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Does Broken Windows Policing Reduce Felony Crime?

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Abstract: The purpose of this study is to test the Broken Windows Hypothesis within the context of New York City's long-term experience, i.e., to see if the City's policing efforts that target minor crimes effectively reduce the commission of more serious felony crime. While the body of work on Broken Windows policing is substantial, the scope of the empirics has remained somewhat narrow, both in the time spans considered, and in the set of time variant factors considered in any given study. This work attempts to close some of this gap by testing the hypothesis within a much broader context, using four and a half decades of data from multiple sources on law enforcement, socio-demographic as well as labor market conditions in New York City. For the empirical tests, the ARDL/Bounds Testing methodology appropriate for a mixture of stationary and non-stationary variables is used to estimate both long run and short run relationships between felony crimes and the factors likely to affect it. Broadly, the findings of this work indicate that while changes in the risk of apprehension, labor market conditions, drug market activity and demographics all explain part of the decline in felony crime in NYC, there seems to exist qualified support for the Broken Windows hypothesis. Specifically, heightened enforcement targeting misdemeanors also leads to fewer economic felonies (i.e., robbery, burglary, larceny and auto theft) while crimes associated with passion, namely murder and assault, remain unaffected.

Keywords :Broken Windows Hypothesis, Crime, New York City, Cointegration, ARDL

JEL Classification: A13, H79, K42

1. Introduction

The precipitous drop in violent crime in the large cities of the U.S., a phenomenon that began to unfold somewhat unexpectedly around the 1990s, has been the subject of intense cross disciplinary research, with New York City (NYC) receiving a disproportionate amount of the attention. NYC's experience is considered sufficiently unique within the broader story for two reasons. First, the extent of the crime drop in the City has been quite dramatic in both magnitude and duration, with felony crimes declining twice as much as elsewhere in the 1990s and continuing their downward, though less steep trend since 2000 (Zimring, 2012). Second, no other city is as strongly associated with a major shift in policing strategy that coincided with much of the crime drop, with the Giuliani administration crediting its 1993 implementation of Broken Windows policing for much of the decline (Kelling & Bratton, 1998). Whether and how much the latter explains the former is still an on-going debate, to which this study contributes.

2. NYC and the Broken Windows Hypothesis

2.1 A Review of the Literature

At its core, Broken Windows theory makes a simple argument - maintaining public order is not an end itself, but instead a means to discourage serious crime. Operationally this implies that strict enforcement of misdemeanor laws that prevent social disorder (like aggressive panhandling, vandalism, public drinking and intoxication, prostitution, excessive noise, criminal trespass, petit larcenies, graffiti, marijuana use and sales, unlicensed vending, etc.) reduces the levels of felony crime. Failing to maintain order, it is argued, creates a climate of disorder with lax community control, where citizens are afraid and withdrawn, thereby inviting more criminal behavior (Wilson and Kelling, 1982).[1]

Despite numerous studies, whether NYC crime levels changed because of evolving NYPD policing practices or other factors remains contentious, largely reflecting differences in model specification, period of study and the level of aggregation (Welsh et al., 2015). The emergent consensus is that no singular mechanism explains the 1990s experience. Rather the interplay of policing and a host of socioeconomic forces created a unique mix of conditions in which the crime drop germinated. The coincident ebbing of the crack epidemic and the beginning of a long period of economic prosperity, nested within longer term demographic trends, all tell different parts of the story. (Blumstein and Wallman, 2006; Chauhan, 2011; Zimring, 2007).

How essential has order-maintenance policing (OMP) been in driving the declining crime numbers? The answer depends on who you ask. The comprehensive but descriptive assessment of criminologist Franklin Zimring (2012) concludes that it has in fact, played a vital role. Critics point out, however, that Zimring makes that inference mainly through the process of elimination: since other factors appear unconvincing, the police must have played an important part (Rosenfeld et al., 2014). While not invalidating Zimring's approach, as Weisburg et al. (2014) argue, his conclusion remains only *one* possible interpretation of the available data. Moreover, two recent warring reports from within the NYPD (that also rely on descriptive analysis) on the effectiveness of Broken Windows policing have placed this debate back at the center of attention. (See Bratton, NYPD Report, 2015, versus DOI Report, 2016, arguing for and against its effectiveness, respectively.)

Moving past descriptive studies to the more econometrically rigorous body of academic research, one again finds that the issue remains unsettled for the time being. Statistical estimates of how broken windows policing (typically proxied by the number of misdemeanor arrests) contribute to the decline in NYC serious crime have ranged from large (Corman and Mocan, 2005; Kelling and Sousa, 2001), to modest (Cerda et al., 2010; Messner et al., 2007; Rosenfeld et al., 2007) to insignificant (Hartcourt and Ludwig, 2006; Chauhan et al. 2011; Greenberg, 2014; Rosenfeld and Fornango, 2014). This substantive body of widely cited research, however, almost singularly focuses on the decade of the 1990s. Post-2000 felony crime rates remain largely unexplored, in large part because their decline has not been as dramatic as in the preceding period or as consistent across city neighborhoods (Chauhan, 2011).[2]

The two earliest papers in this chronology find the strongest support for the effectiveness of OMP, but others since have been less affirming. The first, by Kelling and Sousa, 2001 (hereafter K&S), demonstrates a significant negative relationship between changes in violent crime rates and misdemeanor arrests in the 1990s (controlling for unemployment, age composition, and a drug involvement variable), concluding, in the absence of other significant covariates, that policing deserved most of the credit for the city's crime drop. Their conclusion was subsequently supported by Corman and Mocan's (2005) longer time series (1974-1999) analysis which found robbery and motor vehicle thefts to be negatively related to misdemeanor arrests, after accounting for various economic and demographic factors, as well as police manpower and incarceration rates.[3]

Hartcourt and Ludwig's follow up research in 2006 provides a direct critique of both these works, declaring that the evidence remains inconclusive on this question. Replicating the K&S study, they show that its conclusion was demonstrably affected by relating the *change* in crime rates to the *levels of (*versus *changes in)* misdemeanor arrests. If a mean reversion process underlay the city's crime rates (for which they provide compelling evidence, as do later studies such as Greenberg, 2014), the precincts with the highest crime rates during the crack epidemic of the late 1980s would also see the largest drops in ensuing periods. Since *these very* precincts would have had the highest numbers of misdemeanor arrests, the data may spuriously show a negative relationship of crime rates and misdemeanor arrests. Re-estimating the regression in first differences makes that result disappear.[4]

