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THE EFFECTS OF INFLATION AND DEMOGRAPHIC CHANGE ON PROPERTY CRIME: A STRUCTURAL TIME SERIES APPROACH

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Abstract
This paper extends previous empirical research on the determinants of aggregate property crime rates in two dimensions. First, we examine the effect of inflation on property crime rates. Then, using a structural time-series approach we show that it is possible to estimate consistently the effects of exogenous macroeconomic variables on aggregate property crime rates without introducing endogenous deterrence to the model. Inflation is statistically significant, positive, and persistent for all property crime rates examined. We conclude that price stability contributes considerably to the reduction of property crimes.

Key words: property crime, inflation, female labor force participation, manufacturing employment, structural time series, unobserved component models

JEL Categories: J11, J21

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I. INTRODUCTION

Crime is a chronic and costly ailment of society. In 2005, over ten million property crimes were reported to law enforcement agencies in the United States.[1] Anderson (1999) estimates the total cost of property crimes to victims in the United States to be $603 billion per annum.

A large empirical literature investigating the link between macroeconomic conditions and aggregate crime rates has developed over the last thirty years. The majority of these studies focus on the relationship between unemployment rates and crime incidence (Cantor and Land, 1985; Kapuscinski et al., 1998; Chamlin and Cochran, 2000; Paternoster and Bushway, 2001; Greenberg, 2001a, 2001b). However, a great deal of debate persists concerning the appropriate data and empirical methodology necessary to analyse a society's changing propensity for crime (Greenberg, 2001a, 2001b; Britt, 2001; O'Brien, 2001; Levitt, 2001).

In the United States, the low-income segment of the population commits a disproportionate amount of crime. Numerous studies report a high incidence of non-participation in the legal labour market among criminals (Wilson and Herrnstein, 1985, ch. 12; Grogger, 1992). Research ranging from anthropological ethnographies to micro-level econometric studies cite lack of education and job skills, poor economic opportunity, and social isolation as key explanations for criminal motivation (Wilson, 1987; Grogger, 1998; Kelly, 2000; Bourgois, 2003). For those with low levels of marketable skills the economic return to crime is often greater than that of legal employment (Freeman, 1996; E. Anderson, 1999; Grogger, 1998; Williams and Sickles,

[1] Statistics are referenced from the 2005 Uniform Crime Report. Arson is not included in the estimates of property crime in the Uniform Crime Report.

2002). Since the unemployment rate only measures persons actively seeking jobs, the aggregate unemployment rate may not be an ideal predictor of crime rate fluctuations.

In this paper, we investigate the effect of inflation and labour market dynamics on property crime rates, using data from the Federal Bureau of Investigation's Uniform Crime Report (UCR) for the years 1959 to 2005.[2] In contrast to previous empirical studies of aggregate crime rates, we hypothesize that in an economic environment with unstable prices individuals have additional incentive to bypass legal exchange and obtain material goods by illicit means. Periods of rising prices erode the value of money, which should make property crime more economically attractive, particularly for the lower income segment of society. We contend that inflation accounts for a significant portion of the steady increase in crime through the 1960s and 1970s, along with the dramatic decrease in crime in the mid- 1990s.[3]

Previous studies of unemployment's effect on crime rates do not consider variables capturing the changing demographic composition of the post-World War II United States labour market. In our analysis, we include the rate of female labour force participation and the ratio of manufacturing employment to total employment, as the rise of female labour force participation and the decline in the manufacturing sector represent the most significant transformations of the U.S. labour market.

Most studies in the economics of crime literature focus on the link between deterrence and crime rates. Identifying the parameters of an empirical model of

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[2] According to the F.B.I., property crime is composed of larceny, burglary, and motor vehicle theft. We omit motor vehicle theft from our analysis, because only a single type of good is involved in the crime and would require the inclusion of covariates specific to the market for transportation. We also analyse robbery, because it contains a property component. Our analysis begins in the year 1959 due to the change in crime reporting by the F.B.I.

[3] See FIGURE 1 for graphs of the larceny, robbery, and burglary rates. FIGURE 2 shows graphs of the variables used in predicting property crime rates.

aggregate crime, where deterrence is included as a right-hand-side variable, is a major obstacle for researchers.[4] Likewise, omitting such a theoretically relevant variable can introduce bias to the estimates. To circumvent the identification problems associated with measures of deterrence, an alternative econometric strategy is used to model aggregate property crime rates. We implement a structural time-series model to allow for a stochastic trend in the data for property crime rates (Harvey, 1989, 1997; Koopman et al., 1995).[5] The unobserved components model captures the systematic influence of variables that we omit by choice or necessity through a stochastic trend. By moving the effect of omitted variables, such as deterrence, out of the residual into a stochastic component, we can consistently estimate the effects of macroeconomic conditions on aggregate property crime rates.

We find that inflation is statistically significant, positive, and persistent for all property crime rates examined. The unemployment rate does not appear to play as large a role as previously thought, once female labour force participation, the decline in manufacturing employment, and inflation are also considered.

The remainder of the paper is organized as follows. Section II provides a brief sketch of the theoretical reasons for including the explanatory variables. Section III describes the data. Section IV presents the econometric methodology used in this paper, and discusses how the empirical technique addresses potential problems with previous methodologies. Section V reports the estimation results. Section VI concludes.

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[4] Levitt (1996, 1997, 1998a) specifically addresses the issue of endogenous deterrence in a model of crime.

[5] For the remainder of the paper, we will use the terms structural time series and unobserved component modeling interchangeably.

II. THEORETICAL BACKGROUND

Becker's (1968) economic model of crime suggests that individuals commit crimes based not upon genetic disposition or world-weariness, but rather in response to differentials in costs and benefits. The behaviour of criminals in response to changes in the probability of apprehension and expected punishment for offenses is the traditional object of study in the economics of crime literature.[6] However, much of this literature is also devoted to studying the effect of economic conditions and individual earnings potential on criminal activity.[7]

The primary macroeconomic variable considered in previous studies of aggregate crime rates has been the unemployment rate. Higher unemployment rates could induce a transition from legal employment to illegal employment, as the returns to crime are greater when unemployment is higher and job seekers are accepting lower wages.[8] Recent economic studies do report anomalies with respect to economic factors and their effect on violent crimes, such as rape and murder (Kelly, 2000). However, most studies report results consistent with economic theory concerning the effect of economic well-being on property crimes (Myers, 1983; Grogger, 1998; Kelly, 2000; Gould et al., 2002).

The downward pressure on purchasing power associated with periods of rising inflation affect low-income households more adversely (Wilson, 1987). Since low-income groups commit a high proportion of crimes in the United States, one would

[6] For example, see Sjoquist (1973), Wolpin (1980), Viscusi (1986), Corman et al. (1987), Trumbull (1989), Tauchen et al. (1994), Ehrlich (1996), Levitt (1996, 1997, 1998a, 1998b), and Corman and Mocan (2000).

[7] For example, see Myers (1983), Grogger (1998), Kelly (2000), Williams and Sickles (2002), and Gould et al. (2002).

[8] Grogger (1998) points out that many criminals are simultaneously employed in the legitimate sector. In Grogger's framework, the benefits associated with the first hour of criminal participation must exceed the return to an hour worked in licit employment.

expect periods of higher inflation to be concomitant with higher rates of crime. The low-income segment of society should find crime more attractive during inflationary periods, as wages generally do not adjust as freely as other prices. A positive effect on the rate of crime, attributable to higher inflation, should be observed in crimes with a property component. In periods of high inflation, one would expect society's propensity for property crime to increase because of the reduced purchasing power of the currency. Despite the significant macroeconomic implications of monetary policy, most studies neglect the role of inflation on the aggregate level of property crime.[9]

It has been well documented that the real wage-earnings of low-skilled workers in the United States have fallen since the 1970s (Burtless, 1990a, 1990b; Blackburn et al., 1990; Blank, 1990; Moffitt, 1990; Katz and Murphy, 1992). A disproportionate amount of these low-skilled workers are young minority males in the age group 18-25, the group most likely to commit crimes (Wilson, 1987, 1996; Freeman, 1996). The decline in the percentage of the workforce in the manufacturing industry has been cited as a primary contributor to the high rates of unemployment and non-participation in the labour market among urban male youth. Because larger additions of human capital are required to compete effectively for high-wage jobs (Wilson, 1986, 1996). Gould et al. (2002) use both county-level crime data and individual-level panel data from 1979-1997 to examine the relationship between the labour market opportunities for unskilled male workers and crime rates. The authors find that movements in wage compensation for unskilled

[9] Devine et al. (1988) is a notable exception. The authors estimate a first-differenced model of macroeconomic (i.e. inflation and unemployment) and social control (i.e. imprisonment and relief programs) factors and find a positive effect of inflation on homicide, robbery and burglary. However, the theoretical basis for the inclusion of inflation in a model of crime is not the actual effect of price volatility but rather that the "perception of inflation" motivates behavioral change (See Footnote 1). Additionally, the authors use 2SLS to estimate the effect of imprisonment on crime, yet provide no discussion of the variable(s) which generates the exogenous variation necessary for identification.

workers account for 50 percent in the rise of both violent and property crime rates for the sample period.

