ASYMMETRIC CRIME CYCLES

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Recent theoretical models underscore the potential asymmetric response of various behaviors, ranging from criminal activity to smoking. In this paper we use state-level panel and individual-level panel data to document the previously-unnoticed asymmetric response of crime to changes in the unemployment rate. The results have policy implications, and they have potentially wide-spread ramifications because similar asymmetries may also be prevalent in other domains ranging from the relationship between income and health to peer quality and student outcomes.

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I. Introduction

Macroeconomists have long been concerned about asymmetries in economic phenomena. Over the last two decades one primary line of research has been the investigation of the existence of asymmetry in business cycles. For example, Neftci (1984), Falk (1986), Sichel (1989) Brunner (1997), McQueen and Thorley (1993), Hess and Iwata (1997) analyzed whether the behavior of aggregate economic variables such as unemployment and GDP can be characterized by sudden increases and slow decreases. Another strand of related research has investigated whether macroeconomic variables of interest responded asymmetrically to changes in other variables. For example, Hamilton and Lin (1996) and Schwert (1989) investigated the impact of economic expansions and contractions on the volatility of stock returns and found that stock return volatility was higher during recessions in comparison to expansions. McQueen and Roley (1993) reported that the impact of economic news on stock prices depends on the growth rate of industrial production. Along the same lines, Cover (1992) has shown that the response of output to money supply shocks is asymmetric: while negative money supply shocks have an impact on output, positive money supply shocks have no influence. Chen (2007) found that monetary policy has asymmetric effects on stock returns. Choi (1999) has shown that the extent of the response of the interest rates to a monetary shock depends on the state of the monetary policy regime.

These asymmetry findings are important, because as explained by McQueen and Thorley (1993), they indicate that caution should be exercised in interpreting the empirical results that assume symmetry in their setup. Furthermore, evidence on asymmetry provides motivation for developing theoretical models that can generate such asymmetric behavior.

Although empirical analysis of asymmetry and its theoretical implications have received attention in various domains of macroeconomic analysis as described above, economists have not paid much attention to potential asymmetry in other areas until very recently. One exception is Harris and Gonzales Lopez-Valcarcel (2008), who formulated a learning model of cigarette smoking where each young person gathers information about the risks and benefits of smoking from the behaviors of the peers. The information contained in each peer's behavior is used to update the priors about the benefits (safety, social acceptability, etc.) of smoking. This kind of social interaction within peers (or within the household) generates the possibility that the influence of a peer who is involved in the activity may be different in magnitude from the influence of a peer who is not involved in that activity, which yields hysteresis in aggregate behavior. Harris and Gonzales Lopez-Valcarcel (2008) find that the presence of an additional smoking sibling increases a young person's smoking probability by about 8 percent, but a non-smoking sibling reduces this probability by about 4 percent only.

In this paper, we test whether the response of crime is symmetric to changes in the unemployment rate. The basis for the possibility of asymmetric crime movements can be found in recent theoretical work. For example, as shown in the model of Mocan, Billups and Overland (2005), if an individual engages in criminal activity during an economic downturn, his legal human capital depreciates and his criminal human capital appreciates, which makes it difficult to switch back to the legal sector (or to decrease time spent in crime) after the recession is over. Thus, hysteresis in crime is predicted, which implies that the extent of the decrease in crime during economic recovery is expected to be smaller than the increase in crime observed during a downturn: crime is asymmetric over the business cycle. Asymmetric behavior in crime in this context can also be triggered by some other variable, such as deterrence; i.e. the increase in criminal propensity following a reduction in deterrence could be smaller than the decrease in that propensity due to enhanced deterrence, due to appreciation of criminal human capital and depreciation of legal human capital during the process.[1]

It should be noted that asymmetry in crime can also be generated by other mechanisms such as the existence of personal networks. In a setting with social networks and interaction, the interplay between social structure and information exchange in the labor market and the illegal market would generate asymmetric criminal activity. An example is the model of Calvo-Armengol, Verdier and Zenou (2007). In this model, if a person is pulled towards crime when his peers are also involved in crime, it is extremely difficult for him to get back to the labor market. Social interactions, captured by a positive covariance across individuals' decisions to engage in crime are also proposed as an explanation of the persistence of the crime rates (Glaeser, Sacerdote and Scheinkman 1996).

