contemporaneous unemployment effect) and weak for fluctuations in the rape rate (even though both of the explanatory variables have statistically significant coefficients)—with, in each case the improvements in explanatory power discounted by the losses of degrees of freedom due to the addition of the explanatory variables. In the case of fluctuations in the assault and robbery rates, the BICs imply that the C&L explanatory variables do not provide sufficient in-

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[10] This analysis offers a test of the C&L thesis, as originally stated. However, as noted earlier, some have argued that a lagged rather than a differenced unemployment variable better captures the model's underlying argument. As described by Greenberg (2001) and estimated empirically by others (Greenberg, 2001; Phillips, 2006), the algebra is such that were we to replace the differenced unemployment term with a lagged unemployment term, the signs of the contemporaneous and lagged coefficients would reverse.

[11] About 30% (125) of the 400 counties are clustered within metropolitan areas. To assess how spatial autocorrelation may affect the county-level results, we ran the C–L model with the county data aggregated to the metropolitan area (we have 275 MSAs in the analysis). The results are very similar to those we obtained at the county-level, with two exceptions. The motivational effect of unemployment for vehicle theft and rape is significant only at the $p = 0.10$ level. For rape, the opportunity effect of unemployment is not significant in the full model with controls.

Table 4
Estimated effects of unemployment levels and fluctuations on fluctuations in US index crime rates, 1978–2005.

	Unemployment rate		First-differenced unemployment rate		ρ	Total R^2	BIC
	Coeff.	S.E.	Coeff.	S.E.			
Violent crimes							
Murder (baseline)						0.05	69.38
Without controls	−0.155	(0.12)	0.198	(0.19)	–	0.08	71.76
With controls	−0.328[*]	(0.15)	0.238	(0.20)	–	0.23	75.30
Rape (baseline)						0.02	125.35
Without controls	−0.079	(0.33)	0.198	(0.52)	–	0.02	128.95
With controls	−0.388	(0.43)	0.246	(0.57)	–	0.14	130.95
Robbery (baseline)						0.01	265.52
Without controls	−1.557	(3.91)	7.057	(6.20)	–	0.05	267.77
With controls	−8.443[*]	(3.15)	12.728[*]	(4.67)	0.473	0.42	259.11
Assault (baseline)						0.62	256.18
Without controls	−7.463	(7.57)	9.692	(6.96)	−0.822	0.65	260.63
With controls	−5.646	(8.33)	10.964	(7.19)	−0.895	0.67	269.30
Property crimes							
Burglary (baseline)						0.20	326.59
Without controls	−31.406[+]	(17.90)	34.207[+]	(19.93)	−0.508	0.32	328.84
With controls	−29.821	(19.68)	25.436	(20.30)	−0.463	0.47	320.82
Larceny (baseline)						0.15	351.99
Without controls	−62.553[+]	(31.04)	82.729[*]	(30.65)	−0.658	0.31	353.25
With controls	−53.854	(36.12)	63.911[+]	(34.96)	−0.568	0.34	350.199
Vehicle theft (baseline)						0.55	−56.61
Without controls	−0.031	(0.02)	0.050[*]	(0.02)	−0.808	0.64	−56.136
With controls	−0.049[*]	(0.01)	0.041[*]	(0.02)	–	0.69	−54.27

The lag-one autocorrelation coefficient (ρ) is included only when it is statistically significant. All dependent variables are first-differenced to achieve stationarity, with the exception of assault and motor vehicle theft for which second-differences were necessary. Exploratory analysis indicated that the vehicle theft rate should be logged to stabilize variance in the time series.

Control variables include first-differenced lagged incarceration rates, percent non-white and percent aged 15–24.

[*] $p \leqslant 0.05$.

[+] $p \leqslant 0.10$. All tests are two-tailed. Coeff. = regression coefficient and S.E. = standard error. Standard errors are in parentheses.

creases in predictability for retention. This is consistent with the lack of statistical significance of these variables in the assault models with and without controls and with, for robbery, only the contemporaneous (crime opportunity) unemployment rate being significant in only the model without controls.