Another key economic development of the 20th century was the dramatic increase in female labour force participation which restructured the United States' economy (Goldin, 2006). The decline in the manufacturing sector was roughly concurrent with a sharp rise in the female labour force participation rate.[10] Attendant movements in these two variables indicate that the historical holders of manufacturing jobs, men, exited the field to enter a more competitive market for service jobs where women held a comparative advantage (Welch, 2000). During this reorganization of the labour market women gained access to affordable contraceptives, which granted women greater control over fertility decisions and reduced the costs of long-term investments in human capital (Goldin and Katz, 2000). Remarkable improvements in the economic well-being of women (particularly single women) and the overall prospects for high-wage employment increased the bargaining power of women in the home (Costa, 2000).

The female labour force participation rate and the decline in the manufacturing sector can be seen as proxy measures of rapid socio-economic change which drastically altered the composition of the American family and redefined the division of labour between the sexes.[11] We hypothesize that female labour force participation should be positively related to property crime because increases in the female workforce have decreased the relative earnings of men (Katz and Murphy, 1992). A decline in the manufacturing sector should make it more difficult for males with low levels of human capital to obtain high-

[10] See FIGURE 2.

[11] Witt and Witte (2000) also use the female labor force participation rate as a proxy measure of social change in a model of the aggregate crime rate.

wage jobs (Wilson, 1987; Katz and Murphy, 1992). As a result, we expect manufacturing employment to be negatively related to property crime.

Because the crime rates we examine differ in their degrees of violence and audacity, we might expect to find anomalies with respect to female labor force participation and employment in the manufacturing sector. However, we expect the effects of inflation and unemployment to be consistent across different property crime rates. The economic return to property crime and, as a result, the aggregate rate of property crime should be greater during periods of high unemployment. Inflation should also generate a positive response of property crime because the relative purchasing power of money is diminished and individuals have additional incentive to bypass the licit terms of trade.

III. DATA

We use data on the unemployment rate, inflation rate, percentage of manufacturing employment relative to total employment, and female labour force participation rate as predictors of various property crime rates. All data series span from 1959 to 2005, giving 47 total years of data. Data on property crime rates are collected from the Uniform Crime Report (UCR), and are represented by three different headings: (*i*) larceny, (*ii*) burglary, and (*iii*) robbery (which is classified as a violent crime, but has a property component).[12]

[12] Levitt (2001) criticises the use of national-level crime data to examine the unemployment/crime relationship, because there is local variation in both crime rates and unemployment rates that could be exploited. Levitt (2001, pp. 380) states that criminological explanations for the unemployment/crime relationship found in aggregate national crime data are at best "subtle predictions." Although inflation is calculated at the regional-level and at the local-level for a select number of large cities, the most accurate measure of inflation is at the national-level (See the Bureau of Labor Statistics, http://www.bls.gov/cpi/.). As a result, investigating the role of inflation in an economic model of crime should use national-level crime data.

Begun in 1929, the UCR is a national record of crimes reported to state and local law enforcement agencies in the United States. While homicide is the most accurately measured, all other crimes in the UCR suffer from underreporting bias (DiIulio, 1996). While the UCR has its limitations, no other time series with as many observations of aggregate crime rates is available.[13] The sample period we study captures the dramatic upsurge in crime during the 1960s and 1970s, along with the rapid decrease of the 1990s.

TABLE 1 displays variable names, definitions, and data sources. TABLE 2 presents summary statistics. We employ a test for stationarity to determine if any of the data series follow a unit root.[14] The test statistics with and without a trend are presented in TABLE 3. The variables *unrt* and *infl* appear stationary. However, the variables *manu* and *flfpr* appear non-stationary and enter the model in first differenced form. As a result, all explanatory variables are stationary.

IV. ECONOMETRIC METHODOLOGY

We use a structural time-series framework to analyse property crime rates.[15] Harvey (1989, 1997) and Koopman et al. (1995) advocate the use of structural time series, especially when there is a clear trend in the series. Since all dependent variables are non-stationary, it is necessary to include a trend for each in order to avoid spurious results. Because a deterministic time trend is too restrictive for most time series data, allowing

[13] The long time-span of the UCR accounts its popularity in the crime literature. The second longest running aggregate crime record is the National Crime Victimization Survey (NCVS) annually conducted since 1973 by the Bureau of Justice Statistics (BJS).

[14] We test all variables, excluding various property crime rates for stationarity, employing the test outlined by Kwiatkowski et al. (1992).

[15] Structural time series is an outgrowth of the General-to-Specific empirical methodology advocated by the London School of Economics (LSE). We begin with a general model, and test the model down to a more parsimonious form. Each time a restriction is made the validity of the restriction in terms of the model are tested in order to find the best statistical fit for the data generating process. All models within the LSE tradition are believed to be false. Therefore, the objective is to find a statistically adequate and parsimonious model that outperforms all other known models.

the slope and level components to vary over time is the preferred specification (Harvey, 1997). The general form of the structural time-series model can be written as

$$y_t = \mu_t + \sum_i \sum_j \alpha_{ij}\, x_{i,t-j} + \varepsilon_t \qquad for\ t = 1, 2, ., T . \tag{1}$$

The term y_t is the dependent variable; μ_t is a time-varying intercept term; $x_{i,t-j}$ is regressor i subject to time lag j; α_{ij} represents the coefficient associated with variable $x_{i,t-j}$; and ε_t is a zero mean constant variance disturbance term. The term μ_t enables the researcher to capture unobservable influences that drive the dependent variable.[16] The μ_t process takes the form

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \qquad \eta \sim NID\left(0, \sigma_\eta^2\right) \tag{2}$$

$$\beta_t = \beta_{t-1} + \xi_t \qquad \xi \sim NID\left(0, \sigma_\xi^2\right). \tag{3}$$

μ_t is interpreted as the "level component" of a stochastic trend. β_t represents the drift parameter, which is the "slope" of the level component. The level component is assumed to follow a random walk with drift and the slope component is assumed to follow a random walk. Both level and slope components have white noise disturbances represented by η_t and ξ_t, respectively. The white noise disturbances η_t and ξ_t are assumed to be independent of each other and of ε_t. After estimation of the model's parameters a Kalman filter is applied in order to recover the state vectors, μ_t and β_t.[17]

Equations (1) through (3) present the model in its most general form. Nothing is lost by starting with a general stochastic specification because the model can be tested down to only contain a fixed level, a fixed slope, and/or some combination of both. For

[16] Since criminal deterrence is largely unobservable and has no ideal proxies, μ_t should capture criminal deterrence efforts.

[17] All models are estimated using the program Structural Time Series Analyser, Modeller, and Predictor 6.30 (STAMP). STAMP has a built-in procedure for the Kalman filter.

example, if the model has a fixed level and stochastic slope, the level and slope components take the following form

$$\mu_t = \mu_{t-1} + \beta_{t-1} \tag{4}$$

$$\beta_t = \beta_{t-1} + \xi_t \qquad \xi \sim NID\left(0, \sigma_\xi^2\right). \tag{5}$$

With this specification, the component μ_t is fixed (or constant) when $\sigma_\eta^2 = 0$. Equation (5) implies that the slope component, β_t, remains unchanged. This specification is also referred to as a "smooth trend."[18] A smooth trend model implies the dependent variable is $I(2)$.