Empirical analyses conducted in this paper demonstrate that crime responds asymmetrically to economic activity. We present some evidence which is consistent with criminal human capital explanation, but we do not claim to identify the exact mechanism (human capital appreciation/depreciation, asymmetric peer effects, social networks, or something else) that is the driving force of this behavior. However, detection of the asymmetry in crime is important for at least three reasons. First, given the link between criminal activity and legal human capital formation (Bound and Freeman 1992, Freeman and Rodgers 2000), if the impact of economic conditions on crime is asymmetric, this would imply that the long-run impact of a deterioration in economic conditions would be magnified. Substantial social costs of crime (Miller et al 1995, Anderson 1999),

[1] In early formulations of heterogeneous human capital, people are assumed to possess different types and quantities of skill endowment, and they make decisions about the allocation of labor between different occupations (Rosen 1978, Rosen 1983, Heckman and Sedlacek 1985). Murphy (1986) extended this framework by allowing individuals to posses multiple types of human capital and by allowing them to invest in human capital through schooling and on-the-job investment in skill. His model is well-suited for an investigation of the determinants of specialization in the labor market and the equilibrium distribution of skills. Here, modest amounts of specialized human capital would generate movements between legal and illegal sectors. Recent models of dynamic criminal activity have parallels to Murphy's formulation of human capital investment and specialization.

coupled with the asymmetric response of crime to unemployment might provide support for policies that aim to counteract prolonged recessions.

Second, asymmetric criminal activity may have implications for other contexts. If there is asymmetry in crime, it is conceivable that a number of other behaviors exhibit asymmetric responses to their determinants as well, such as the policy tools in education as mentioned by Harris and Gonzales Lopez-Valcarcel (2008). For example, the positive impact of a high-performing classmate could be different in absolute value from the negative impact of a low-performing classmate, which has implication for policies such as ability-tracking. Another example is the impact of income on health, where asymmetry can provide a potential explanation for the contradictory results of the impact of recessions on health (Ruhm 2000, Ruhm 2003, Svensson 2007, Ahs and Westerling 2005). Third, the presence of a robust asymmetric behavior would provide motivation for theoretical models that generate such asymmetries; and empirical implementations which incorporate these asymmetries can generate new and perhaps deeper insights into these behaviors.

Although some recent studies found small positive effects of unemployment on some crimes (Corman and Mocan 2005; Gould, Weinberg and Mustard 2002), others reported even weaker effects (Corman, Joyce and Lovitch 1987), yet some others found no impact (Butcher and Piehl 1998) or even a negative impact (e.g. Ruhm 2000). As summarized by Freeman (1995), the lack of evidence on the impact of economic conditions on crime has been puzzling. Asymmetric impact may also help explain the contradictory findings in the literature on the impact of unemployment on crime.

Section II describes the methods that are applied to test the asymmetry hypothesis. Section III describes the data. Section IV presents the empirical results. Section V concludes the paper.

II. Empirical Implementation

Standard static crime models and their dynamic variants postulate a negative relationship between job market opportunities and criminal activity. At the aggregate level, this implies that α_1>0 in equation (1) below, where CR_t stands for the crime rate and UR_t represents the unemployment rate.

$$CR_t = \alpha_0 + \alpha_1 UR_t + \varepsilon_t \,. \tag{1}$$

Note that in equation (1) the implied relationship between *UR* and *CR* is symmetric. That is, α_1 represents the increase in *CR* in reaction to a given increase in *UR*, which can be viewed as the impact of a recession. At the same time, α_1 signifies the decrease in crime in response to a decrease in unemployment, indicating the decline in crime in times of economic recovery. In this standard setting, the impact on crime of an increase in unemployment is postulated to be equal to the impact on crime of a decrease in unemployment.

