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THE IMPACT OF MACROECONOMIC CONDITIONS ON PROPERTY CRIME

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Abstract: This paper examines the impact of inflation, (un)employment, and stock market growth on the rates of larceny, burglary, motor vehicle theft, and robbery. The study uses U.S. data for the time period 1948 to 2009. We employ an unobserved component approach to circumvent the problems associated with omitted variables. We find that the three macroeconomic variables have a statistically significant impact for most of the property crime rates. However, taken together the macroeconomic variables explain no more than 15 percent of the surge in property crimes from the 1960 to the 1980s and their subsequent fall during the 1990s. Among the macroeconomic variables, almost all of the explanatory power is provided by changes in the inflation rate.

Key words: property crime, inflation, manufacturing employment, stock market growth.

JEL Categories: J10, J11

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1. Introduction

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 and crime (e.g., Cantor and Land, 1985; Greenberg, 2001a, 2001b). As a result, the literature largely neglects the role of inflation as a potential determinant of crime.[1] Likewise, the extent to which changing macroeconomic conditions contribute to the explanation of the "bubble-like" behavior of aggregate property crime rates over time remains unclear.

In this study, we have three goals. First, we investigate the effects of inflation on property crime rates from 1948-2009. Second, we assess how much of the variation in property crime rates can be explained by other macroeconomic variables. For this purpose, we include as additional explanatory variables the unemployment rate, an index of manufacturing employment, and the return on the stock market. Third, we identify the macroeconomic variable that has the strongest explanatory power.

A key innovation in our study is the use of an econometric methodology that circumvents a problem present in many previous studies in the economics-of-crime literature: the endogeneity of crime deterrence efforts. Simply omitting such a theoretically relevant variable from a standard regression is a problem, as it can bias the coefficient estimates of the variables of interest. The problems of omitting a deterrence variable are negligible for the methodology we employ, the unobserved component or structural time series modeling approach advocated by

[1] Devine et al. (1988) and Land and Felson (1976) are notable exceptions. These studies find a positive relationship between inflation and crime. A key limitation of these studies is their inability to examine the sharp and steady decline in crime that occurred in the early-1990s. In addition, the study by Land and Felson (1976) does not fully capture the continued run-up in crime throughout the late-1970s and 1980s.

Harvey (1989, 1997), Durbin and Koopman (2001), and Commandeur and Koopman (2007).[2] The unobserved component model (UCM) captures the influence of variables omitted by choice or necessity through a stochastic trend or some other unobserved component. By moving the effects of omitted variables, such as deterrence, out of the residual series into an unobserved, yet estimable, stochastic component, we are able to consistently estimate the effects of macroeconomic conditions on property crime rates.

We find that our three macroeconomic variables tend to be statistically significant and of the correct sign for the four types of property crime considered. Taken together the macroeconomic variables can explain, on average, approximately 15 percent of the rapid rise in property crime rates starting in the 1960s and their subsequent decline in the 1990s. Changes in the inflation rate explain the majority of the 15 percent captured collectively by all macroeconomic variables considered.

2. Macroeconomic Conditions and Property Crime

Becker's (1968) economic model of crime suggests that individuals commit crimes in response to differences in expected costs and benefits. The behavior of criminals in response to changes in the probability of apprehension, the probability of conviction, and expected severity of punishment is the traditional object of study in the economics of crime literature (Levitt 1996, 1997, 1998a, 1998b; Corman and Mocan 2000). But a significant portion of the literature is focused on studying the effects of economic conditions and earnings potential on criminal activity (Grogger 1998; Kelly 2000; Williams and Sickles 2002; Gould et al. 2002).

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

The primary macroeconomic variable considered in previous studies of aggregate crime rates is the unemployment rate. Higher unemployment rates are thought to induce a transition from legal to illegal employment, as the returns to crime are greater when unemployment is higher and job seekers are accepting lower wages.[3] Most studies report results consistent with economic theory on the effect of economic well-being on property crimes (Myers, 1983; Grogger, 1998; Kelly, 2000; Gould et al., 2002). But some studies either find the absence of an effect or even a negative effect of unemployment on crime (see Allen 1996).

Although the unemployment rate is a logical variable to include in an economic model of property crime, it suffers from three potential problems. First, unemployment varies substantially across regions, which makes it difficult to pin down its true effects using national data. Second, unemployment does not capture discouraged workers, who have ceased searching for jobs because they believe that it is a futile effort. Third, unemployment is only partially connected to the manufacturing sector, which disproportionately effects the urban poor and, as a result, has been linked to crime rates (Wilson 1987, 1996). Declining employment in the manufacturing sector more than proportionately reduces the labor market options among urban male youth, a group with a relatively high likelihood of committing crime, because high-wage jobs outside of manufacturing typically require larger amounts of human capital (Wilson, 1986, 1996). We test for the importance of changes in employment in the manufacturing sector for the property crime rate by comparing the relative explanatory power of the general unemployment rate to the Supply Management Institute's (SMI) index of employment in manufacturing.