As noted earlier, three different types of property crimes are investigated. Numerous models are estimated for each of the dependent variables. The models' respective components and parameters are tested using standard methods outlined in Harvey (1989).

Previous studies that analyse aggregate crime rates use a variety of econometric techniques: (*i*) ordinary least squares (OLS), (*ii*) vector autoregressions (VARs), and (*iii*) cointegration. In what follows, we discuss each of these empirical methodologies and how the structural time- series approach addresses potential problems associated with these techniques.

Visual inspection of a plot of crime rates over time suggests the presence of a trend.[19] As a result, estimating crime rates with OLS can produce spurious results, unexplainable

[18] If the variances of the disturbance terms in both the level and slope components are zero (i.e. σ_η^2 = σ_ξ^2 = 0), then the structural time-series model collapses to a deterministic trend model (Harvey, 1997). However, when the unobserved component is constant (i.e. $\beta_t = \sigma_\eta^2$ = 0), the structural time-series model collapses to an OLS specification.

[19] See Figure 1.

lags on the variables, and residual series that indicate a misspecification.[20] Cantor and Land's (1985) seminal paper, from the sociology literature, examining the effects of unemployment on aggregate crime rates has come under criticism because of the paper's empirical technique, which is an OLS model in first differenced form (Greenberg, 2001a, 2001b; Britt, 2001; O'Brien, 2001). The most notable problem with differencing is that the trend in the series is eliminated, and emphasis is on changes from period to period. To warrant elimination of the trend, the researcher must assume the short-run dynamics are theoretically different from the long-run dynamics in the estimation (Harvey, 1997).[21] One other problem with estimating the effect of changes in the unemployment rate on changes in the crime rate is that the variables may be of different order.[22] In response to Cantor and Land (1985), a number of alternative estimation techniques are used to investigate the relationship between crime and unemployment in the short-run and long-run.

VARs are reduced-form models, where all variables are considered jointly endogenous (Enders, 2004). Corman et al. (1987) use a VAR approach to estimate the interrelationship between the supply of crime in New York City and variables meant to capture changes in the business cycle, demographic composition, and criminal deterrence. While VARs are useful for uncovering dynamic relationships (i.e. crime and criminal deterrence) without imposing ad hoc identification restrictions, VARs are not a

[20] If the model takes the smooth trend specification, the dependent variable would need to be differenced twice in order to make it stationary. Failure to do so can result in spurious estimates. This applies to other specifications as well, not only OLS.

[21] Detrending implicitly assumes that the variable follows a stochastic trend without corroborating evidence.

[22] If the crime rate is an $I(1)$ variable, differencing the crime rate would make it an $I(0)$ variable. Assuming also that the unemployment rate is stationary over time, differencing the unemployment rate, as in Cantor and Land (1985), would result in an $I(-1)$ variable. Such improper ordering of the variables could result in spurious results.

substitute for structural modeling where more clearly defined causal relationships can be determined (Corman et al., 1987). VARs make restrictive assumptions requiring the number of lags to be limited, the number of lag lengths to be the same for all variables, and that no structural breaks occur during the sample period (Corman et al., 1987). VARs also require strong assumptions regarding the ordering of the equations in the system to identify impulse response functions (Enders, 2004).[23]

Greenberg (2001a, 2001b) advocates using cointegration techniques to identify the long-run relationship between the unemployment rate and the crime rate. One well-known problem with cointegration analysis is its sensitivity to structural change over time. As a consequence, the absence of cointegration between variables does not necessarily imply that they are truly unrelated. This problem may arise in the case of Greenberg (2001a, 2001b). Greenberg interprets the lack of a cointegrating relationship to mean there is no stable long-run relationship between the unemployment rate and crime rates.

When compared with other empirical strategies previously mentioned, structural time-series models have several advantages. They (*i*) model the trend in the data for property crime rates as an unobserved component, (*ii*) allow for trend changes through time-varying parameters, and they (*iii*) attribute omitted right-hand side variables to the

[23] As Harvey (1997) notes, VARs become more meaningful when altered in a way that allows for detection of long-run relationships. One example is the vector error correction model (VECM), which allows for one to test for the number of cointegrating vectors by employing the Johansen (1988) test. Harvey (1997) also suggests that VAR-based cointegration techniques have poor statistical properties and problems arise when one relies on unit-root tests to determine the order of integration in a series. The use of unit-root tests may result in one concluding that a series is $I(1)$ when in fact it is $I(2)$.

unobserved component.[24] Also, the unobserved component methodology does not rely on unit root tests to specify the dependent variable.[25]

Naturally, one would prefer to have a model with no unobserved component, as this model would completely capture the data generating process. However, in some (if not most) cases, the elimination of an unobserved component may not be possible or desirable because of data limitations. An unobserved component can also provide insight with respect to the underlying developments not explained by included explanatory variables.

V. RESULTS

Each of the property crime rates are estimated with identical right-hand side variables and an equal number of lags for each. First, all models are estimated with a stochastic slope and level. These general models are tested down to a more parsimonious form. The variance of the disturbance in the level component for both larceny and burglary rates is zero. Therefore, the unobserved component for larceny and burglary rates takes the form of equations (4) and (5). This is not the case for the robbery rate, which takes the general stochastic form shown in equations (2) and (3).

The model results for larceny, burglary, and robbery rates are presented in TABLES 4, 5, and 6, respectively. Tests are employed to check for non-normality, higher-order

[24] This allows for consistent estimation of the model's parameters.

[25] Most unit root tests rely on autoregressive models which may have poor statistical properties (Harvey, 1997). Harvey and Jaeger (1993) show that unit root tests are unlikely to detect integration of order two in a time series.

autocorrelation, heteroskedasticity, and the models' out-of-sample performance. We rely on the out-of-sample forecasting properties to justify any further parameter restrictions.[26]

The models for the larceny rate do not indicate statistical adequacy problems. There are statistical adequacy problems detected in the estimation of both burglary and robbery rates. The model for the burglary rate appears to have a problem with higher-order autocorrelation, as indicated by the Box-Ljung statistic provided in Model 2 of TABLE 5. Inspection of the residual series indicates a large value for one observation, the year 1977. To correct for autocorrelation, an observation-specific dummy variable is included for the year 1977. The robbery rate has a non-normality problem (see TABLE 6). The residual series indicates large values for the years 1986 and 1987. To address the non-normality problem, we include observation-specific dummy variables for the years 1986 and 1987.

The residual graphics for the final models of the property crime rates are displayed in FIGURES 3, 4, and 5. As indicated by the residual graphics, the models fit the data relatively well. FIGURES 6, 7, and 8 display the remaining slope and level components of larceny, burglary, and robbery rates not explained by the included explanatory variables. The remaining components imply that the included explanatory variables alone do not fully capture the data generating process for the various property crime rates. A large portion of the remaining trend components may be attributable to criminal deterrence efforts.

Consistent with our theory, inflation is statistically significant, positive, and persistent for all property crime rates considered. The change in manufacturing

[26] More detail regarding the statistical adequacy tests are presented in the *Notes* section at the bottom of TABLES 4, 5, and 6.

employment is statistically significant and negative for all property crime rates, which is also consistent with our hypotheses. There are results unsupported by the theory of this paper. The model results for burglary indicate female labour force participation has no statistically significant effect. A possible explanation is that burglary requires a greater investment of criminal human capital than other crimes, which makes it less sensitive to long-run demographic changes. For the robbery rate, unemployment is statistically insignificant, and the female labour force participation rate is statistically significant but has a negative coefficient. Robbery is a violent crime. As a result, an increase or decrease of the robbery rate may be more a response to institutional change than a response to temporary shocks in the labor market. The negative sign of female labor force participation in the model for robbery could be attributable to the rising affluence of women, corresponding to the increase in female labour force participation. Robbery is most common in less affluent neighborhoods (E. Anderson, 1999). As women become more prosperous they are able to afford additional security measures (e.g., living in safer neighborhoods).