The next four papers in the chronology make use of NYC precinct level data and similar research design (that all account for several socio-demographic and crime relevant factors) to study different aspects of problem. Rosenfeld et al. (2007) find a modest impact of misdemeanor arrests on robbery and homicide rates, while Messner et al. (2007) show them influential for gun related homicides and robberies, but not for non-gun related homicides. In follow-ups, Cerda et al (2010) and Chauhan et al (2011) dissect the relationship by age group and race/ethnicity, respectively, but find inconsistent effects for misdemeanor arrests. The former study shows that misdemeanor arrests reduce gun related homicides in specific age groups (adults above 35). The latter, however, fails to find a significant misdemeanor effect when the data are disaggregated by racial categories. Instead cocaine consumption and firearms availability appear to be the important determinants of Black and Hispanic homicide rates, respectively.

The two most recent studies, contained in a Special Issue of the *Justice Quarterly*, also fail to support the Broken Windows hypothesis. Greenberg (2014), reanalyzing 1990s precinct-level data, finds no evidence that misdemeanor arrests reduce homicide, robbery or aggravated assault. Similarly, Fornango (2014), using 2000s precinct data, shows that neither robbery nor burglary are impacted by misdemeanor arrests. He did, however, demonstrate that both felonies are decreased by NYPD's "stop and frisk" program.

In summary, a mixed picture has emerged from the body of prior empirical work, with the earliest studies demonstrating the strongest support for the Broken Windows hypothesis. The studies that have followed either provide qualified support for the strategy or find no evidence for its effectiveness.

2.2 Motivation for this Study

Among the aforementioned set of studies, Corman and Mocan (2005) take a different tack from the rest. They analyze the longer time-series (1974-99) properties of crime and its determinants, and they do so at the City level, while the others rely on disaggregated precinct level crime statistics spanning much shorter periods. The difference is essentially one of focus, on the variation of city-wide crime over time versus across precincts. The precinct is the "ground level" where enforcement practices are set and carried out (Greenberg, 2014), so pinning down the patterns in crime rates and enforcement strategies between precincts is a useful exercise. This particular line of enquiry provides useful insight for police practitioners, allowing more sophisticated statistical analyses to inform evidence based policing.

However, some basic concerns about this body of research remain. First, putting a singular emphasis on the 1990s as the vast majority of these studies have done may be imprudent. Baumer and Wolff (2014) argue that there may be reason for skepticism as to whether the early 1990s truly represent a structural break in crime trends. An alternative plausible interpretation of the data is that the 1990s ebb in crime was merely a resumption of a longer-term decline in property crimes (except auto theft) that dates to the early 1980s. That trend was interrupted by an "aberrant" drug fueled crime wave of the late 1980s which ended in the early 1990s, leading to a resumption of the downward trend. NYC's experience in the 1990s, while remarkable, may be the result of longer-term forces, so researchers should be careful in over-generalizing the implications of their findings from that period. By using a much longer time series in both directions, (1970-2014), this study sidesteps that debate, instead letting four and a half decades of data inform its conclusions so they are unhindered by how the time-series are bookended.

The second limitation of the bulk of the existing studies that focus on short time series is that they cannot incorporate time-varying economic indicators like the unemployment rate or changing demography, which may potentially be quite important in changing crime rates. Baumer and Wolff (2014), in their extensive review of the literature, deem this to be a "major limitation." While such papers do use a range of sociodemographic factors as controls, they are based on decennial census tract data and are time invariant in the specification, so while they vary across precincts, they do not across time. Choosing city level data (as Corman and Mocan do) gives us access to the time series properties of important economic and demographic variables, a choice that can be further justified by the broad consistency in within-city crime trends. In a retrospective comparison of the precinct versus city level approach, Greenberg (2014) argues that while crime variation across precincts can be quite informative, the trends have been consistent enough so as to not "wash out" at the city level. He also conducts a further check of this consistency at the borough level, finding that "the similarities are much more striking than the differences".

Finally, different researchers have studied different sets of causes for the crime drop (Chauhan, 2011), so all pertinent causes have not been considered in any given study, a broader weakness found in criminological research (Greenberg, 2014). While degrees of freedom considerations necessitate pruning the number of variables we consider, as a set, they map out changing demographics, labor market conditions, policing tactics, drug usage and institutional engagement of youth. Together, they broadly capture the set of plausible determinants of crime discussed most consistently in the literature, setting up the rich context within which we test the Broken Windows hypothesis.

3. Empirical Analysis

3.1 Variables of Interest in the Model

Since the Broken Windows Theory proposes a hypothesis about serious crime, as others before us, we look at felonies committed in NYC, both violent and non-violent. Following the broad arc of the literature, we expect that these crime levels will be influenced by i) the intensity of law enforcement efforts, ii) the socio-demographics of the community and iii) the opportunity to work in the legal labor market.

With respect to the first, we consider police presence in the City (as gauged by the size of the police force) and the arrest rates for serious crimes as well as those for lesser ones (misdemeanors). We expect that the propensity to commit crime decreases as the police force expands and as the own probability of being arrested increases, reflecting both deterrence and incarceration effects. We also consider possible substitutability between crimes; because most criminals are opportunists, not crime specialists, levels of a particular crime may be influenced by the arrest rates for substitute crimes. As Levitt (1998) has noted, if enforcement efforts against robbery intensify, burglary and grand larceny levels might either increase (as offenders switch from robbery) or decrease (as offenders are incarcerated). The number of misdemeanor arrests is the final policing variable. If the Broken Windows hypothesis is valid, we expect that greater numbers of misdemeanor arrests, by reducing social disorder, would generate declines in the felony crime levels. While the mechanism through which perceptions affect behavior is complex, evidence suggests that a greater number of social disorder incidents creates a sense of diminished personal safety and reduces citizen engagement in the prevention of crime. (Ren et al, 2017) Incarceration effects of misdemeanor arrests on serious crime may be a separate, if not more important mechanism through which felonies may fall (Fulda, 2010).