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

[3] Grogger (1998) points out that many criminals are simultaneously employed in the legitimate sector.

a high proportion of crimes in the United States, one would expect periods of higher inflation to be concomitant with higher rates of crime, especially property 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 (See Christiano et al. 2005). One can also think of inflation as a tax that generates a dominant income effect for "labor supply" in the underground sector of the economy. Despite the potential for significant implications, most studies neglect the role of inflation as a determinant of the aggregate level of property crime.[4]

Tang and Lean (2009) examine the impact of the "misery index," which is the sum of unemployment and inflation, on crime. They find a strong positive relationship between the misery index and crime. Our study differs in that we estimate separate parameters for unemployment and inflation rate. We contend that it is important to separate the two effects for two reasons. For example, the two variables could have opposite effects on crime, thereby obscuring the true impact of either variable on crime rates. For instance, it could be that unemployment has little or no effect on crime, which would mean that the strong positive relationship found by Tang and Lean (2009) is driven primarily by inflation rather than unemployment.

In contrast to previous time-series studies on property crime rates, we also consider the impact of changes in stock market wealth. The intuition behind including this variable is to capture the impact on crime of a widening disparity in wealth that has occurred since WWII, which is primarily a result of rising stock market wealth for those participating in the stock market relative to those who are not. The latter group, whose members commit most property crimes, may develop what is known in the micro-level literature on property crime as a

[4] See footnote 1 for a list of exceptions.

"perception of relative deprivation" during periods of rising stock market wealth (Chester, 1976; Stiles et al., 2000).[5] The development of such a perception has been shown to be related to increased rates of property crime. This proposition is directly related to the theoretical literature on relative poverty as a determinant of property crime (Ehrlich 1973; Deutsch et al. 1992), which suggests that potential criminals are less driven by absolute poverty but more by poverty relative to a reference group. As relative poverty and the perception of relative deprivation increases during a stock market boom, we would expect a positive relationship between stock market gains and the rate of property crimes.

3. Data

We use annual data from 1948 to 2009 on the inflation rate, the unemployment rate, an index of manufacturing employment, and the return on the Dow Jones stock market index. We examine each of the following property crime rates: larceny, burglary, motor vehicle theft, and robbery.[6] Data on property crime rates are collected from the Uniform Crime Report (UCR). Initiated 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 crime, 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.[7] For our purposes, the sample period captures the dramatic upsurge in crime during the 1960s and

[5] Walker and Smith (2001) provide an excellent survey of the concept of relative deprivation.

[6] Robbery is classified as a violent crime, but we consider it in our analysis because it has a property component.

[7] The long time-span of the UCR accounts for its popularity in the crime literature. The second longest running aggregate crime record is the National Crime Victimization Survey (NCVS), which has been conducted annually since 1973 by the Bureau of Justice Statistics (BJS). The primary drawback of the NCVS is that it post-dates the beginning of the run-up in crime.

1970s, along with the rapid decrease during the early-1990s. It is important to note that the F.B.I. changed its crime-reporting methods in 1958. We account for this change by including an observation-specific dummy variable for this year.

Table 1 provides variable names, definitions, and data sources. Table 2 presents summary statistics of the variables used in the analysis. Figure 1 shows time-plots of the property crime rates. The time-plots of the four crime rates behave similarly over time, each resembling a bubble like series. All property crime rates rise in the 1960s, but the drop-off occurs at different times. For example, the burglary rate drops from its peak much earlier than the other series. Larceny is by far the largest crime category, as it is larger than the remaining three categories combined. If all four categories were summed to an aggregate measure of property crime, larceny would clearly dominate the results.

Because the dependent variables have some of the characteristics of a bubble series, they are well-suited for an UCM. A bubble arises when the observable fundamental driving forces cannot predict the magnitude of the upswing or downswing in the series. In our case, the "bubble" is the rapid rise in the property crime rate in the 1960s and the strong decline in the 1990s. In this study, we are interested in determining the impact on crime rates of macroeconomic influences. These are observable fundamental drivers of property crime rates. The unobserved component modeling allows us to decompose the crime rate into those observable factors and those determinants, such as crime deterrence, that we know exist but are difficult to identify theoretically or impossible to measure appropriately, especially over longer time horizons.

Time-plots for the explanatory variables are shown in Figure 2: (*i*) the inflation rate in the upper-left panel, (*ii*) the unemployment rate in the upper-right panel, (*iii*) the manufacturing employment index in the lower-left panel, and (*iv*) the return on the Dow Jones Industrial in the lower-right panel. A casual inspection of the trends in these variables does not reveal any apparent relationships between them and the property crime rates. The only exception is the inflation and unemployment rates, as these series track the changes in property crime rates reasonably well.

As a robustness check, we include a control for the share of young people in the population (i.e. 15-29 year-olds). The literature has stressed the importance of age composition as an important predictor of crime (Hirschi and Gottfredson 1983; Allen 1996). However, empirical research on the relationship between age composition and crime has produced mixed results (Levitt 1999). Levitt (1999, 2001) argues that age composition can explain a relatively small share of the variation in crime rates. However, a recent study using time-series data shows a strong positive relationship between the percentage of the population aged 15-29 years and the murder rate (Nunley et al. unpublished).

4. Econometric Methodology

The UCM decomposes each dependent variable into (a) a number of unobserved components that are required by the particular application and (b) an observed component vector that consists of the macroeconomic determinants of property crime and control variables identified in the last section:[8]

$$y_t = (\mu_t + \psi_t) + \alpha' x_t + \varepsilon_t \qquad \text{for } t = 1, 2, ..., T. \tag{1}$$

In equation (1), the parenthesis term consists of two unobserved components, a stochastic trend (μ) and a stochastic cycle (ψ). The observed components are given by the regression vector x and the associated coefficient vector α. The term ε is a zero mean constant variance disturbance term.