As discussed in the introduction, these impacts could be asymmetric. That is, the decrease in crime after the recession (when the unemployment rate is declining) may be not as large as the increase in crime during a recession. To test this hypothesis, we define the crime rate as an asymmetric function of the unemployment rate, where the conditional mean of the crime rate is specified to follow two different paths depending on the change (increase or decrease) in unemployment rate:

$$CR_t = \alpha_0 + \beta UR_t^+ + \gamma UR_t^- + \varepsilon_t \tag{2}$$

where $$UR_t^+ = \begin{Bmatrix} UR_t & \text{if } UR_t \geq UR_{t-1} \\ 0 & \text{if } UR_t < UR_{t-1} \end{Bmatrix} \text{ and } UR_t^- = \begin{Bmatrix} UR_t & \text{if } UR_t < UR_{t-1} \\ 0 & \text{if } UR_t \geq UR_{t-1} \end{Bmatrix}.$$

Put differently, UR_t can be used to construct two variables UR_t^+ and UR_t^- based on the change in UR_t between time periods.[2] A simple example demonstrates the creation of UR_t^+ and UR_t^-:

	1990	1991	1992	1993	1994
UR_t	5.6	6.8	7.5	6.9	6.1
UR_t^+	--	6.8	7.5	0	0
UR_t^-	--	0	0	6.9	6.1

This implies that

$$E(CR_t) = \alpha_0 + \beta UR_t^+ \qquad \text{for} \qquad UR_t - UR_{t-1} \geq 0$$

$$E(CR_t) = \alpha_0 + \gamma UR_t^- \qquad \text{for} \qquad UR_t - UR_{t-1} < 0$$

We estimate crime equations using state-level annual panel data, where we investigate whether increases and decreases in state unemployment rates have symmetric impacts on state property and violent crime rates. In this analysis we estimate specifications such as

$$CR_{it} = \alpha_0 + \beta UR_{it}^+ + \gamma UR_{it}^- + X_{it}^{'}\Omega + \mu_i + \Psi_t + \Gamma_{it} + \varepsilon_{it}\,. \tag{3}$$

where CR_{it} represents property or violent crime in state i for year t, X_{it} stands for a vector of state characteristics, μ_i represents unobserved state attributes that influence the crime rate, Ψ_t stands for year effects, Γ_{it} represents state-specific time trends, and ε_{it} is the error term.

We also employ individual-level panel data pertaining to a birth-cohort born in Philadelphia. We estimate models similar to the ones depicted in equation (3), except that the dependent variable is an indicator of whether the individual was arrested for a particular crime in a given year, or the number of crimes committed by that person. *UR* pertains to the

[2] A similar parametric specification is used by Bali (2000) to test the presence and significance of asymmetry in the conditional mean and conditional volatility of interest rate changes.

unemployment rate in Philadelphia. We estimate various econometric specifications including negative binomial and ordered-probit models.

As a supplementary analysis, we look at cohorts from 1965 to 2000 and investigate the impact of unemployment on age-specific arrests for different cohorts that were exposed to differential unemployment rates.

III. Data

We employ two main data sets. The state-level panel, including Washington, D.C., covers the years 1978 to 2004. The obvious advantage of this data set is that it allows us to exploit significant state-level variations that exist in crime and unemployment over time, and it allows us to remove the influences of unobserved omitted variables. By including year fixed-effects we control for unobserved factors that impact all the states, and including state fixed-effects and state-specific time trends allows us to control for unobserved differences between states. The data include state-level violent and property crime rates, the state unemployment rate, the proportion of the population which is white, black or Hispanic, the age distribution of state population, the proportion of state population in urban areas, and the number of prisoners in custody of state correctional authorities divided by state population. Crime data are obtained from the Bureau of Justice Statistics. State population, age representation, ethnic and racial distribution, and urbanization are obtained from the U.S. Department of Commerce, Bureau of the Census. Prison population data are obtained from the Bureau of Justice Statistics. Also included is per capita consumption of malt beverages in the state obtained from Brewer's Almanac by Beer Institute.