Second, three socio-demographic traits are expected to influence the level of crime, namely the numbers of young adults (15-24) in the population, new undergraduates enrolling in the local public university system and accidental drug overdose deaths. Since crime is most prevalent in the young demographic, we expect it to increase with the proportion of young adults in the population, but to decrease with heightened institutional engagement of youth (McCall et al., 2013). As a measure of the latter we use new undergraduate enrollment in the City University of New York (CUNY) system, which currently serves more than a half million students. It is also expected that crime levels would move in step with the level of illegal drug market activity, proxied in this study by the number of accidental drug overdoses (ODs) each year.[5] Our OD proxy mirrors the eras identified by Johnson, et.al. (2000), who noted that the injectable heroin era was waning in the 1970s, followed by the cocaine/crack era which began in 1980 and peaked around 1990.

Finally, as a measure of labor market opportunities, the unemployment rate in NYC was included as the final explanatory variable in our model, but its effect on criminal activity is unknown *a priori*. As Janko and Popli (2015) have noted, tight labor markets increase the opportunity cost of engaging in criminal behavior but also increase the number of potential targets as persons engage in work away from home. This competing *motivation* versus *guardianship* hypotheses framework of how labor markets influence crime levels was first put forth by Cantor and Land (1985).

3.2 Broad Trends in the Data

For the 1970-2014 study period, the annual numbers of three violent felony crimes (murder/non-negligent manslaughter, aggravated assault and robbery) and three non-violent felonies (burglary, grand larceny and grand theft auto) in NYC were obtained from FBI Uniform Crime Reports (UCR) sources (source: FBIUSDOJ and USDOJBJS websites).

Figures 1 and 2 present time series plots for the differing crimes, with the robbery, assault and all three non-violent felonies expressed as the rate per 10,000 persons while the murder level is the number per 100,000 persons. Between 1970 and 2014, all six types of crime started at relatively low levels, increased markedly (+50 to 150%) to a peak, and then receded, almost always to much lower levels. Four of the six, namely assault, murder, larceny and auto theft peaked around 1990 while robbery and burglary reached their apex a decade earlier. The post-peak declines in crime were dramatic, i.e., 60 - 80% for the violent crime categories and 70 – 95% for the non-violent felonies.

Figure 3 shows that arrests for violent felonies, non-violent felonies and misdemeanors all increased over the study period. None of the arrest rate patterns, however, correlated very well with the crime trends, nor did NYPD force levels. Violent and non-violent felony arrests began to increase in 1993, considerably after felony crimes started to decline but exactly at the time the NYPD started employing Compstat management reforms. The variable assessing the Broken Windows hypothesis, namely misdemeanor arrests, however, trended steadily upwards from 1970 onward before peaking in 2010. The violent and non-violent felony arrest measures both reflect the risk of apprehension (in %) and were calculated by dividing the number of arrests made (drawn from the New York State Data.NY.Gov website) by the corresponding number of felonies committed recorded in the FBI's UCR database.[6] However, a comparable arrest risk rate could not be calculated for misdemeanors because data for the number of misdemeanors committed in each year were unavailable, so the misdemeanor arrest value is expressed as a per 10,000 population value.[7] The number of full-time officers (per 10,000 population) declined nearly 25% between 1970 and 1981, then slowly rebounded to its former high by 1999, before again declining by another 25% by 2014 (source: CIUS Annuals 1970-2014).

The time-series patterns (Figure 4) of NYC's young (15-24) adult population and drug overdose deaths suggest that they might be important factors influencing the commission of crime. The young adult percent started to decline at about the same time that burglaries and robberies started to decline, while drug abuse deaths (expressed as deaths per 100,000) started to decline at the same time as the other felonies. The young adult[8] and overdose deaths data series, as well as NYC's population, were drawn from the NY Bureau of Vital Statistics (source: NYCDOHOVR). The time-trend behaviors of unemployment (source: NYSDOLLAUSP) and new City of New York University undergraduates (source: CUNYOIP) were not, however, consistent with the trends in crime. One period of declining unemployment (1991 – 2006) occurred while criminal activity was declining but another (1976-1987) occurred when most crimes were increasing. Similarly, the pattern of CUNY's enrollment, measured in the Fall semester, peaked in 1974, declined until 1999 and then resumed growing thereafter, and did not move consistently with any of the crime types.

3.3 Statistical Methodology

In order to identify which, if any, of the law enforcement, demographic and labor market measures influence the propensity to commit crime, a multivariate regression format was utilized, with all of the series transformed to logs. Because time-series data is frequently nonstationary, Augmented Dickey Fuller (ADF) and Elliott-Rothenberg-Stock point optimal tests for unit roots were first conducted on all series. Both tests demonstrated that all of the variables except two had unit roots, i.e., were nonstationary in levels but stationary in first differences I(1) variables. The two exceptions, i.e., the unemployment rate and CUNY enrollment, were stationary in levels I(0) variables. Since the data consists of both I(1) and I(0) series, the autoregressive distributed lag (ARDL) approach to cointegration was employed to analyze the relations between each crime type and the explanatory variables (Pesaran et al., 2004). The following describes the unrestricted error correction ARDL model estimated for each type of crime:

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$$Crime_t = \beta_0 + \theta_1 VArrests_{t-1} + \theta_2 NonVArrests_{t-1} + \theta_3 Misdemeanors_{t-1} + \theta_4 Officers_t + \theta_5 YoungAdults_t + \theta_6 DrugDeaths_t + \theta_7 CUNYStudents_t + \theta_8 Unemployed_t + \sum \lambda_{t-1} \Delta Crimes_{t-1} + \sum \delta_{t-1} \Delta VArrests_{t-1} + \sum \phi_{t-1} \Delta NonVArrests_{t-1} + \sum \gamma_{t-1} \Delta Misdemeanors_{t-1} + \sum \eta_t \Delta Officers_t + \sum o_t \Delta YoungAdults_t + \sum \pi_1 \Delta DrugDeaths_t + \sum \psi_t \Delta CUNYStudents_t + \sum \kappa_t \Delta Unemployed_t + \varepsilon_t \quad (1)$$

where *Crime* is the number of felonies in each year, *VArrests* and *NonVArrests* are the arrest rates for violent and nonviolent felony crimes and *Misdemeanors* and *Officers* are the number of misdemeanor arrests and NYPD officers per capita. Since the violent and nonviolent arrest rates were calculated as the number of arrests divided by the number of crimes, their values were lagged one period to avoid simultaneity biases. The number of misdemeanor arrests per capita was also similarly lagged one period. Unlike the arrest rates, contemporaneous measures of the police force were included to gauge their presence in the community. While changing crime levels could influence the size of the force, training and budgetary delays would necessitate that force level changes occur in future years. The remaining variables include per capita values of the numbers of young adults (15-24), drug overdoses and new undergraduate enrollment in the City University system, as well as the unemployment rate.