[8] See Harvey (1989, 1997), Durbin and Koopman (2001) and Commandeur and Koopman (2007) for more details on the UCM approach.

The key part of the unobserved component is the stochastic trend (μ), which captures the apparent non-stationarity in all four property crime rates (Figure 1).[9] The typical way to model the stochastic trend is via a layered system of two equations of the form:

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

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

The term μ follows a random walk with drift term (β), which is itself following a random walk. The stochastic trend, which is given by equations (2) and (3), is fully determined by the variances of the two stochastic terms η and ξ. These two variances are the only two estimable parameters of the stochastic trend. For the particular models we are estimating, the data allow us to further simplify the stochastic trend by setting the variance of η equal to zero. This simplification generates what is known as a smooth stochastic trend.[10] It contains only one estimable parameter, the variance of ξ.[11] Further simplifications are possible. For example, setting σ_η^2 = 0 condenses the UCM to a deterministic trend model; restricting in addition the drift term to β = 0, collapses the UCM to an ordinary-least-squares (OLS) specification with fixed constant.

The cycle component is meant to capture cyclical movements that may arise as a consequence of crime rates being closely tied to macroeconomic cycles, or other unknown recurring changes, such as deterrence efforts (Levitt 1997). The cycle component is modeled as a sine-cosine wave with an intervening disturbance term (κ) and a damping factor (ρ):

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[9] Since criminal deterrence is largely unobservable and has no good proxies, μ can be thought of as capturing these efforts, among other factors.

[10] We note that the well-known Hodrick-Prescott (HP) filter is based on a smooth stochastic trend, with the additional restriction that the variance of ξ is set equal to 1/1600.

[11] All models are estimated using Stamp 8.0 (Structural Time Series Analyzer, Modeller, and Predictor), which is based on work by Koopman et al. (2007).

$$\psi_t = \rho(cos\lambda_c\psi_{t-1} + sin\lambda_c\psi^*_{t-1}) + \kappa_t, \qquad t = 1, \ldots, T, \tag{4}$$

$$\psi^*_t = \rho(-sin\lambda_c\psi_{t-1} + cos\lambda_c\psi^*_{t-1}) + \kappa^*_t, \quad t = 1, \ldots, T. \tag{5}$$

The frequency parameter (λ_c) determines the period in years as $2\pi/\lambda_c$, and the two disturbance terms κ_t and κ^*_t are uncorrelated with mean zero and common variance.

Previous studies that analyze aggregate crime rates use a variety of econometric techniques: (*i*) OLS, (*ii*) vector autoregressions (VARs), and (*iii*) cointegration. In what follows, we briefly mention some of the problems pointed out in the literature with these approaches and how the unobserved component approach compares.

The non-stationary behavior of the crime rates over time (Figure 1) suggests that OLS can produce spurious results, unexplainable lags on the variables, and residual series that indicate a misspecification. Using instead first differences to eliminate the trend, as in Cantor and Land's (1985) seminal paper on the effects of unemployment on aggregate crime rates, removes any long-run relationship that may exist among the variables. It can also cause spurious relationships among the variables to the extent they are of different order.[12] 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.

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

[12] If the crime rate is an $I(1)$ variable, differencing the crime rate would make it an $I(0)$ variable. Assuming a right-hand side variable is stationary over time, differencing this variable would result in over-differencing and spurious estimation results.

restrictions, VARs are not a substitute for structural modeling when it comes to uncovering causal long-run relationships.[13]

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. Greenberg (2001a) fails to identify a stable long-run relationship between the unemployment rate and crime rates.

When compared to the previously employed estimation strategies, UCMs have several advantages: (*i*) the trend in the data for property crime rates is modeled through a flexible, data-driven stochastic trend that can easily follow a bubble-like form (Figure 1); (*ii*) there is no need for pretesting the integration status of the dependent variable or to first difference it;[14] and (*iii*) omitted right-hand side variables are relegated to the unobserved component(s) rather than having them appear in the residual series which could lead to biased parameter estimates.[15]

Naturally, one would prefer to have a model that fits the data well with no unobserved components. However, in this as in many other cases, appropriate observable variables may not exist for what we want to measure or, worse yet, there is no complete theory available that could even suggest the appropriate variables to include. Even within such a limited information

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[13] 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) in conjunction with cointegration tests of the Johansen (1988) type. However, 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.

[14] 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, which can result in model misspecification.

[15] This allows for consistent estimation of the parameters of interest, which are the macroeconomic variables discussed earlier.

framework, however, the use of an UCM allows us, in principle, to generate believable parameter estimates for those variables that are observable. In addition, it is sometimes possible to derive some clues from the estimated representations of the unobserved components what variables may likely be driving the unexplained portion of the trend in property crime rates. Such clues may help in identifying some additional observable variables for the statistical analysis or in making the underlying theory more precise.

5. Results

Larceny is by far the largest component of the four types of property crime we consider in this study. Hence, movements in the larceny rate dominate the aggregate property crime rate. We use the larceny rate to test a number of different specifications, including checking whether the unemployment rate or manufacturing employment better captures movements in the property crime rate.