We find that the unemployment rate does not provide consistent predictive power across property crime rates. However, the percentage of total employment in the manufacturing sector is a reliable predictor of property crime rates. As TABLE 7 reveals, the long-run effect of manufacturing employment is greater than all other explanatory variables. TABLE 7 also shows inflation has a greater long-run effect than that of unemployment.

VI. CONCLUSIONS

Unobserved component models of various property crime rates are constructed using annual data for the unemployment rate, inflation rate, percentage of total employment in the manufacturing sector, and the female labour force participation rate. Structural time series is the preferred empirical specification, as it models the trend in the dependent variable as an unobserved component.

Because trend components remain in each model we estimate, the included explanatory variables do not completely capture the data generating process. The theoretical relevance of deterrence efforts would suggest a large portion of the remaining trends could be attributable to these measures. However, our focus is the impact of inflation and other labour market dynamics on property crime. Hence, the inclusion of a stochastic trend, which captures unobservable and omitted variables, provides an attractive alternative to obtain consistent estimates for these covariates.

The unemployment rate does not appear to play a consistent and significant role in the determination of property crime rates. The variables used to proxy for the dramatic change in the U.S. labour market, particularly the decline in manufacturing employment, have considerable explanatory power with respect to property crime. The sizeable long-run effects of manufacturing employment suggest that larger additions of human capital investment, particularly for low-income males, could greatly reduce property crime. Public policies that encourage human capital accumulation could decrease the economic incentive to commit property crime through increases in earnings potential in the service economy.

Our results are robust with respect to inflation; inflation is positive, statistically significant, and persistent for all property crime rates considered. Both the short-run and long-run effects of inflation on property crime rates are considerable. Thus, a monetary policy regime meant to stabilize prices may indirectly reduce property crime.

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TABLE 1
VARIABLE NAMES AND VARIABLE DEFINITIONS

Variable	Variable Definition
burglary	Burglary rate of the population per 100,000
larceny	Larceny rate of the population per 100,000
robbery	Robbery rate of the population per 100,000
unrt	Percentage of workforce who is unemployed but is actively pursuing employment
manu	Ratio of manufacturing to total payroll employment
infl	Log of the ratio of the Consumer Price Index (CPI) at time *t* relative to the log of the CPI at time *t*-1
flfpr	Percentage of females participating in the workforce

Notes: All property crime rates come from the FBI's Uniformed Crime Report. The other variables all come from the Bureau of Labor Statistics (BLS).

TABLE 2
SUMMARY STATISTICS

Variable	Mean	Std. Deviation	Minimum	Maximum
burglary	1.0522	0.3369	0.4881	1.6841
larceny	2.4380	0.6917	1.0347	3.2288
robbery	0.1745	0.0636	0.0583	0.2727
unrt	5.8901	1.4169	3.4917	9.7083
infl	4.2122	3.0103	0.6710	13.2550
manu	19.9642	5.6833	10.6657	28.7141
flfpr	50.7222	8.0622	37.1333	60.0417

Note: All data relate to United States for the years 1959 to 2005 (obs. = 47).

TABLE 3
TEST FOR STATIONARITY

Variable	**KPSS Test**	
	Trend {H0 = *I*(0)}	**No-trend {H0 = *I*(0)}**
unrt	0.1641	0.1699
infl	0.1896	0.2115
manu	0.1002	1.0425*
flfpr	0.2278	1.0066*

Notes: * indicates significance at the one percent level. Details of the KPSS test are outlined in Kwiatkowski et al. (1992). The KPSS uses stationarity as the null and tests against the alternate hypothesis of a unit root. We do not test the property crime rates for stationarity because of our modeling approach. Structural time series models allow for a unit root process to be present in the dependent variable.

TABLE 4
MODEL RESULTS FOR THE LARCENY RATE

Variable	Model 1 coeff.	Model 1 p-val.	Model 2 coeff.	Model 2 p-val.
μ	1.3091	0.000	1.4247	0.000
β_t (for last year)	-0.0420	0.055	-0.0448	0.043
$larceny_{t-1}$	0.7430	0.000	0.6601	0.000
$larceny_{t-2}$	-0.4118	0.000	-0.3922	0.000
$infl_t$	0.0119	0.029	0.0121	0.009
$infl_{t-1}$	0.0257	0.000	0.0279	0.000
$infl_{t-2}$	-0.0028	0.710		
$unrt_t$	0.0041	0.749		
$unrt_{t-1}$	0.0247	0.089	0.0256	0.028
$unrt_{t-2}$	-0.0039	0.773		
$\Delta\ manu_t$	-0.0570	0.014	-0.0685	0.001
$\Delta\ manu_{t-1}$	0.0254	0.322		
$\Delta\ flfpr_t$	0.0431	0.133	0.0480	0.041
$\Delta\ flfpr_{t-1}$	0.0805	0.003	0.0819	0.001
R^2	0.9946		0.9944	
AIC	5.4489		5.5937	
SIC	4.8467		5.1521	
Heterosk. $F(14,14)$	1.1751		1.4821	
Cusum $t(6)$	0.4432		0.5228	
Cusum $t(10)$	-1.1168		-1.0267	
p-values:				
Normality $\chi^2(2)$	0.9540		0.9849	
Box-Ljung $\chi^2(6)$	0.3750		0.4448	
Forecast $\chi^2(6)$	0.9257		0.8965	
Forecast $\chi^2(10)$	0.7880		0.7318	

Notes: There are 43 observations for all models. AIC represents the Akaike Information Criterion developed by Akaike (1974). SIC is the Schwarz Information Criterion. The SIC is sometimes referred to the Bayesian Information Criterion (BIC). Heterosk. is a test for heteroskedasticity, which has homoskedasticity as the null. The Heteroskedasticity test is the ratio of the squares of the last h residuals to the first h residuals (See Koopman et al., 2000). The critical value for the Heterosk. at the five percent level is 2.48. The Doornik and Hansen (1994) test is employed to check for normality; normality is the null hypothesis. The test Box-Ljung represents the Ljung and Box (1978) test for higher-order autocorrelation, which has a null of no-autocorrelation. The test Forecast $\chi^2(h)$ are one-step-ahead predictive tests h observations into the future. Cusum $t(h)$ are one-step-ahead predictive tests h observations into the future for the residuals. Model 1 represents the general specification of the model. Subsequent models successively restrict parameter values, while checking the validity of each set of restrictions with the statistics mentioned above.

TABLE 5
MODEL RESULTS FOR THE BURGLARY RATE

Variable	Model 1 coeff.	Model 1 p-val.	Model 2 coeff.	Model 2 p-val.	Model 3 coeff.	Model 3 p-val.
μ	0.2919	0.001	0.3188	0.000	0.3784	0.000
β_t (for last year)	-0.0106	0.364	-0.0103	0.355	-0.0098	0.393
$burglarly_{t-1}$	0.7877	0.000	0.7772	0.000	0.7489	0.000
$burglarly_{t-2}$	-0.4302	0.000	-0.4062	0.000	-0.4727	0.000
$infl_t$	0.0107	0.002	0.0102	0.002	0.0110	0.000
$infl_{t-1}$	0.0138	0.001	0.0135	0.000	0.0141	0.000
$infl_{t-2}$	-0.0080	0.115	-0.0094	0.039	-0.0077	0.061
$unrt_t$	0.0133	0.096	0.0140	0.039	0.0145	0.021
$unrt_{t-1}$	-0.0016	0.864				
$unrt_{t-2}$	0.0071	0.419				
$\Delta\ manu_t$	-0.0226	0.098	-0.0192	0.102	-0.0233	0.029
$\Delta\ manu_{t-1}$	-0.0144	0.286				
$\Delta\ flfpr_t$	-0.0084	0.647				
$\Delta\ flfpr_{t-1}$	0.0179	0.247				
D_1977					0.0769	0.004
R^2	0.9920		0.9912		0.9929	
AIC	6.4510		6.5696		6.7459	
SIC	5.8488		6.1681		6.3042	
Heterosk. F(14,14)	0.8479		0.9702		0.8535	
Cusum $t(6)$	1.2531		1.3437		1.5450	
Cusum $t(10)$	0.6978		0.7110		0.8221	
p-values:						
Normality $\chi^2(2)$	0.6530		0.4813		0.4679	
Box-Ljung $\chi^2(6)$	0.0971		0.0149*		0.3743	
Forecast $\chi^2(6)$	0.8158		0.8051		0.7330	
Forecast $\chi^2(10)$	0.8605		0.7852		0.6187	