The second data set we analyze is the 1958 Philadelphia Birth Cohort. This is a panel which includes all children born in Philadelphia in 1958. The purpose of the panel was to follow this birth cohort with a special focus on criminal activities. As described in Williams and Sickles (2002) and Figlio (1994), the complete official criminal history of the individuals was collected from various sources, including the Philadelphia Police Department, Common and Municipal Courts, and the FBI. The panel includes information about the types of crimes and their specific dates, committed by 27,160 individuals from 1970 to 1984.[3] Most individuals lived within the Philadelphia SMSA or within a 100-mile radius of the urban area even toward the end of the panel when they were young adults (Williams and Sickles 2002). We created an annual panel which also included the Philadelphia unemployment rate, the size of the police force at the Philadelphia Police Department, and the following Pennsylvania-specific variables: the proportion of the population which is white, percent black, the proportion who live in urban areas, real per capita income, and population.[4] For each individual, dichotomous variables for various crimes are created to identify whether the person committed that particular crime in a given year. We also investigate the impact of increases and decreases of unemployment on the number of crimes committed by these individuals.

For a supplementary analysis we utilize data from the FBI Uniform Crime Reports (UCR) pertaining to age- and crime-specific arrests from 1965 to 2000. To calculate age-specific arrest rates we obtained population values reported by UCR covering the jurisdictions

[3] One useful detail of these data is that, in addition to the date of an arrest, the date of the crime for which the arrest took place is also reported. For example, an individual may be arrested in January 1980 for a burglary that he committed in November 1979. Both of these dates are recorded. We used the date of the crime, not the date of the arrest.

[4] Philadelphia unemployment rate is available starting in 1970 from Philadelphia Department of Labor and Industry. Variables pertaining to Pennsylvania are obtained from the Bureau of the Census.

that provide crime reports, and we adjusted them by age group proportions obtained from the Census Bureau.

III. Empirical Results

A. Evidence from State-level Panel Data

Models are estimated as depicted by equation (3), where the dependent variables are state-level property crime rate (the sum of burglary, motor-vehicle theft, and larceny theft per 100,000 population) and the violent crime rate (the sum of murder, robbery and rape per 100,000 population). UR^{+} and UR^{-} are generated based on the changes in state unemployment rates between years.

The results are presented in Table 1. All specifications include state fixed-effects, year fixed-effects and state-specific time trends. The regressions are estimated with the weighted least squares where state populations are used as weights. In column 1 we report the results where property crime rate is explained by UR^{+} and UR^{-} only (in addition to year and state fixed-effects and state-specific time trends). A one percentage-point increase in state unemployment rate increases the property crime rate by about 97, or 2.22 percent (the mean of the sample is 4,356). On the other hand, a one percentage point *decrease* in the unemployment rate *lowers* the property crime rate by 86 (1.97%). The difference is statistically significant at the 4 percent level, indicating that the extent of the increase in property crime during a particular rise in unemployment is greater than the decrease in property crime when unemployment declines by the same amount. Column 2 reports the results where the same specification is run with additional controls that may have an influence on state-level criminal activity. A one-percentage point increase in the unemployment rate is associated with an increase in property crime rate by

73, while a one-percentage point decrease in the unemployment rate decreases property crime rate by only about 61 and the difference is statistically significant at the 1 percent level. These results indicate that property crime reacts asymmetrically to increases and decreases in the unemployment rate. These estimates imply that a one percentage point increase in unemployment generates 3,762 additional property crimes per year in a state, while a percentage point decrease in unemployment reduces property crimes by only 3,143.[5]