Table 3 provides five alternative models for the larceny rate over the period 1948 to 2009. All five models use the same unobserved component specification[16] but differ in terms of the included observable variables. Model 1 uses the standard unemployment rate as a measure of job opportunity or the lack thereof. Model 2 is directly comparable to Model 1; it contains the well-known SMI employment index for the manufacturing sector in lieu of the unemployment rate. Both variables have the expected sign. However, Models 1 and 2 differ not only in their overall goodness of fit, but also in the measured impact of several independent variables and their statistical significance. Model 2 is the preferred model in terms of statistical fit. Both coefficients of determination, the one around the trend (Rd^2) and the overall R^2, are larger for Model 2 than

[16] A smooth stochastic trend is used. It consists of a non-stochastic random walk with a drift, which follows itself a standard random walk. This unobserved trend component is driven by only one parameter, the variance of the random walk that is determining the drift term.

for Model 1, and the two information criteria, Akaike (AIC) and Bayes-Schwartz (BIC), are lower. Of the four macroeconomic variables, the return on the Dow Jones index is most affected by switching the unemployment rate out with the manufacturing employment index. The coefficient on the stock return rises appreciably in magnitude and becomes statistically significant as one moves from Model 1 to Model 2. The coefficient of the inflation rate drops somewhat and so does its statistical significance, but it remains statistically significant at the five-percent level. Both control variables, the percentage of 15 to 29 year olds and the dummy variable for the change in crime reporting procedures in 1958, receive lower coefficient values and the dummy variable turns statistically insignificant.

Models 3, 4 and 5 of Table 3 provide some variation of the model specification relative to our preferred larceny Model 2. In particular, we drop the stock market variable in Model 3, which lowers the measured impact of both inflation and manufacturing employment on crime. The coefficient of determination around the trend of the crime rate (Rd^2) falls appreciably. Model 4 drops instead the demographic control variable. The measured impact of all remaining coefficients decreases and so does the explanatory power of the equation (Rd^2). Model 5 removes all macroeconomic variables and leaves only the control variables in the model. The impact of the demographic variable drops somewhat, but that of the dummy variable increases. The equation loses a large amount of explanatory power around the trend as the Rd^2 measure falls to a fraction of its value for Model 2. Yet, we notice that the overall coefficient of determination (R^2) does not change much at all across models, which is expected for an UCM: left-out variables are absorbed in the stochastic trend. This also explains why the coefficients of the included variables do not change dramatically as the number of explanatory variables is reduced. Overall, these results support the idea suggested in the methodology section: the impact of individual observed variables can be pinned down by UCMs even if some key variables are missing from the equation because they are either unknown or not measurable.

Table 4 presents estimation results for burglary, motor vehicle theft, and robbery. The models are analogous to Model 2 of Table 3. The explanatory power around the trend (Rd^2) of the included observable variables is slightly better than that for the preferred larceny model; but the overall fit of the three models (R^2) is somewhat less. The models for motor vehicle theft and robbery use the same unobserved component model as the larceny model. The burglary model also contains a cycle component, which is represented in Section 4 by equations (4) and (5).[17]

All four crime rate models (Model 2 of Table 3 and all models of Table 4) have in common that inflation and manufacturing employment have the expected signs and are consistently significant, although at different levels. The return on the Dow Jones price index has the positive sign consistent with the relative deprivation or poverty theory. It is also statistically significant at conventional levels, except for its impact on motor vehicle theft.

The impact of the two control variables on crime rates is mixed. Demographic change, as proxied by the percentage of young adults in the population, is highly influential for larceny, but has little perceptible influence on the rates of burglary, motor vehicle theft and robbery. A possible explanation is that the latter three crimes require a greater investment of criminal human capital than larceny. They may, therefore, be more likely conducted by career criminals rather than young adults shifting into and out of property crime based on opportunistic behavior. The 1958 changes related to the collecting and processing of crime data have had a perceptible but limited influence on the reported crime rates and their determining equations. They primarily affect motor vehicle theft and robbery; they are not statistically significant at all for burglary,

[17] We note that the cycle has a period of slightly under 6.5 years.

which is the reason why it is left out of the final equation for this crime rate. Interestingly, the sign of the impact is not consistent across crime rates.[18]

While Tables 3 and 4 focus on the statistical significance of the estimates, Table 5 emphasizes their economic significance. In particular, Table 5 converts the coefficients of Tables 3 and 4 into elasticities. For each coefficient and crime rate, four elasticities are provided, one for the sample mean (1948-2009), and one for each of the three-year periods centered on 1960, 1980, and 2000. Table 5 reveals that the large estimated coefficients for larceny (Table 3) reflect mostly that the larceny rate is far larger than any other crime rate, not that it reacts far more strongly to a change in every independent variable. In fact, the elasticities of the larceny rate with respect to the inflation rate are lower than for the other three property crime rates; the other two elastiticies of larceny with respect to the other macroeconomic variables also tend to be on the low side. Only the elasticity of larceny with respect to the demographic control variable is far larger than those for the other property crime rates, which supports the earlier finding that the percentage of young adults is only statistically significant for the larceny rate.

Table 5 also reveals a fair amount of variation in the elasticities over time. The elasticities of the property crime rates with respect to inflation peak around the time when inflation reaches its maximum, around 1980. At the same time, the crime rate elasticities with respect to manufacturing employment reach a minimum. The elasticities with respect to both the return on the Dow Jones index and the demographic control variable reach a maximum around 1960.