Notes: There are 43 observations for all models. AIC represents the Akaike Information Criterion developed by Akaike (1974). SIC is the Schwarz Information Criterion. The SIC is sometimes referred to the Bayesian Information Criterion (BIC). Heterosk. is a test for heteroskedasticity, which has homoskedasticity as the null. The Heteroskedasticity test is the ratio of the squares of the last *h* residuals to the first *h* residuals (See Koopman et al., 2000). The critical value for the Heterosk. at the five percent level is 2.48. The Doornik and Hansen (1994) test is employed to check for normality; normality is the null hypothesis. The test Box-Ljung represents the Ljung and Box (1978) test for higher-order autocorrelation, which has a null of no-autocorrelation. The test Forecast $\chi^2(h)$ are one-step-ahead predictive tests *h* observations into the future. Cusum $t(h)$ are one-step-ahead predictive tests *h* observations into the future for the residuals. Model 1 represents the general specification of the model. Subsequent models successively restrict parameter values, while checking the validity of each set of restrictions with the statistics mentioned above.

TABLE 6
MODEL RESULTS FOR THE ROBBERY RATE

Variable	Model 1 coeff.	Model 1 p-val.	Model 2 coeff.	Model 2 p-val.	Model 3 coeff.	Model 3 p-val.	Model 4 coeff.	Model 4 p-val.
μ_t (for last year)	0.0632	0.002	0.0624	0.001	0.0565	0.001	0.0598	0.000
β_t (for last year)	-0.0010	0.751	0.0019	0.608	0.0016	0.731	0.0017	0.715
$robbery_{t-1}$	0.6824	0.000	0.7278	0.000	0.4656	0.000	0.4405	0.000
$robbery_{t-2}$	-0.0424	0.762	-0.0895	0.387				
$infl_t$	0.0010	0.178	0.0017	0.004	0.0019	0.000	0.0019	0.000
$infl_{t-1}$	0.0036	0.000	0.0029	0.000	0.0039	0.000	0.0039	0.000
$infl_{t-2}$	-0.0017	0.088	-0.0147	0.073	-0.0002	0.805		
$unrt_t$	-0.0007	0.727	-0.0003	0.837				
$unrt_{t-1}$	-0.0014	0.429	-0.0020	0.172				
$unrt_{t-2}$	-0.0018	0.324	-0.0015	0.345				
$\Delta\ manu_t$	-0.0422	0.140	-0.0033	0.096	-0.0039	0.037	-0.0038	0.032
$\Delta\ manu_{t-1}$	-0.0446	0.114	-0.0033	0.102	-0.0042	0.024	-0.0043	0.021
$\Delta\ flfpr_t$	-0.0046	0.193	-0.0069	0.009	-0.0063	0.003	-0.0062	0.003
$\Delta\ flfpr_{t-1}$	0.0028	0.435	0.0016	0.560				
D_1986			0.0081	0.223				
D_1987			-0.0192	0.067	-0.0249	0.000	-0.0245	0.000
R^2	0.9895		0.9943		0.9922		0.9922	
AIC	9.5010		10.007		9.9682		10.014	
SIC	8.8586		9.2838		9.4864		9.5721	
Heterosk. F(14,14)	1.9092		1.8447		1.4491		1.4545	
Cusum $t(6)$	1.6079		1.6324		1.1143		1.1384	
Cusum $t(10)$	0.0065		1.0167		0.9637		0.9996	
p-values:								
Normality $\chi^2(2)$	0.0433*		0.1089		0.6909		0.6758	
Box-Ljung $\chi^2(6)$	0.7856		0.1079		0.3395		0.3362	
Forecast $\chi^2(6)$	0.6069		0.1822		0.2169		0.5650	
Forecast $\chi^2(10)$	0.7993		0.4081		0.5384		0.8231	

Notes: There are 43 observations for all models. AIC represents the Akaike Information Criterion developed by Akaike (1974). SIC is the Schwarz Information Criterion. The SIC is sometimes referred to the Bayesian Information Criterion (BIC). Heterosk. is a test for heteroskedasticity, which has homoskedasticity as the null. The Heteroskedasticity test is the ratio of the squares of the last *h* residuals to the first *h* residuals (See Koopman et al., 2000). The critical value for the Heterosk. at the five percent level is 2.48. The Doornik and Hansen (1994) test is employed to check for normality; normality is the null hypothesis. The test Box-Ljung represents the Ljung and Box (1978) test for higher-order autocorrelation, which has a null of no-autocorrelation. The test Forecast $\chi^2(h)$ are one-step-ahead predictive tests *h* observations into the future. Cusum $t(h)$ are one-step-ahead predictive tests *h* observations into the future for the residuals. Model 1 represents the general specification of the model. Subsequent models successively restrict parameter values, while checking the validity of each set of restrictions with the statistics mentioned above.

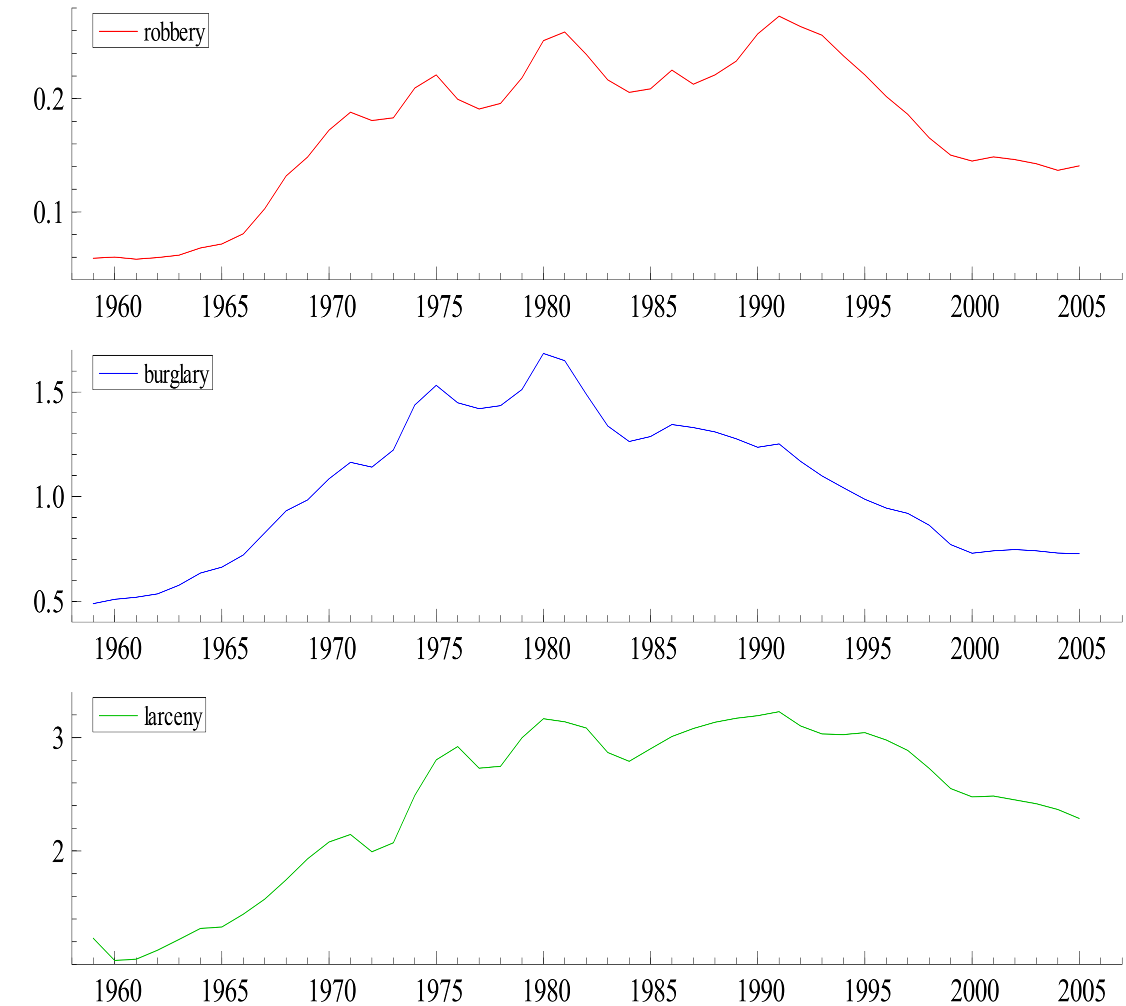
TABLE 7

LONG-RUN MULTIPLIERS FOR PROPERTY CRIME RATES

Variable	Larceny	Burglary	Robbery
infl	0.0544	0.0240	0.0104
unrt	0.0350	0.0200	
Δ *manu*	-0.0936	-0.0322	-0.0145
Δ *flfpr*	0.1774		-0.0111