Table 3 reports estimates of the C&L model when the county-level data are aggregated up to the state level. For all seven Index crimes, a negative contemporaneous effect and positive effect of sustained unemployment is found although the effects of unemployment on crime are statistically significant in only some cases. For the property crimes of burglary and larceny, the effects are statistically significant in models with and without controls. However, in the case of murder and motor vehicle theft, only the contemporaneous negative coefficients on unemployment are statistically significant (in both the model with and without controls).[12]

As observed in the county-level analysis, the changes in the BIC statistics across the three models in Table 3 provide positive support in favor of the C&L model at the state level for the three property crimes—burglary, larceny, and vehicle theft. The BIC statistics imply that the evidence in favor of the models with the C&L explanatory variables moves from positive to strong or very strong when the control variables are included in the models. For all four violent crimes, the BICs similarly indicate very strong evidence in favor of the models with the C&L variables plus the control variables. However, the statistically insignificant coefficients for the C&L variables and the trends in the BICs show that the gains in evidence for these models are due primarily to the inclusion of the control variables. This is consistent with the patterns of weak and statistically insignificant coefficients for the C&L variables in the violent crime models at the state level, such as those observed by Arvanites and DeFina (2006) in their state-level analysis.

Table 4 displays the findings when counties are aggregated up to the national level. Again, the pattern of algebraic signs of the effects of unemployment and changes therein is as predicted by the Cantor–Land thesis for all seven Index crimes. However, only in the models for robbery and motor vehicle theft that include controls do these coefficients reach statistical significance at the 0.05 level. As at more disaggregated units of analysis, patterns suggest that the opportunity effects of unemployment fluctuations are more salient for homicide; for property crimes, some evidence of both opportunity and motivation effects is detected although some of these effects are statistically significant at only the 10% level.

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[12] Regarding control variables in the state level analysis, we find that the coefficient for the first-differenced percent non-white was negative and statistically significant for all crimes. In the case of assault, the coefficient for the first-differenced lagged incarceration rate was statistically significant and positive. No other control variables were statistically significant. By comparison, Arvanites and DeFina (2006, p. 156) estimated a negative regression coefficient for lagged incarceration rates for burglary and larceny, but only that for burglary was statistically significant. They estimated negative coefficients of the percentage of the population that is non-white for burglary, larceny, and motor vehicle theft, with only that for larceny being statistically significant.

A comparison of the BIC statistics across the three models for each crime corroborates these weak relationships. That is, except for robbery, the BICs do not show substantial evidence in favor of the models with the C&L variables. For the crimes with a property component, the BICs show stronger evidence for the C&L explanatory variables for robbery, burglary, and vehicle theft than for larceny. And all of these improvements are evidenced for the models with the control variables, which suggest that the effects of the C&L variables are suppressed in absence of the control variables. In addition, as compared to the findings reported above for the county- and state-levels of analysis, the relatively marginal contributions of the C&L explanatory variables at the national level in Table 4 indexed by the BIC statistics highlight the importance of sample sizes and statistical power in evaluations of the C&L model.

Compared with earlier national-level studies for the years 1946–1990 by Land et al. (1995), the strength of the relationships in Table 4, as measured by total R-squared statistics, are on the same order of magnitude for three of the four crimes with a property component – robbery, burglary, and larceny; for murder and rape, they are weaker, and for assault and motor vehicle theft they are stronger. However, these comparisons must be interpreted in light of the following differences. First, the national-level data analyzed here are aggregated up from data on the 400 largest US counties. While trends in these aggregated data may be reasonably representative of trends in the corresponding total US Index crime rates, the national data series used here are not complete. Second, the national-level time series used in this study are relatively short and, thus, the analysis may be statistically underpowered. In addition, in comparison to previous findings that focus on an earlier time period (e.g. 1946–1982) (Cantor and Land, 1985), the effect coefficients themselves appear to have moderated or declined in the most recent historical period. This may be due to the fact that, for much of the 1978–2005 period over which the present analyses are conducted, business cycles were more moderate than in the early decades following World War II (Sum et al., 2009).