When the sample-average elasticities of Table 5 are combined with the percentage changes of the average values of the dependent and independent variables (Table 6), it is possible to

[18] It should be noted that the estimates for the macroeconomic variables are not materially affected by the inclusion of the observation-specific dummy variable for 1958. The lack of sensitivity in the estimates highlights the attractiveness of the unobserved component modeling strategy.

gauge the relative importance of changes in the three macroeconomic variables in explaining the observed changes in the crime rates over time. Table 7 presents such a comparison.

Table 7 presents in the first two rows the observed percentage changes in the four crime rates based on the sample averages given in Table 6. The rise in crime rates from around 1960 to 1980 is dramatic, well over 100 percent for all four types of property crime. The predictions based on the sample-average elasticities (Table 5) and the percentage changes of the three macroeconomic variables as well as the demographic variable (implied by Table 6) fall significantly short of the observed increases for three of the four crime rates. Only for the larceny rate is the predicted increase of the correct order of magnitude. The significant underestimate of the increase in the three other crime rates reveals that there are forces at work other than those related to macroeconomic factors or the share of young adults in the population.[19] The predictions of the decrease in the four property crime rates from 1980 to 2000 are far better for burglary, motor vehicle theft and robbery, but much worse for larceny.

The last seven rows of Table 7 present some numerical evidence on the extent to which the three macroeconomic variables contribute to predicting percentage changes in the four crime rates. The first two rows of this section of Table 7 relate the crime predictions based solely on the macroeconomic variables to the predictions that also include the demographic variable. It is apparent that the macroeconomic variables play only a small role in explaining the variation in the larceny rate relative to the demographic variable. By contrast, the macroeconomic changes between 1960 and 1980 play a sizable role in predicting the surge in burglary, motor vehicle theft, and robbery relative to the demographic variable. But they are far less important in explaining the downturn in the crime rates after 1980.

[19] In the estimated model, these other forces are captured - although not economically explained - by the smooth stochastic trend.

The last five rows of Table 7 relate the predictions based on the macroeconomic variables to the actual changes in the four crime rates. When taken together and averaged over the periods 1960 to 1980 and 1980 to 2000, the macroeconomic variables can explain about 15 percent of the variation in the rate of motor vehicle theft. The contribution attributable to macroeconomic variables is less for the other three property crime rates, on average about 10 percent for robbery, 9 percent for larceny, and 8 percent for burglary. The last three rows of Table 7 identify the average contribution over the periods 1960 to 1980 and 1980 to 2000 for each of the three macroeconomic variables. It is apparent that inflation accounts for almost all of the contribution of the three macroeconomic variables. The contribution of manufacturing employment is hardly noticeable and changes in the Dow Jones index appear irrelevant. These results suggest that inflation is by far the most important macroeconomic variable that can account for variations in property crime rates, with its impact being largest for motor vehicle theft.

6. Conclusions

This study analyzes to what extent changes in the macroeconomic environment have contributed to changes in the rates of property crime over time. The empirical analysis is conducted for the U.S. using annual data over the time period from 1948 to 2009. Three types of macroeconomic variables are considered: the rate of inflation, employment in manufacturing, and the rate of return on the Dow Jones stock price index. Four property crime rates are investigated: larceny, burglary, motor vehicle theft, and robbery. The empirical analysis relies on unobserved component models, also known as structural time series models. These models are particularly useful for the analysis of crime rates over time because they generate meaningful estimates of the role played by macroeconomic variables in determining property crime rates even though our empirical models do not explicitly include measures of crime deterrence. By excluding variables for crime deterrence, we avoid the well-known issues associated with endogeneity and lack of consistent data. In addition, we avoid the problems normally associated with omitted variables in the context of standard estimation techniques, such as ordinary least squares, by implicitly accounting for their influence through the specification of unobserved components.

We find that our three macroeconomic variables have, on average, a statistically significant impact on the four rates of property crime and in the expected direction. In particular, a rise in inflation increases property crime rates, so does a decrease in manufacturing employment and an increase in the annual return on the Dow Jones stock price index. We determine that our manufacturing employment index fits the data better than the commonly used unemployment rate. We also show that the percentage of young adults in the population significantly affects the larceny rate, but that it has no statistical significance for the burglary, motor vehicle theft and robbery rates. All property crime rates except the burglary rate are also significantly affected by the change in crime reporting standards in 1958, although not all in the same direction.

In determining the economic significance of our findings, we examine to what extent the surge in property crime rates from 1960 to the 1980s or their subsequent decline can be predicted by the observed changes in our macroeconomic variables given our estimated crime rate elasticities. We find that all three macroeconomic variables combined can, on average, explain about 15 percent of the observed change in motor vehicle theft, and less of the change in other property crime rates (10 percent for robbery, 9 percent for larceny and 8 percent for burglary). If one asks which of our three macroeconomic variables has the most impact, the answer leaves no room for interpretation. Almost all of the impact of the three macroeconomic variables falls on the inflation rate. The predictive content of manufacturing employment is negligible and the impact of the return on the Dow Jones index is hardly noticeable. We conclude that containing inflation is the key contribution of macroeconomics for the stabilization of property crime.