Columns 3 and 4 repeat the same exercise for violent crime. In the model with no controls, UR_t^+ is significant at the 6-percent level, but the significance disappears when the model includes control variables, indicating that violent crime does not react to changes in the unemployment rate. The bottom panel of Table 1 presents the results pertaining to specific property crimes: burglary, theft and motor-vehicle theft. In each case we find that the impact of UR_t^+ is greater than the impact of UR_t^-. When we estimated the models with individual crimes that comprise violent crime, the coefficients of both unemployment variables were insignificant.[6]

It could be the case that that the identified asymmetry effect is just the result of a nonlinear impact of unemployment on crime. It may be the case that changes in unemployment when unemployment is high have a bigger impact on crime in comparison to changes in unemployment when the unemployment rate is close to the natural rate.[7] To address this issue, we regressed property crime on both linear and quadratic unemployment rates in state-level panel data. The coefficient on the linear unemployment variable was positive and significant,

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[5] When we replace UR_t^+ and UR_t^- with total unemployment rate, we find a coefficient of 61.

[6] We also ran the models using the logarithms of violent and property crimes. For violent crimes we obtained small and statistically insignificant impacts of unemployment. For property crimes, the coefficient of UR^+ was 0.017, and the one for UR^- was 0.014 in the model with no additional controls (the equivalent of column I), and they were 0.0126 and 0.0099, respectively, in the model with controls (the equivalent of column II). In both cases the difference was statistically significant at the 1 percent level.

[7] We thank an anonymous referee for this insight.

whereas the coefficient on the quadratic term was negative and statistically insignificant with very low t-statistic; rejecting the hypothesis of non-linearity.

As discussed in the introduction, serving time in prison is expected to reduce legal human capital, and it may enhance criminal human capital. The incarceration rate in the United States has been increasing steadily since 1970s.[8] The associated stigma and the decline in legal human capital, coupled with an enhanced criminal capital of being an ex-offender, may have enhanced the differential impact of the unemployment rate on criminal activity over time. To investigate this hypothesis, we experimented with three alternative specifications. First, we created a dummy variable which takes the value of one for the years before 1985, and zero otherwise. This variable splits the sample into two periods. The first period consists of relatively low incarceration rate, but still includes the 1982-83 recession.[9] We interacted the dummy variable with UR^{+} and UR^{-}, and estimated the property crime model depicted in the second column of Table 1 with the addition of these variables. The results showed that during the post-1985 period, the coefficient of UR^{+} was 69.81 (p=0.00), and that of UR^{-} was 56.64 (p=0.00), and the difference was statistically significant at the 2 percent level. The coefficients of the interaction terms were not different from zero, but we could not reject the hypothesis of symmetry for the period before 1985 (when the dummy variable takes the value of one). As an alternative model, we created a time trend and included ($trend \times UR^{+}$) and ($trend \times UR^{-}$) as two variables in the property crime models of Table 1. This specification investigates the impact of an increase and decrease in unemployment as a function of time. The estimated coefficient of ($trend \times UR^{+}$) was 2.82 with a p-value of zero, and the coefficient of ($trend \times UR^{-}$) was 2.05 with a p-value of 0.04;

[8] The number of prisoners in state facilities was 267,936 in 1977. It rose to 462,284 in 1985, to 708,393 in 1990 and 1,245,845 in 2000 (Bureau of Justice Statistics).
[9] The number of prisoners in state facilities increased by 47% from 1977 to 1984, but it increased by 105% from 1984 to 1999.

and they were statistically different from each other at the 1 percent level. This indicates that the discrepancy in the differential impact of unemployment has risen over time. Finally, we created two variables by interacting UR^+ and UR^- with per capita prisoners in the state, which is already included as a control variable. In this specification, the coefficient of the interaction between per capita prisoners and UR^+ was 14,477.6 (p=0.00), and that of UR^- was 10,040.8 (p=0.05)[10], indicating that as the number of prisoners in a state goes up, this increases the extent of the asymmetric impact of unemployment. These results suggest that the asymmetric impact of unemployment on crime has been getting stronger in more recent years, and this effect may be attributable to increased incarceration.