7. Discussion and conclusion

The empirical analyses presented here and findings therein show remarkable consistency with regard to contemporaneous opportunity and delayed motivation effects of unemployment on crime rates – at the county, state and national levels, and for a variety of different crimes. Thus, findings are consistent with the hypotheses stated earlier on the basis of the C&L theoretical model and prior empirical studies. First, consistent with Hypothesis 1, the algebraic pattern of relationships postulated in the C&L model is almost always corroborated. Specifically, in 78 of the 84 test cases (seven Index crime rates with two coefficients each at three levels of analysis with and without controls), the postulated positive and negative effects of levels and fluctuations of the unemployment rate are evidenced. If the directional effects of the unemployment rate and its fluctuations in the 84 relationships estimated were determined only by chance, by say the tossing of a fair coin, the probability of 78 successes out of 84 trials in the resulting binomial distribution would be a very unlikely outcome with a p-value less than 0.00001.

This assessment of the likelihood of this number of successes is not entirely applicable here, as it is based on a model of independent trials. Because the samples of data at the three levels are not independent (the state-level data are aggregates of the county-level data and the national-level data are aggregates of the county- and state-level data), and because the estimated regression coefficients themselves are not completely statistically independent, this model must be modified. Fortunately, recent contributions to statistical theory by Efron (2010) provide some guidelines for the implications of such modifications. These contributions imply that the main consequence of non-independent trials would be a "fattening" of the binomial distribution, that is, to increase the likelihood that a large (or small) number of successes of the trials would occur by chance.[13] The precise extent to which the binomial would be fattened is difficult to quantify, but, given the extremely small probability of 78 successes in 84 independent trials cited in the previous paragraph, it is clear that an enormous fattening would be required in order to conclude that this number of successes was due to chance. In brief, the high relative frequency of occurrence of the algebraic patterns of relationship predicted by C&L is unlikely due to random effects alone. In addition, however, also consistent with Hypothesis 1, the overall U–C relationship through the two countervailing pathways posited in the C&L model is weak.

Second, as posited in Hypothesis 2, stronger effects for crime motivation are found for property crimes than for violent crimes. Indeed, for burglary, larceny, and motor vehicle theft, estimates of the algebraic patterns of effects not only are as predicted in the C&L model, but they also are statistically significant across all three levels of analysis. For violent crimes, especially homicide, only the crime opportunity effect tends to achieve statistical significance at all three levels of analysis, indicative of the impact of reduced circulation of goods and people during an economic downturn on decreasing encounters that lead to homicide.

Third, given the larger sample sizes, greater homogeneity of the units of analysis, and associated increases in statistical power, and consistent with Hypothesis 3, higher levels of statistical significance almost always are attained for effects esti-

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[13] Specifically, Efron (2010, pp. 1051–1053) studied the non-null distributions of values of z-statistics, that is, of correlated z-values and showed that such distributions closely follow normal distributions. He found that the normality property of the distribution of z-values degrades more slowly than the unit standard deviation property as the z-values become more correlated. Since, the binomial probability distribution is well approximated by a normal distribution (see, e.g., Parzen 1960, p. 239), it can be inferred that Efron's findings apply to the behavior of the binomial as the trials move from independence and become more and more dependent. That is, under non-independence of binomial trials, the distribution of the number of successes q in n trials will be fatter than the binomial, but nonetheless will closely follow the binomial.

mated for counties and states than at the national level. In fact, a comparison of empirical estimates reported above across all three levels of analysis shows the merits of the research design we have followed. That is, the estimates of the effects of the C&L explanatory variables and of the contributions to these variables to the probabilities (as measured by the BIC statistics) of the corresponding models is very strong at the county level of analysis. These relationships and the probabilities of the models weaken somewhat when the county-level data are aggregated to the state level of analysis. They become very weak indeed when the data are further aggregated to the national level.