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TABLE 1
VARIABLE NAMES AND VARIABLE DEFINITIONS

Variable	Variable Definition
larceny	Larceny rate of the population per 100,000
burglary	Burglary rate of the population per 100,000
motor vehicle theft	
robbery	Robbery rate of the population per 100,000
Inflation rate	Log difference of the Consumer Price Index
Unemployment rate	Percentage of workforce that is unemployed
Mfg employment	Supply Management Institute (SMI) manufacturing employment index (napmei)
Return on Dow Jones	Log difference of Dow Jones stock price index
Percent 15-29 years	percent of the population in the age bracket 15 to 29
D_1958	0/1 variable, 1 from 1958 onward
D_1970	0/1 variable, 1 from 1970 onward

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**
larceny	2.1751	2.3251	0.8949	3.2291
burglary	0.9203	0.8449	0.3472	1.6841
motor vehicle theft	0.3905	0.4307	0.1534	0.6590
robbery	0.1523	0.1493	0.0396	0.2727
Inflation rate	3.5879	2.9456	-0.9856	12.6650
Unemployment rate	5.6869	5.5917	2.9250	9.7083
Mfg employment	0.4931	0.5005	0.3178	0.6543
Return on Dow Jones	0.0623	0.0430	-0.2954	0.4088
Percent 15-29 years	0.2292	0.2201	0.1966	0.2749
D_1958	0.8387	1	0	1
D_1970	0.6452	1	0	1

Note: All data relate to the United States for the years 1948 to 2009.

TABLE 3
MODEL RESULTS FOR THE LARCENY RATE

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Inflation rate	0.0188	0.0123	0.0093	0.0108	
	[0.002]	[0.037]	[0.125]	[0.085]	
Unemployment rate	0.0323				
	[0.008]				
Mfg employment		-0.5000	-0.3570	-0.4682	
		[0.000]	[0.008]	[0.002]	
Return on Dow Jones	0.0486	0.1237		0.1190	
	[0.236]	[0.010]		[0.018]	
Percent 15-29 years	37.1471	32.6926	32.4086		27.3278
	[0.002]	[0.003]	[0.005]		[0.027]
D_1958	-0.2665	-0.1332	-0.1578	-0.0911	-0.1753
	[0.003]	[0.108]	[0.066]	[0.287]	[0.044]
Rd^2	0.3933	0.4238	0.3373	0.3107	0.1527
R^2	0.9855	0.9863	0.9842	0.9836	0.9806
AIC	-4.3380	-4.3895	-4.3003	-4.2610	-4.1711
BIC	-4.0635	-4.1150	-4.0602	-4.0208	-3.9995
DW	2.154	2.050	2.081	2.060	1.970
p-values:					
Normality	0.773	0.932	0.293	0.010	0.154
Heteroskedasticity	0.960	0.948	0.983	0.982	0.908

Notes: all models contain a smooth stochastic trend, i.e. a combination of fixed level and stochastic slope. See the discussion in the text on the details. P-values are provided in brackets below the coefficient estimates. The estimates relate to the United States for the years 1948 to 2009. Variables are defined in Table 1.

TABLE 4
MODEL RESULTS FOR BURGLARY, MOTOR VEHICLE THEFT, AND ROBBERY

Variables	Burglary	Motor Vehicle Theft	Robbery
Inflation rate	0.0069	0.0029	0.0018
	[0.054]	[0.028]	[0.012]
Mfg employment	-0.3439	-0.0619	-0.0719
	[0.000]	[0.049]	[0.000]
Return on Dow Jones	0.0648	0.0171	0.0122
	[0.042]	[0.135]	[0.038]
Percent 15-29 years	4.6032	1.2965	0.9840
	[0.129]	[0.568]	[0.411]
D_1958		-0.0395	0.0267
		[0.044]	[0.009]
Rd^2	0.5280	0.4749	0.4407
R^2	0.9843	0.9790	0.9766
DW	1.563	1.960	1.879
p-values:			
Normality	0.091	0.184	0.289
Heteroskedasticity	0.089	0.938	0.315

Notes: all models contain a smooth stochastic trend, i.e. a combination of fixed level and stochastic slope. The burglary model contains in addition a stochastic cycle component. See the discussion in the text on the details. P-values are provided in brackets below the coefficient estimates. The estimates relate to the United States for the years 1948 to 2009.

Table 5
Economic Interpretation of Preferred Crime Rate Models

Driving variable	Crime Rate Elasticities: Larceny	Burglary	Motor vehicle theft	Robbery
Inflation rate				
evaluated at:				
sample mean	0.020	0.027	0.027	0.042
average of 1959-61	0.013	0.016	0.017	0.035
average of 1979-81	0.044	0.047	0.065	0.082
average of 1999-01	0.014	0.025	0.019	0.034
Mfg employment				
evaluated at:				
sample mean	-0.113	-0.184	-0.078	-0.233
average of 1959-61	-0.234	-0.352	-0.159	-0.628
average of 1979-81	-0.075	-0.099	-0.058	-0.138
average of 1999-01	-0.093	-0.214	-0.068	-0.226
Return on Dow Jones				
evaluated at:				
sample mean	0.004	0.004	0.003	0.005
average of 1959-61	0.013	0.015	0.010	0.025
average of 1979-81	0.002	0.002	0.002	0.003
average of 1999-01	0.003	0.005	0.002	0.004
Percent 15-29 years				
evaluated at:				
sample mean	3.445	1.146	0.761	1.481
average of 1959-61	5.827	1.792	1.268	3.272
average of 1979-81	2.889	0.781	0.719	1.111
average of 1999-01	2.716	1.282	0.640	1.385

Notes: The elasticities use the estimated coefficients of Model 2 (Table 3) and of the models of Table 4. These coefficients are multiplied by the sample values of the driving variables (left column) and divided by the corresponding values of the dependent variable.