The ARDL model was estimated for each type of crime, with the Schwartz and Akaike information criteria selecting the optimal number of lags, and the Lagrange Multiplier (LM), ARCH & Jarque-Bera tests confirming that the error terms were well-behaved. For five of the six crime types, the Bounds test for cointegration (where the null hypothesis is H_o: all Θ_s in the above model are zeros) showed that crime levels had long run relationships with at least some of the explanatory variables (i.e., at the 10% level for murder and at ≤ 5% for assault, robbery, larceny and auto theft). The test result, however, was inconclusive for burglary as the sample F was less than the critical I(1) value at 10% significance but greater than the I(0) value at 10%, thereby making a discussion of its findings somewhat tentative.

Given that crime levels and the explanatory factors are cointegrated, we can then rearrange the ARDL model above into a familiar error correction model that describes both the long run relations between crime and the explainers and how short run changes lead to adjustments around the equilibrium. The long run relationship is given by:

$$Crime_t = \alpha_0 + \alpha_1 VArrests_{t-1} + \alpha_2 NonVArrests_{t-1} + \alpha_3 Misdemeanors_{t-1} + \alpha_4 Officers_t + \alpha_5 YoungAdults_t + \alpha_6 DrugDeaths_t + \alpha_7 CUNYStudents_t + \alpha_8 Unemployed_t + \nu_t \quad (2)$$

while the short run error correction model (ECM) is:

$$\Delta Crime_t = \beta_0 + \sum \lambda_{t-1} \Delta Crimes_{t-1} + \sum \delta_{t-1} \Delta VArrests_{t-1} + \sum \phi_{t-1} \Delta NonVArrests_{t-1} + \sum \gamma_{t-1} \Delta Misdemeanors_{t-1} + \sum \eta_t \Delta Officers_t + \sum o_t \Delta YoungAdults_t + \sum \pi_1 \Delta DrugDeaths_t + \sum \psi_t \Delta CUNYStudents_t + \sum \kappa_t \Delta Unemployed_t + \varpi ECT_{t-1} + \varepsilon_t \quad (3)$$

The ECT_{t-1} is the lagged error correction term derived from the estimated error terms (ν_t) for the long run relationship equation (#2), while ϖ shows the speed of adjustment back to equilibrium when short run disturbances occur.

3.4 Results

Table 1 presents the estimation results of the long-run equilibrium relationship between crime and its posited determinants. Although the Bounds test results' highly significant (<1%) error correction terms for all six felonies demonstrated that each crime type was cointegrated, few consistent explainer effects proved to be statistically significant. The notable exception was the role played by non-violent felony arrests, which significantly reduced the level of assaults, robberies and auto thefts (and murders if the significance level is relaxed to 7%). The estimated coefficients demonstrate that the commission of crime, even crimes of violence, is quite sensitive to changes in the rate of apprehension for a non-violent felony. Specifically, the coefficients, ranging from -1.2 (for murder) to -2.5 (for auto theft), show that a 10% increase in the non-violent felony arrest rate leads to a 12.5 – 25% reduction in all three violent felonies as well as auto theft.

Only auto theft responded to a change in its own risk of arrest, suggesting that heightened law enforcement, at least in NYC, has little deterrent effect on the propensity to commit most property crimes. Rather felonies decrease, particularly crimes of violence, because arrests for less serious non-violent felonies decrease the number of future perpetrators through incarceration. These results add support to the research of Rosenfeld (2009) who found that homicides were positively influenced by acquisitive crime levels (both violent and non-violent), and who also posits that other violent crimes should be similarly affected. The only other significant long run relationship observed was between the level of auto thefts and the size of the young adult (15-24) population, with increases in the latter leading to large (8x) proportional increases in the former.

Table 2 presents the results for the error-correction model, identifying how short run dynamics impact the level of each crime, with the reported coefficients showing the elasticities of each crime with respect to changes in each explainer. The two most consistent determinants of short run change in crimes were changes in labor market conditions and the size of the young adult population. Every type of crime, except murder, declines as the level of unemployment rises, demonstrating that a declining number of targets markets dominates the increase in motivation to crime as labor markets slacken. The estimated elasticities were, however, quite modest, ranging from -.09 to -.2 indicating that a 10% increase in unemployment dampens crime between .9 to 2%. Similarly, the number of young adults (15-24) also explained short term changes in nearly all (save assaults) of the felony types. In contrast to the findings for unemployment, the estimated elasticities of crime with respect to the number of young adults were quite large, ranging from .8 to 2.4, demonstrating that increases in this cohort's size lead to sizable short term increases in felony activity. Periods of heightened drug abuse, indicated by high numbers of accidental overdose, also generated greater numbers of robberies, burglaries and larcenies, but had no effect on murders, assaults and auto thefts.

With respect to the law enforcement variables, the findings provide support for the Broken Windows hypothesis that serious crime is sensitive to policing efforts that focus on lower level crime. Increasing misdemeanor arrests diminishes the commission of all the economic felonies (i.e., robbery, burglary, larceny and auto theft) while the crimes ordinarily associated with passion, namely murder and assault, remain unaffected. In terms of specific effects, the estimated coefficients (ranging between -.3 to -.7) demonstrate that a 10% rise in misdemeanor arrests leads to a 3 to 7% decrease in felony robberies, burglaries, larcenies and auto thefts.