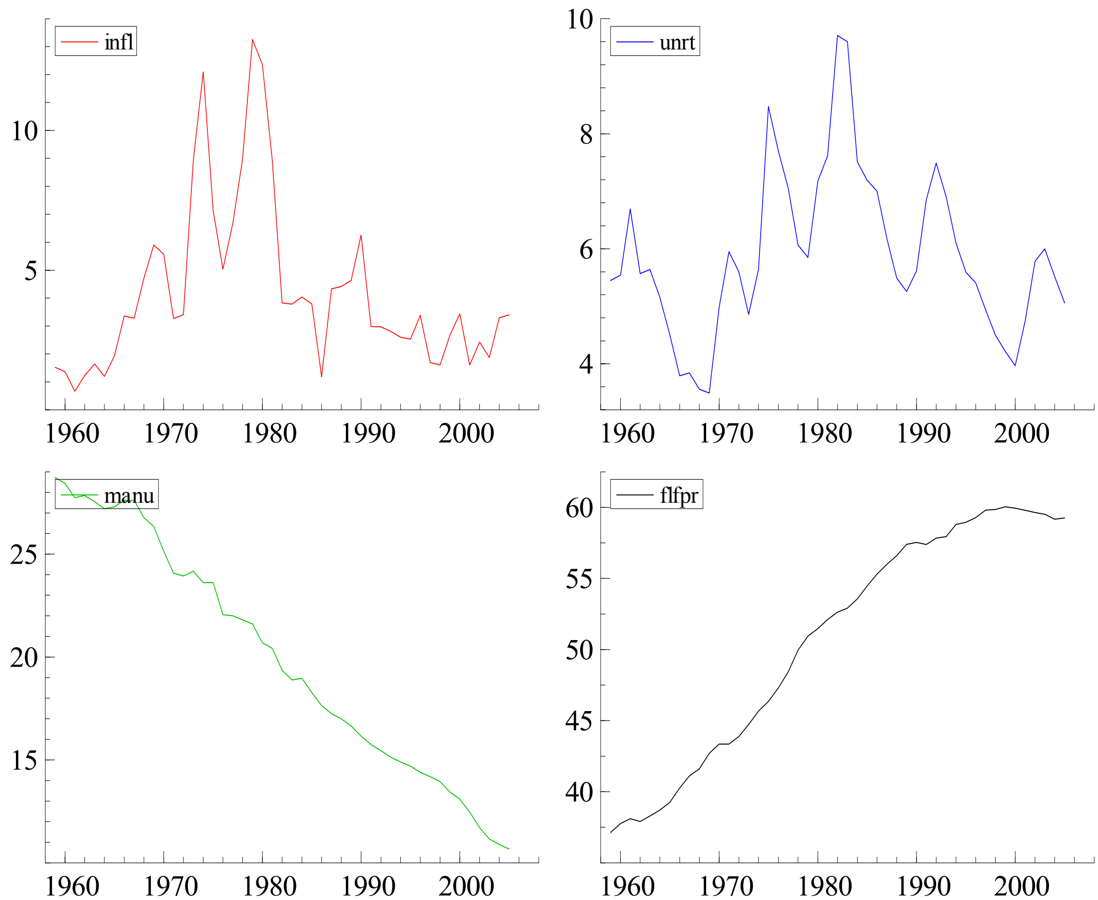
Notes: Long-run multipliers are calculated by dropping the time subscripts in each of the final models and solving for the dependent variable. Note that some of the long-run multipliers are equal to the impact multipliers. Recall that the variable *unrt* is not significant in the estimates for robbery and Δ *flfpr* is not significant in the estimation of the burglary rate.

FIGURE 1: PLOTS OF THE ROBBERY, BURGLARY, AND LARCENY RATES OVER TIME



Note: The *y-axis* measures the various property crime rates per 100,000 persons.

FIGURE 2: THE INFLATION RATE, UNEMPLOYMENT RATE, RATIO OF MANUFACTURING EMPLOYMENT TO TOTALEMPLOYMENT, AND FEMALE LABOR FORCEPARTICIPATION RATE OVER TIME



Note: The upper-left graph shows the inflation rate and the upper-right graph shows the unemployment rate over time. The bottom-left graph shows the decline in manufacturing employment and lower-right graph shows the increase in female labour force participation over time. The *y-axes* measure the rate of the explanatory variable; the *y-axis* for the variable *manu* is in percentage form.