B. Some evidence from Cohort Analysis

Before we present the results from individual level panel data, in this section we demonstrate that individuals who are in the same age group exhibit differential criminal propensities if they were exposed to differential unemployment rates when they were younger. For example, individuals who were in the age group of 20-to-24 in 1987-88 have higher crime rates than those who were 20-to-24 in 1984-85. When these individuals were younger (when they were 15-to-19) the former cohort was exposed to a higher unemployment rate (9.7%) than the latter cohort (6.5%). Such evidence is suggestive that illegal human capital formation in young age may have an impact on future criminal activity and such capital formation may be influenced by increased unemployment rates.

To investigate this issue more formally, consider the following setup.

$$CR_t^c = \lambda UR_t + \pi UR_{t-k} \tag{4}$$

[10] The coefficients are large because the mean of per capita prisoners is 0.0028.

where CR_t^c stands for the crime rate of cohort "c" in year t, (e.g. the crime rate of 18-to-19 year olds in 1999) and UR_t stands for the unemployment rate in year t. Equation (4) postulates that the crime rate of a given cohort in a particular year is influenced by the contemporaneous unemployment rate (UR_t), and also by the unemployment rate prevailing k years earlier. For example, the crime rate of the 18-to-19 year cohort in year t will be influenced by the prevailing unemployment rate in year t, and also by the unemployment rate the cohort was exposed to 4 years earlier when they were 14-to-15 years old (if k = 4).

Consider equation (5) below, which depicts a different cohort "c" in year t-i.

$$CR_{t-i}^c = \lambda UR_{t-i} + \pi UR_{t-i-k} \,. \tag{5}$$

For example, if CR_t^c stands for the crime rate of the 15-to-17 year olds in 1999, and if i=2, CR_{t-i}^c represents the crime rate of the 15-to-17 year cohort in 1997. Subtracting (5) from (4) gives

$$\Delta^i CR_t^c = \lambda \Delta^i UR_t + \pi \Delta^i UR_{t-k} \,, \tag{6}$$

where Δ^i stands for the i*th* difference. For instance, consider that "c" represents the 20-to-24 year olds, and assume i = 2 and k = 4. Then, the left-hand side of equation (6) represents the difference in crime rates of 20-to-24 year old cohorts that are 2 years apart. The first term on the right hand side is the difference in the contemporaneous unemployment rates faced by these cohorts at the time when they were 20-to-24, and the second term is the difference in the unemployment rates that these 2-year apart cohorts each faced 4 years earlier (when they were 16-to-20 years old).

We compiled data from FBI Uniform Crime Reports pertaining to age- and crime-specific arrest, ranging from 1965 to 2000 for the United States. Table 2 presents the results obtained from running regressions depicted by equation (6). The dependent variable is the property crime rate of various age groups shown in the table measured by the age-specific arrest rates. The first panel pertains to the models that compare cohorts that are 2 years apart (i=2), and that are influenced by contemporaneous unemployment and also by unemployment 4 years earlier (k=4). For example, the second column indicates that the difference in the crime rates of the 18-to-19 year old cohorts that are 2 years apart is explained by the difference in the contemporaneous unemployment they faced, and also by the difference in the unemployment rate they faced when they were 14-to-15. As the top panel shows, all cohorts are influenced by current unemployment. Furthermore, exposure to differential unemployment rates 4 years ago explains the difference in the crime rates of the same-age-cohorts that are 2 years apart from each other until the age of 25-to-29. This suggests that variations in the exposure to unemployment have a significant impact on future crime if the exposure takes place at the age of 20 and younger. The second panel repeats the same exercise with one difference: here we compare the same-age-cohorts that are 3 years apart (i=3). The same conclusion is reached in this panel.

The bottom two panels of Table 2 present the results that are obtained by comparing the cohorts that are 2 or 3 years apart as before. But in these regressions we stipulated that current crime is impacted by exposure to unemployment rate 5 years earlier (k=5). Not surprisingly, a pattern emerged which is consistent with the top two panels.