While the size of the police force had no measurable influence on the propensity to commit crime, most of the crimes, excepting robbery and burglary, were also sensitive to changes in their own risk of apprehension. Specifically, increasing arrest rates for violent crime leads to significantly fewer murders and assaults while increasing non-violent apprehensions reduces the commission of larcenies and auto thefts. Additionally, felony larceny is not only influenced by its own chance of arrest but also by the risk of arrest for serious violent crimes. Since robberies constitute nearly 60% of violent crimes, the observed positive relationship between larceny and violent crime arrests suggests that some felons substitute non-violent theft (i.e., larceny) for violent thefts (i.e., robbery) as the risk of apprehension for the latter increases. Levitt's study (1998) of US big-city crime found a similar positive substitution effect for felony larcenies as well as robberies.

Except for assaults, all of the estimated speed of adjustment terms (ϖ), while statistically significant, were quite modest ($\geq$ -.21) in magnitude, demonstrating that it takes a very long time ($\geq$ 5 years) for crime levels to return to their long-term relatives once short term disturbances have occurred. This suggests that crime levels will rarely be "in equilibrium" and will instead largely reflect short term changes in the explainers.

4. Conclusion

This study contributes to the existing, often contradictory findings in the literature on the effectiveness of Order Maintenance Policing in New York City – as summarized through the Broken Windows hypothesis. While this body of work is substantive, drawing research interest from practitioners and academics alike, the scope of the enquiry has often remained narrow, either in the time dimension studied (with disproportionate emphasis on the 1990s) or in the number of relevant factors considered in any given study. This paper hopes to close some of this gap by drawing on more than four decades of data from multiple sources, with time varying indicators of policing strategy, social demographics and labor market forces, allowing for longer cycles of cause and effect in the statistical estimation.

Our findings suggest that while changes in labor market conditions, drug market activity and demographics explain part of the decline in felony crime in NYC, changes in police efficiency and practice were also important factors. Police efforts that increased the own risk of apprehension reduced all types of crime except robbery and burglary. In addition, increasing arrest rates for non-violent property felonies provided an added benefit of reducing violent felonies by reducing the number of possible violent encounters and incarcerating potential future perpetrators. The results also support the Broken Windows hypothesis that heightened enforcement intended to decrease social disorder leads to additional reductions in more serious crimes. Specifically economic felonies (i.e., robbery, burglary, larceny and auto theft) were diminished by the NYPD's targeting of misdemeanors while crimes associated with passion, namely murder and assault, remained unaffected.

Endnotes

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1. In addition to heightened misdemeanor arrests, the new commissioner (William Bratton) simultaneously instituted several additional policing reforms designed to improve the efficiency of New York Police Department (NYPD) operations. Dubbed Compstat, they included decentralizing operational decisions to the precinct commanders, twice-weekly meetings with these commanders to hold them accountable for crime in their precincts, and an increased reliance on geographical mapping to identify crime "hot spots" to allocate extra police resources (White, 2014).
2. Indeed, only one of the papers (Rosenfeld and Fornago, 2014) goes beyond the 1990s to study NYC robbery and burglary rates from 2003 to 2010. The other exception in the set is the work of economists Corman and Mocan (2005), who look at an earlier longer period, spanning 1974 to 1999, to find support for Broken Windows policing.
3. Interestingly, they do not include a drug activity measure in the specification, though in an earlier paper (Corman and Mocan, 2000) they explore and find a significant relationship between property felony crimes and drug usage, an omission we account for in the current study.
4. They follow this exercise with a more generic critique of C&M, arguing that single city time series findings are vulnerable to any number of plausible explanations, not having as a reference, trends in other cities or the nation.
5. For a comprehensive review of the literature on the Drug-Crime linkage in the U.S., please see MacCoun et al, 2006.
6. Arrest rates for each of the six particular felonies under study were not available for our entire study period (1970 – 2014). However, an analysis of available data (BJS and Easy Access sources) for a sub period (namely 1980 – 2012) demonstrated that the arrest levels for each crime were highly correlated to the corresponding aggregated arrest rates employed by this study, making the latter suitable instruments for the risk of apprehension. Specifically, the correlations between the sub period's murder, assault and robbery arrest rates with our aggregated violent crime arrest rate were very high, namely .76 to .94. Similarly, the correlations between the sub period's burglary, larceny and auto theft arrest rates to our overall nonviolent nondrug arrest rate were .89 and higher.
7. In 1995 the Housing and Transit police forces were merged with the New York Police Department (NYPD) force. To create a consistent measure of officer strength for the NYPD we have subtracted the number of 1995 Housing and Transit officers from the NYPD total in the post-merger years.
8. The young adult values were only available for 1960, 1970, 1980, 1991, 2000, and 2006 thru 2014 so a cubic spline function was used to interpolate the missing values.

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Table 1: Long run determinants of crime