While the postulated algebraic pattern is almost always present, it is also the case that the estimated effects of the unemployment rate and its first differences generally are not strong and highly statistically significant. Indeed, the same point can be made about the Arvanites and DeFina (2006) analysis using unemployment rates. Since the C&L hypothesis about the differential timing structures of the opportunity and motivation mechanisms is combined with the calendar year reporting of unemployment and crime rates, relatively weak empirical relationships among the variables are to be expected.[14] As Cantor and Land (2001, p. 334) noted:

"... given the fact that economic expansions and contractions commence in various months or quarters of calendar years, as well as numerous social, economic, and psychological mechanisms operating on the motivation for criminal acts, the lag structure we specified is arbitrary and, at best, an approximation."

We caution readers about possible biases that may arise due to poor data quality. For example, estimated unemployment rates at any point in time may understate the real level of unemployment because they exclude those who have given up looking for work and those who never sought work because they did not think they had a chance of finding full time employment (Arvanites and DeFina, 2006, p. 146). If such patterns change over time, the measurement of unemployment rates may be biased, with more variation in the actual than in the official unemployment rate. Undercounting is an inherent problem in crime statistics, although we attempted to minimize this possible bias by incorporating only the largest US counties with more reliable data (Maltz and Targonski, 2002). The estimated demographic characteristics of counties are subject to error, but the careful methodology[15] adopted by the Census and our focus on the largest US counties minimize this potential bias. However, to the extent that these large counties differ in important ways from the excluded counties (e.g., being more urban), we must be circumspect in generalizing our results to the entire US.

Furthermore, the data used in this study do not include the 2008–2011 period, the years of the Great Recession and the subsequent slow recovery, during which the US experienced national unemployment rates approaching 10%. To the surprise of many criminologists, national level crime rates for all major offenses have continued to decline during this period, although there are variations across cities. Research is needed to understand the reasons for this departure from prior periods although we offer some conjectures. First, the Great Recession is unique in that the middle-class has been hardest hit – between January 2008 and March 2010, 60% of net job losses came from mid-wage occupations, compared to 21.3% and 18.7% from lower and higher wage workers, respectively (Bernhardt, 2011). The increased guardianship and reduced levels of circulation of goods and people mechanisms articulated by C&L may have diminished criminal opportunities, but the delayed effects of the upturn in unemployment rates on crime motivation may have had an attenuated effect. The unemployed members of the middle class are likely to be more committed to mainstream values and to have better support networks and savings in place to sustain them during a period of economic hardship. In addition, because of the unprecedented post-World War II length of the upturn in the unemployment rate, federal jobless benefits were extended for up to 99 weeks (Evans, 2009).

Second, cultural changes may explain some of the continued lower crime rates (Wilson, 2011) – for example, the legalization of abortion (Donohue and Levitt, 2001) and phasing out of lead gasoline (Reyes, 2007) during the 1970s may have reduced the number of potential criminals 20 years later and subsequently. Among teens and young adults today, other cultural shifts, such as the widespread use of social media and computer games, have changed the nature of social interaction and thus may have diminished opportunities for criminal offending and victimization. Increased incarceration levels and changes in the nature of drug use may also play a role (Wilson, 2011). As data are made available, criminologists should investigate these possible explanations for any changes in the way economic conditions affect crime.

Still, in sum, our results (for the 1976–2005 period) are consistent with the theoretical model articulated by Cantor and Land (1985), Land et al. (1995), and Cantor and Land (2001). We conclude that this model has considerable empirical applicability in the explanation of how changes in the aggregate economy affect changes in Index crime rates and for understanding why the unemployment-crime relationship is relatively weak and productive of contradictory inferences in different studies.