Table 6
Average Values of Dependent and Independent Variables over Time

Variables	**Sample Mean**	**Average 1959-61**	**Average 1979-81**	**Average 1999-01**
Dependent Variables				
Larceny	2.175	1.104	3.102	2.505
Burglary	0.920	0.505	1.615	0.747
Motor vehicle theft	0.391	0.201	0.494	0.422
Robbery	0.152	0.059	0.243	0.148
Independent Variables				
Inflation rate	3.588	1.158	11.068	2.753
Mfg employment	0.493	0.517	0.465	0.464
Return on Dow Jones	0.062	0.119	0.059	0.053
Percent 15-29 years	0.229	0.197	0.274	0.208

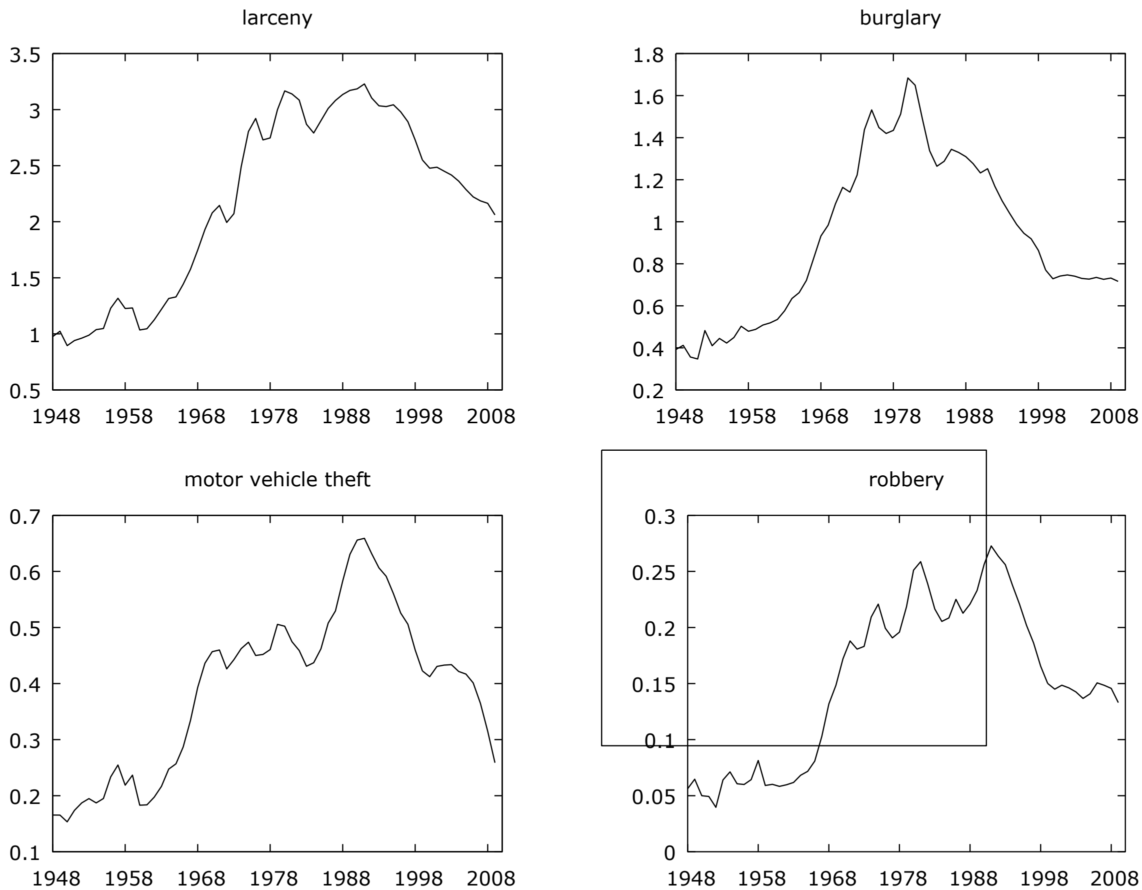
Notes: See Table 1 for variable definitions and Table 2 for basic statistics over the complete sample.

Table 7
Actual and Predicted Percentage Changes of Crime Rates And Percentage Contribution of Macroeconomic Variables

	Time Horizon	*Larceny*	*Burglary*	*Motor vehicle theft*	*Robbery*
% change					
Actual crime rates	1960-80	1.81	2.20	1.46	3.10
	1980-00	-0.19	-0.54	-0.15	-0.39
Predicted rates based on all variables	1960-80	1.54	0.70	0.53	0.97
	1980-00	-0.85	-0.30	-0.20	-0.39
Predicted rates based on macro variables only	1960-80	0.18	0.25	0.24	0.38
	1980-00	-0.02	-0.02	-0.02	-0.03
% contribution of macro variables					
in generating predicted crime rate changes	1960-80	0.12	0.35	0.44	0.40
	1980-00	0.02	0.07	0.10	0.08
in predicting actual crime rate changes	1960-80	0.10	0.11	0.16	0.12
	1980-00	0.08	0.04	0.14	0.08
% contribution of individual variables					
Inflation rate	average of	0.088	0.071	0.147	0.099
Mfg employment	1960-80 &	0.003	0.004	0.002	0.003
Return on Dow Jones	1980-00	0.000	0.000	0.000	0.000