Violent Felonies	Coefficient	Std.Error	Non-Violent Felonies	Coefficient	Std.Error
Murder$_t$			Burglary$_t$		
ViolentArrests$_{t-1}$	-1.513	2.851	ViolentArrests$_{t-1}$	1.053	22.516
NonViolentArrests$_{t-1}$	-1.224	.816	NonViolentArrests$_{t-1}$	-9.645	72.209
Misdemeanors$_{t-1}$	1.251	1.904	Misdemeanors$_{t-1}$	7.697	64.618
Officers$_t$	.820	1.993	Officers$_t$	22.448	196.675
YoungAdults$_t$	4.751	7.449	YoungAdults$_t$	-19.464	224.529
DrugDeaths$_t$	-.448	-.116	DrugDeaths$_t$	-13.993	122.198
CUNYEnrollmentr$_t$	1.236	1.749	CUNYEnrollmentr$_t$	22.025	194.836
Unemployed$_t$	-1.774	1.849	Unemployed$_t$	-3.741	31.534
Constant	-.573	20.378	Constant	19.229	261.139
Assault$_t$			Larceny$_t$		
ViolentArrests$_{t-1}$	.359	1.338	ViolentArrests$_{t-1}$	24.171	107.953
NonViolentArrests$_{t-1}$	-1.379**	.442	NonViolentArrests$_{t-1}$	-5.371	19.274
Misdemeanors$_{t-1}$	.895	.666	Misdemeanors$_{t-1}$	-6.985	34.155
Officers$_t$	1.181	.629	Officers$_t$	8.733	41.466
YoungAdults$_t$	.346	1.606	YoungAdults$_t$	36.744	161.982
DrugDeaths$_t$	-.316	.309	DrugDeaths$_t$	-.371	2.503
CUNYEnrollmentr$_t$	1.477	.913	CUNYEnrollmentr$_t$	5.153	22.289
Unemployed$_t$	-.154	.222	Unemployed$_t$	-3.353	14.093
Constant	-2.281	5.675	Constant	-182.337	852.773
Robbery$_t$			Auto Theft$_t$		
ViolentArrests$_{t-1}$	.876	1.705	ViolentArrests$_{t-1}$	-1.478	1.884
NonViolentArrests$_{t-1}$	-1.985**	.712	NonViolentArrests$_{t-1}$	-2.515**	.744
Misdemeanors$_{t-1}$	1.653	1.106	Misdemeanors$_{t-1}$	2.416	1.391
Officers$_t$	.198	.806	Officers$_t$	2.059	1.280
YoungAdults$_t$	12.719	8.719	YoungAdults$_t$	8.363*	4.950
DrugDeaths$_t$	.171	.379	DrugDeaths$_t$	-.305	.469
CUNYEnrollmentr$_t$	2.203	1.632	CUNYEnrollmentr$_t$	1.357	1.490
Unemployed$_t$	-1.174	.854	Unemployed$_t$	-1.164*	.570
Constant	-25.274	23.541	Constant	-11.785	13.640

Note: ** indicates significant at the 1% level and * at the 5% level.

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Table 2: Short run determinants of crime

Violent Felonies	Coefficient	Std.Error	Non-Violent Felonies	Coefficient	Std.Error
ΔMurder			ΔBurglary		
$\Delta Murder_{t-1}$ (0)	---	---	$\Delta Burglary_{t-1}$ (1)	.340*	.142
ΔViolentArrests (1)	-1.008**	.373	ΔViolentArrests (1 to 2)	.310	.232
ΔNonViolentArrests (1)	-.0133	.226	ΔNonViolentArrests (1 to 2)	.289	.149
ΔMisdemeanors (1)	.372	.239	ΔMisdemeanors (1 to 2)	-.616*	.156
ΔOfficers (0)	.090	.314	ΔOfficers (0 to 1)	-.187	-.187
ΔYoungAdults (0)	2.089**	.808	ΔYoungAdults (0 to 1)	1.586*	.637
ΔDrugDeaths (0)	.071	.085	ΔDrugDeaths (0 to 1)	.174**	.058
ΔCUNYEnrollment (0)	.137	.232	ΔCUNYEnrollment (0)	.080	.133
ΔUnemployed (0)	-.114	.104	ΔUnemployed (0)	-.094*	.045
ECT_{t-1}	-.141**	.031	ECT_{t-1}	-.022**	.003
ΔAssault			ΔLarceny		
$\Delta Assault_{t-1}$ (1 - 2)	.289*	.142	$\Delta Larceny_{t-1}$ (0)	---	---
ΔViolentArrests (1 - 2)	-.520*	.281	ΔViolentArrests (1)	.812**	.182
ΔNonViolentArrests (1 - 2)	.029	.141	ΔNonViolentArrests (1)	-.779**	.109
ΔMisdemeanors (1 - 2)	-.302	.213	ΔMisdemeanors (1)	-.304**	.119
ΔOfficers (0)	.308	.169	ΔOfficers (0)	.079	.153
ΔYoungAdults (0)	.250	.453	ΔYoungAdults (0)	.756*	.392
ΔDrugDeaths (0 – 1)	-.027	.060	ΔDrugDeaths (0)	.087*	.041
ΔCUNYEnrollment (0 - 1)	.207	.182	ΔCUNYEnrollment (0)	-.118	.113
ΔUnemployed (0)	-.135*	.052	ΔUnemployed (0)	-.130*	.050
ECT_{t-1}	-.432**	.071	ECT_{t-1}	-.031**	.004
ΔRobbery			ΔAuto Theft		
$\Delta Robbery_{t-1}$ (0)	---	---	ΔAuto $Theft_{t-1}$ (0)	---	---
ΔViolentArrests (1)	-.055	.213	ΔViolentArrests (1)	-.305	.332
ΔNonViolentArrests (1)	-.182	.128	ΔNonViolentArrests (1)	-.376*	.206
ΔMisdemeanors (1 to 2)	-.675**	.185	ΔMisdemeanors (1 to 2)	-.484*	.272
ΔOfficers (0)	.068	.118	ΔOfficers (0)	-.293	.262
ΔYoungAdults (0)	2.358**	.435	ΔYoungAdults (0)	1.527*	.674
ΔDrugDeaths (0)	.104**	.045	ΔDrugDeaths (0)	-.049	.069
ΔCUNYEnrollment (0)	-.114	.121	ΔCUNYEnrollment (0)	-.020	.192
ΔUnemployed (0)	-.122*	.056	ΔUnemployed (0)	-.197*	.085
ECT_{t-1}	-.183**	.023	ECT_{t-1}	-.210**	.030