FIGURE 3: RESIDUAL GRAPHICS FOR THE LARCENY RATE

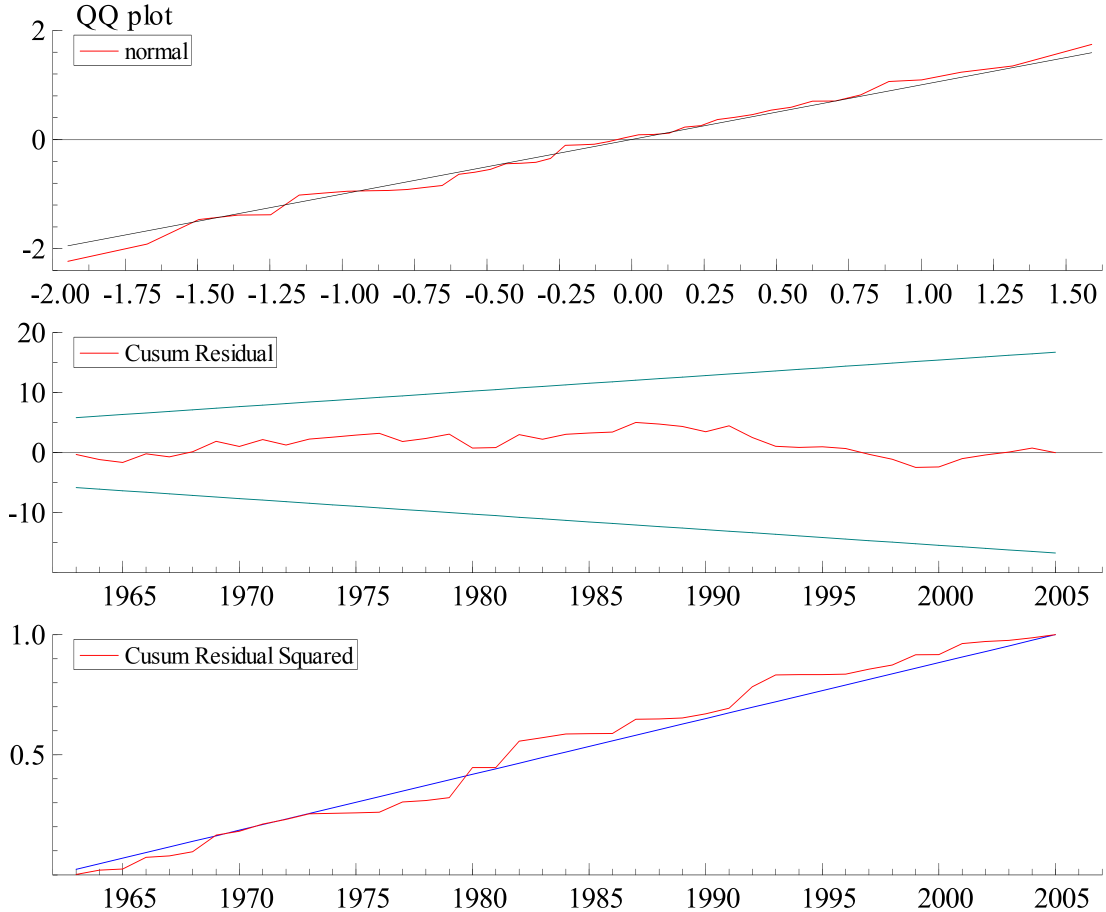


FIGURE 4: RESIDUAL GRAPHICS FOR THE BURGLARY RATE

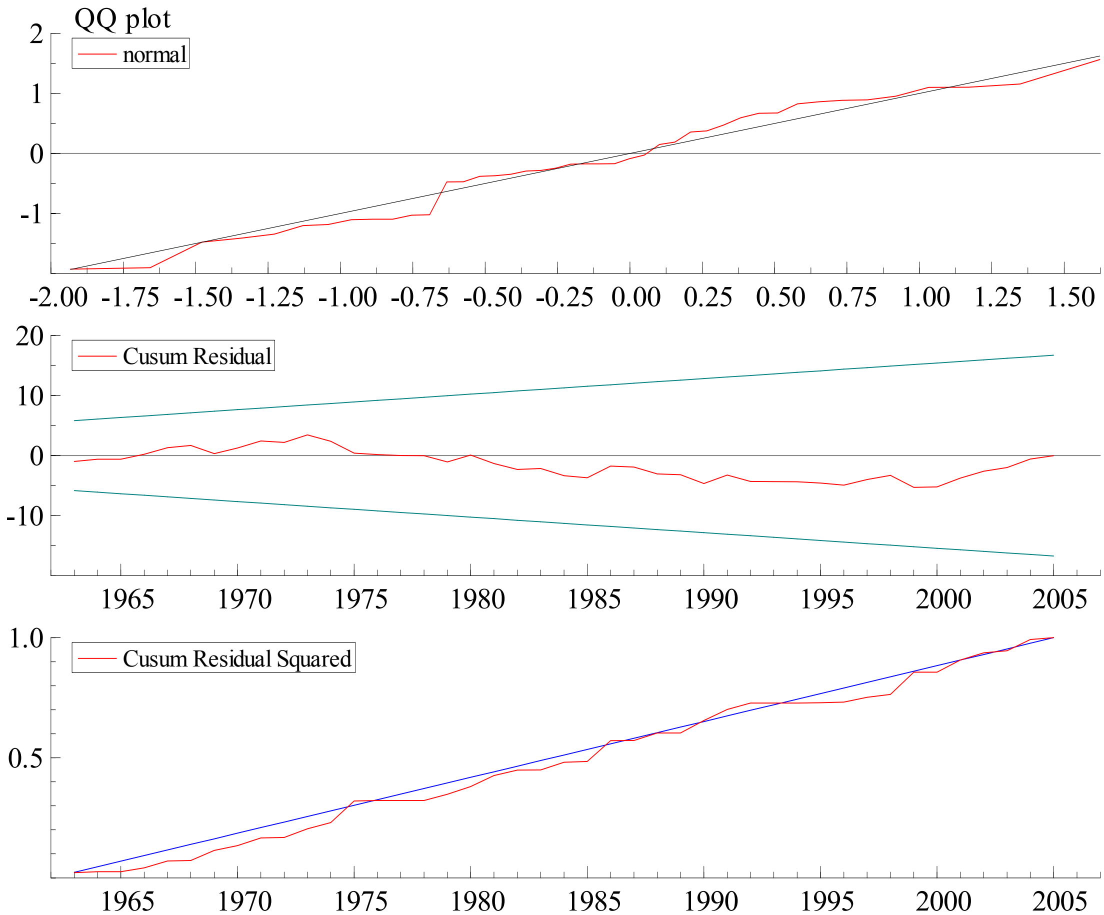


FIGURE 5: RESIDUAL GRAPHICS FOR THE ROBBERY RATE

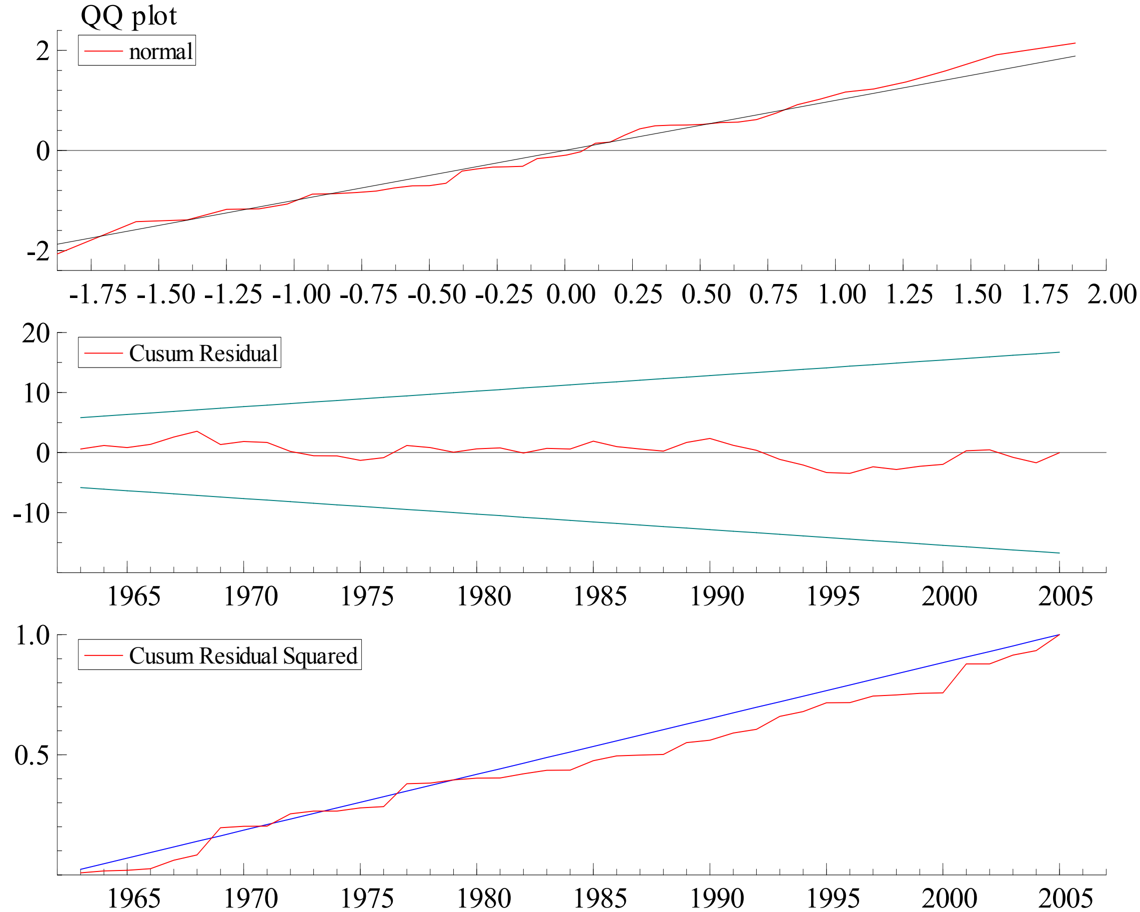
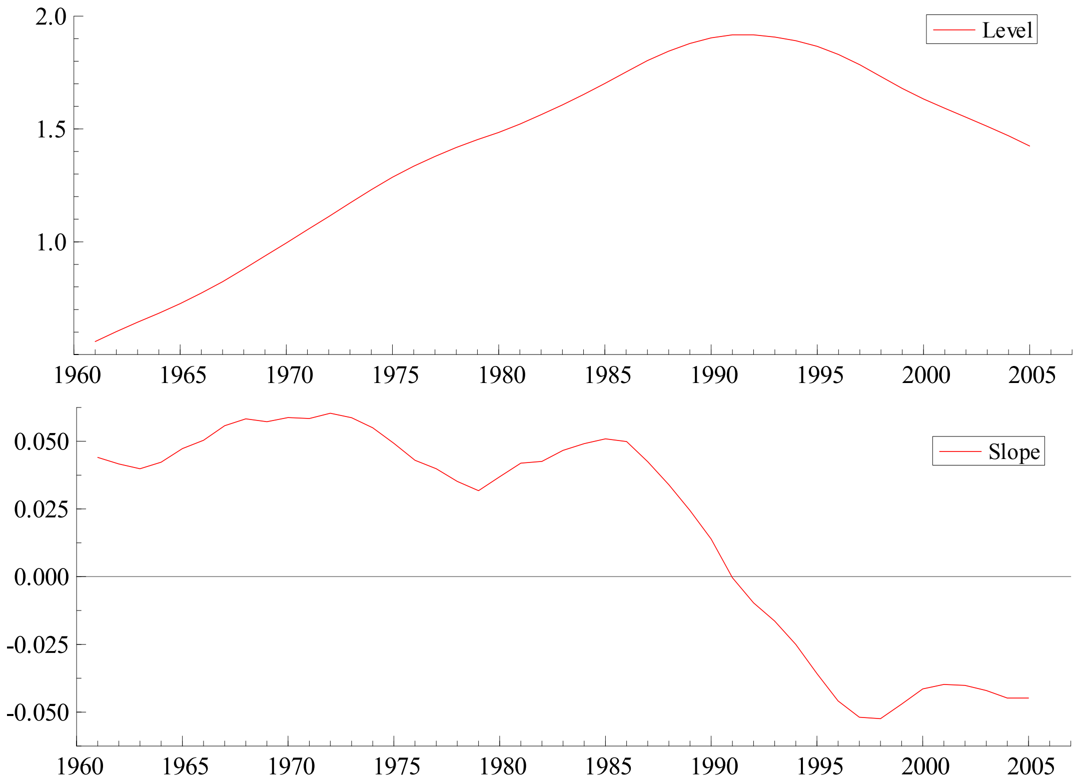
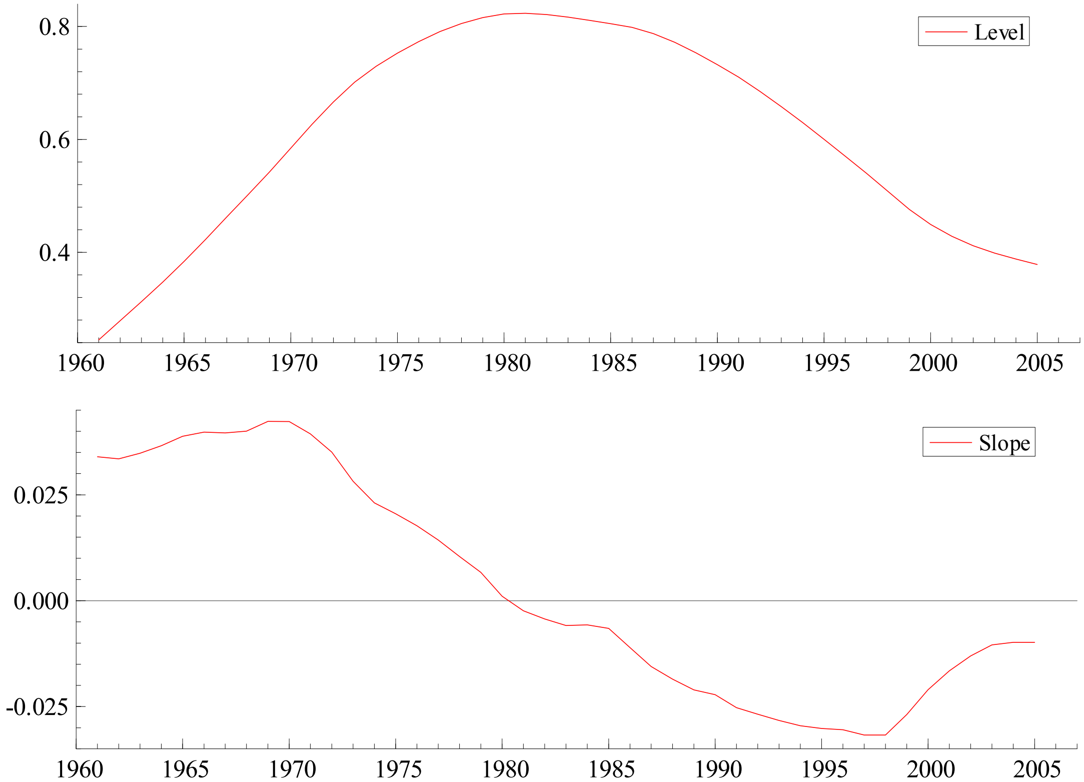


FIGURE 6: REMAINING COMPONENTS OF THE LARCENY RATE



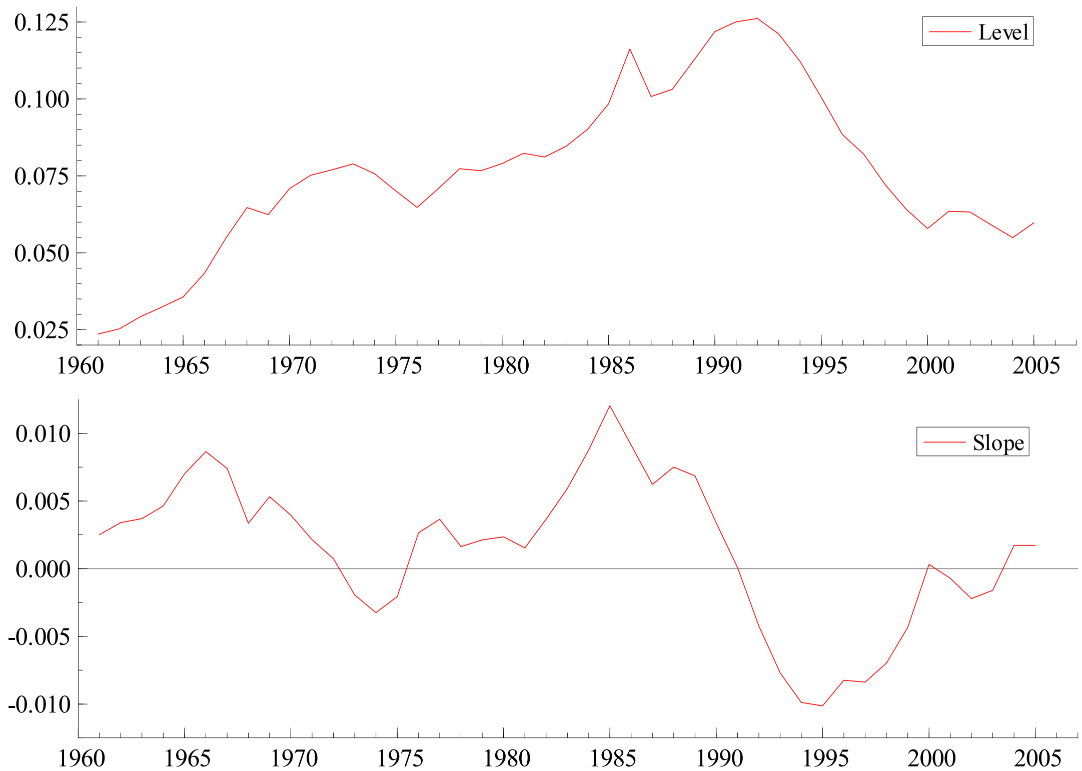
Note: The y-axis for both graphs represents the larceny rate per 100,000 persons. The upper graph is the remainder of the level component and the lower graph is the remaining portion of the slope.

FIGURE 7: REMAINING COMPONENTS OF THE BURGLARY RATE



Note: The y-axis for both graphs represents the burglary rate per 100,000 persons. The upper graph is the remainder of the level component and the lower graph is the remaining portion of the slope.

FIGURE 8: REMAINING COMPONENTS OF THE ROBBERY RATE



Note: The y-axis for both graphs represents the robbery rate per 100,000 persons. The upper graph is the remainder of the level component and the lower graph is the remaining portion of the slope.