We believe that additional research on this topic could benefit greatly, as Land et al. (1995, pp. 74–75) emphasized, from contextual analyses of the impacts of changing aggregate economic conditions on the delinquency/criminal behavior of individuals. For instance, Schmidt and Witte (1984) estimated negative effects of the "unemployment rate of the county of re-

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[14] Arvanites and DeFina (2006, p. 146) cite a third reason that estimated relationships between aggregate unemployment rates and crime rates can be expected to be relatively weak–measurement error. As they note, estimated unemployment rates at any point in time may underestimate the real level of unemployment because they exclude those who have given up looking for work and those who never sought work because they did not think they had a chance of finding full time employment. Unless these patterns change over time, however, they would seem to be less of a concern for temporal analyses, as such measurement errors would mainly affect levels of reported unemployment rates, not temporal trends or changes therein over time.

[15] http://www.census.gov/popest/topics/methodology/2009-stco-char-meth.pdf.

lease at the time of release" on arrest rates in a longitudinal, micro-level study of recidivism among samples of adult men released from prison in North Carolina (in 1969, 1971, and 1975). They found these coefficients to be "unexpectedly negative" (Schmidt and Witte, 1984, p. 254). Similarly, Good et al. (1986) found a negative (opportunity) effect of the general community unemployment rate on rates of police contact in a longitudinal, micro-level study of youths aged 13–18 in Philadelphia. Good et al. (1986) also found a negative effect of a youth's own current employment on his/her rate of contact with the police. Since for individuals in the labor force, current employment is the obverse of current unemployment, this finding implies a positive (motivation) effect of current unemployment on the police contact rate. While Good et al. did not explicitly address the lag structure posited by C&L, the algebraic pattern of relationships they found (a positive or motivational effect of personal unemployment and a negative opportunity effect of the community unemployment rate due to changes in routine activities) is consistent with the C&L model.

Other work (Paternoster and Bushway, 2001) attempts to tease out the opportunity and motivation effects of economic conditions by examining different types of motor theft – that committed for the purpose of joyriding and largely a function of opportunity as opposed to that conducted for profit and thus due to motivation. They distinguished between the two types of theft using age of offender and found that the rate of growth in juvenile arrests for motor vehicle theft (an indicator of theft for joyriding) is generally greater during periods of economic expansion; for adult arrests (a proxy for theft for profit), the rate of growth was greater during periods of expansion only in about half of the business cycles, suggesting either no relationship between business cycles and auto theft or the presence of countervailing motivation *and* opportunity effects. More creative tests of the C&L thesis in this vein would be another useful direction for further research. For example, work that considers additional crimes such as domestic violence may provide insight. Although the routine activities approach predicts that increases in guardianship will lower rates of property crime, the mechanism may *increase* the prevalence of domestic violence as it leads to greater interaction with frustrated unemployed workers. However, such analyses will have to overcome difficult measurement issues (Felson and Pare, 2005), as domestic violence is a vastly under-reported crime and the extent of underreporting may vary substantially over the time period examined and across geographic area.

Finally, as Cantor and Land (1985, 2001) indicated, the use of annual measures of current unemployment level and first-differenced unemployment rates as proxies for opportunity and motivation is crude. Analyses with more refined measurement of time (e.g. monthly rather than annual data) to better capture the timing of economic cycles and/or that include specific measures of the opportunities and motivations presented by economic expansions and contractions would be valuable additions to the literature. Furthermore, research that can incorporate alternative measures of the contextual impact of poor economic conditions, such as foreclosure rates or Temporary Assistance for Needy Families payments, would be valuable, although admittedly difficult to conduct for any extensive period of time or set of locations.

These are examples of the kinds of micro-level research to which aggregate analyses of the C&L model point. That is, given that the algebraic pattern of effects posited in the C&L model appears to be empirically valid across several time periods and multiple levels of analysis, research attention needs to focus on embedding micro-level data within community contexts that vary by levels of aggregate economic activity and unemployment levels and changes therein. Such an approach could explicate more fully the processes by which these aspects of the economic environment affect delinquent/criminal behavior.

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