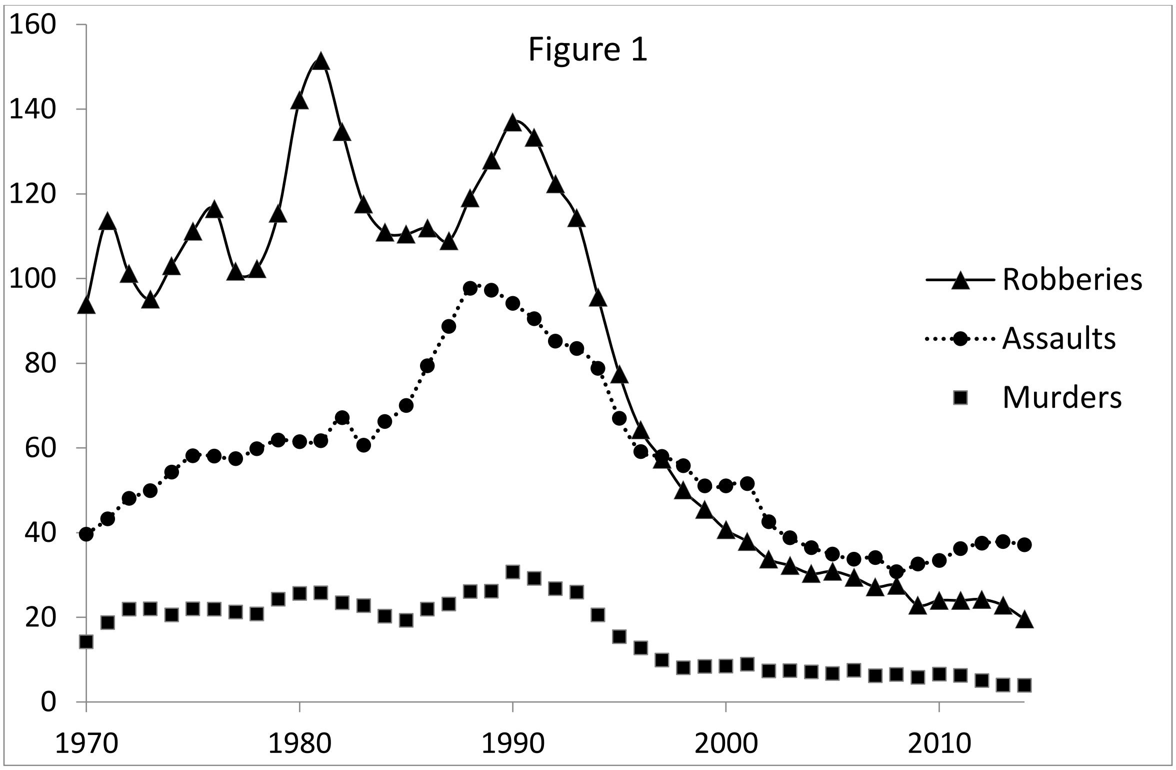
Figure 1
160
140
120
100
80
60
40
20
0
1970
1980
1990
2000
2010
Robberies
Assaults
Murders

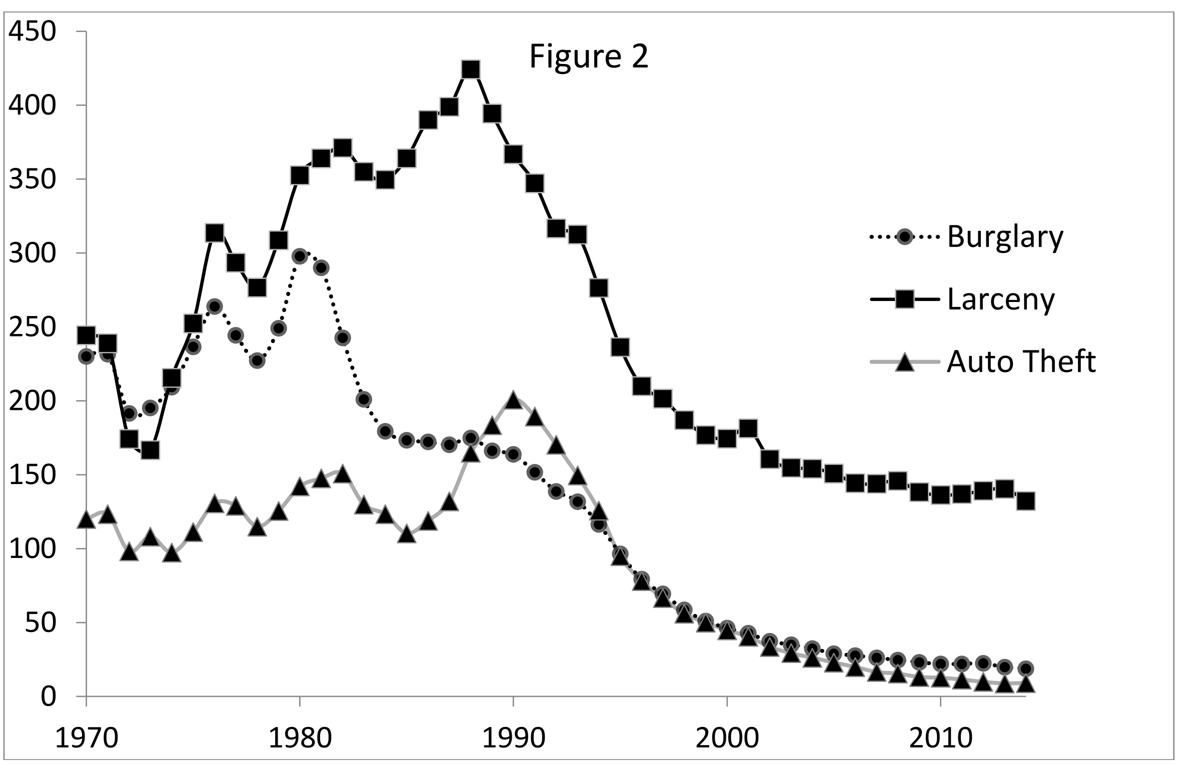
Figure 2
450
400
350
300
250
200
150
100
50
0
1970
1980
1990
2000
2010
Burglary
Larceny
Auto Theft