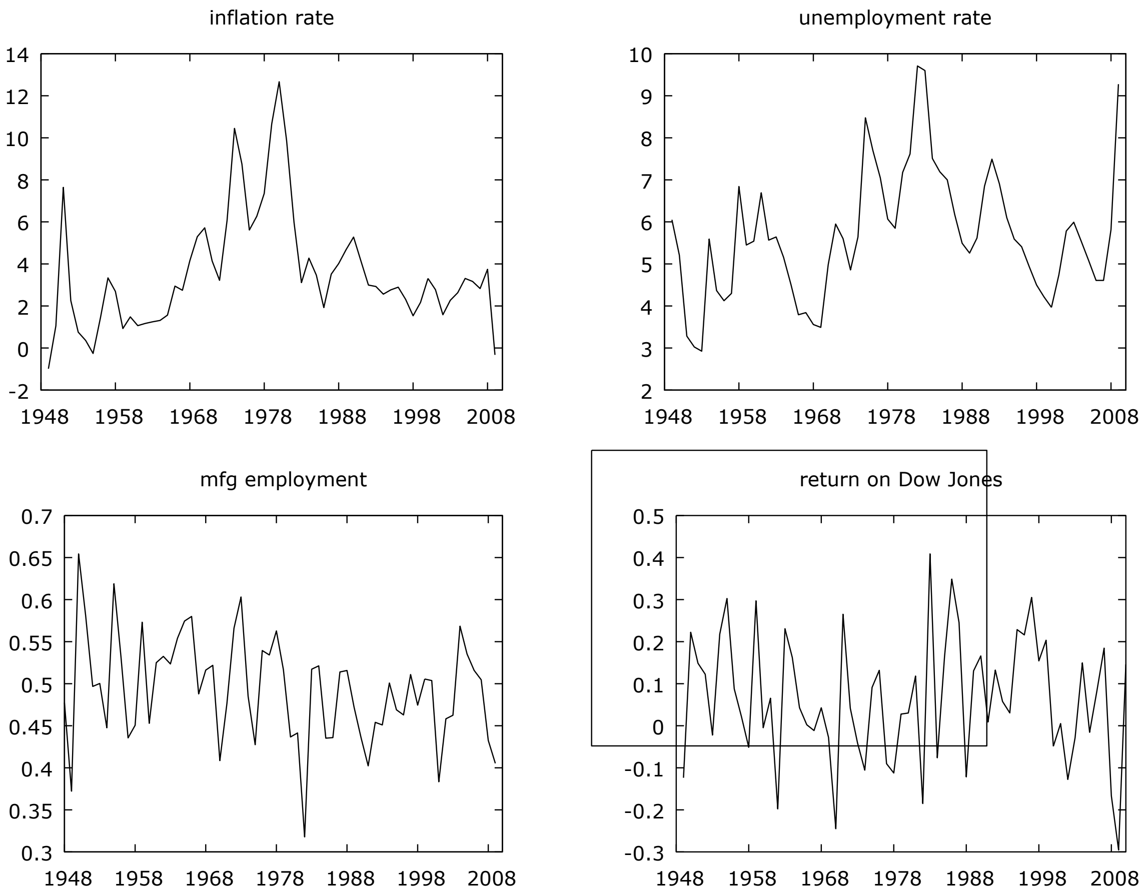
Notes: predictions use mean elasticities, as given in Table 5, and percentage changes as given in Table 6. Unobserved components are not used for any of the predictions. Therefore, differences between actual and predicted values reflect the impact of estimated unobserved components and random noise.

FIGURE 1: PROPERTY CRIME RATES OVER TIME



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

FIGURE 2: EXPLANATORY MACROECONOMIC VARIABLES OVER TIME



Note: variable definitions are provided in Table 1.

For those unfamiliar with the econometric methodology employed in this study, we also offer some alternative estimates via ARMAX modeling. We consider these models to be inferior in quality relative to the unobserved component models in the paper. But the parameter estimates show a significant degree of similarity, at least in terms of order of magnitudes, to those of the unobserved component models.

Appendix Table 1
Model Estimates by ARMAX Method

Variables	**Larceny**	**Burglary**	**Motor vehicle theft**	**Robbery**
Inflation rate	0.0110	0.0093	0.0034	0.0022
	[0.067]	[0.009]	[0.030]	[0.002]
Mfg employment	-0.3025	-0.3847	-0.0320	-0.0393
	[0.019]	[0.000]	[0.359]	[0.030]
Return on Dow Jones	0.0761	0.0834	0.0160	0.0037
	[0.068]	[0.017]	[0.149]	[0.496]
Percent 15-29 years	12.0336	7.4955	0.2742	0.9212
	[0.009]	[0.000]	[0.803]	[0.061]
D_1958	-0.1779		-0.0571	0.0257
	[0.019]		[0.006]	[0.002]
AR(1)	0.9833	0.9822	0.9769	0.9456
	[0.000]	[0.000]	[0.000]	[0.000]
MA(1)	0.6745		0.5238	0.6075
	[0.000]		[0.000]	[0.000]
constant	-0.7063	-0.8242	0.2726	-0.0801
	[0.564]	[0.070]	[0.325]	[0.486]

Notes: all estimates are based on ARMAX models; the error terms are specified as ARMA(1,1) models, except for the burglary equation, for which an AR(1) suffices. P-values are provided below the coefficient estimates.