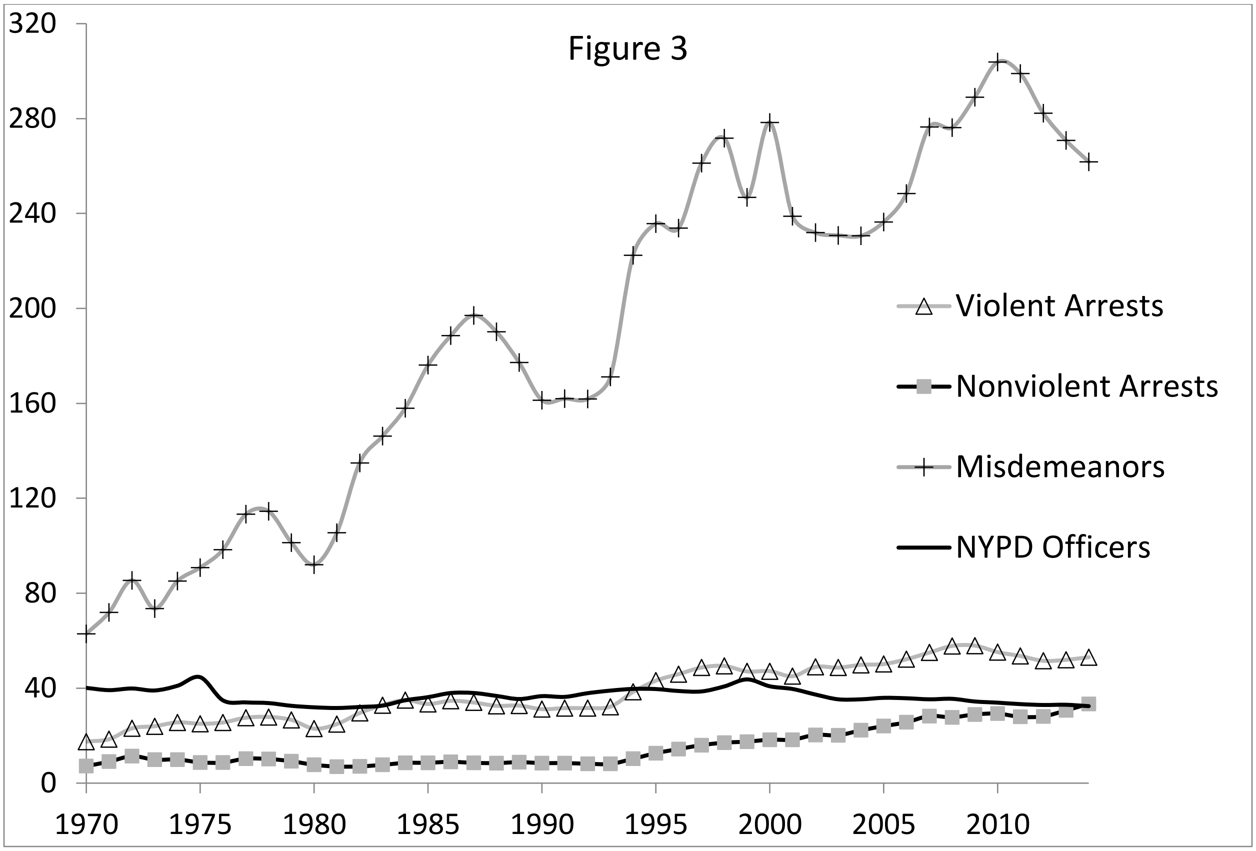
Figure 3
320
280
240
200
160
120
80
40
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
Violent Arrests
Nonviolent Arrests
Misdemeanors
NYPD Officers

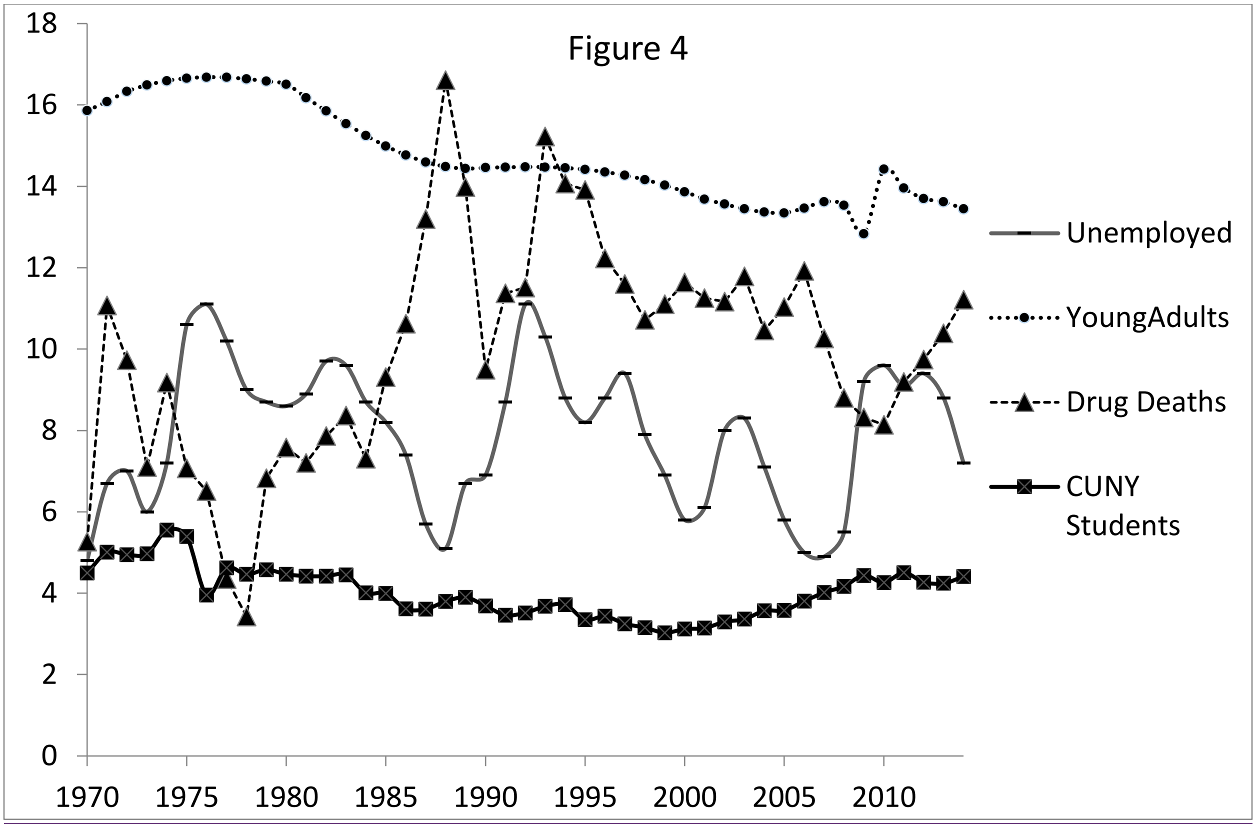
Figure 4
18
16
14
12
10
8
6
4
2
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
Unemployed
YoungAdults
Drug Deaths
CUNY Students