If the theory of human capital appreciation/depreciation is meaningful, the impact of unemployment on very young workers is expected to be symmetric (or more symmetric) than older workers. This is because older workers would have had enough time to have acquired human capital in both legal and illegal sectors.[11] To test this simple hypothesis, we employed the

[11] We thank an anonymous referee for this insight.

same cohort data and regressed the crime rates of various age groups on UR^+ and UR^-.[12] The results are presented in Table 3. UR^+ and UR^- do not exert statistically significant impacts on the property crime rate of the 15-to-17 year olds. On the other hand, there is significant asymmetry in the impact of unemployment on the crime rate of 18-to-19 year olds, 20-to-24 year olds and those who are 25-to-29. The values in the third column are the test statistics for the equality of the coefficients of UR^+ and UR^-. The cohorts of 30-to-34 and 35-to-39 are impacted by UR^+ and UR^-, but the hypothesis of a symmetric impact cannot be rejected for these cohorts at conventional levels. The *p*-values for the null hypothesis of the symmetry are 0.129 and 0.160, respectively. These results suggest that asymmetric response to unemployment may be more relevant for the crime rates of those who are between 18 and 30.

C. Evidence from Individual-level Panel Data

The second data set we analyze is the 1958 birth cohort panel from Philadelphia. For each individual, the exact date of each crime is recorded in the data along with the description of the type of offense. Dichotomous indicators of various crimes are generated to indicate if the person committed those crimes in a given year. Note that if a person is arrested for a crime, other crimes he/she has committed in the past can be cleared.[13] The dependent variable in each model is dichotomous indicator for a crime committed by the individual between years of 1971 and 1984. Compiling each individual's history generated a panel of 27,160 individuals who are observed over 14 years.[14] We merged these data with Philadelphia unemployment rate, and added the

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[12] To eliminate serial correlation, we also included lagged dependent variables in each specification.
[13] For example, if somebody is arrested for assault in a given month, that arrest may link the person to a burglary, robbery etc. committed in previous time periods.
[14] The first observation is in year 1971, both because we lose one year due to the creation of the unemployment variables and 1970 is the first year that the unemployment rate is available on a consistent

following control variables to the panel: the annual values of the Philadelphia police force, the size of the Pennsylvania population, the proportion of white, and the proportion of black of the Pennsylvania population, percent population that lives in an urban area, and real per capita income in Pennsylvania.

Of the 27,160 individuals observed in the panel, 11% (9.5%) percent committed at least one property crime (violent crime) between 1971 and 1984. Seven percent (6.2%) involved in property crimes (violent crimes) in one year, and 2.2% (1.8%) involved in property crimes (violent crimes) in two different years.[15] The models contain individual fixed-effects and time trend. Robust standard errors are adjusted for clustering at the individual level. Column 1 of the top panel in Table 4 displays the results of the analysis for property crime, which includes burglary, theft and motor vehicle theft. Columns two, three and four present the results for violent crime, murder and rape. In addition to murder and rape, violent crime also includes robbery and assault. In case of property crime, there is strong evidence for asymmetry. A one-percentage point increase in the unemployment rate generates an increase the probability of committing property crime by 0.37 percentage points; but a one-percentage point decline in the unemployment rate decreases the propensity to commit property crime by 0.32 percentage points. The F-statistics reported in the table pertain to the hypothesis of the equality of the unemployment coefficients. In case of property crime reported in column 1, the difference between the coefficients is highly significant with a *p*-value of zero. There is no impact of unemployment on murder or rape, but the propensity to engage in violent crime is influenced by unemployment and the impact is asymmetric, where a one percentage point increase in the

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basis, and also because in 1970 the individuals of the panel are 12 years old, and consequently there is not much criminal activity.

[15] About 48% of the sample is male. Among males 19.8% (16.5%) committed at least one property crime (violent crime) over the duration of the panel.

unemployment rate increases the propensity to commit violent crime by 0.18 percentage points, but a decline in the unemployment rate by the same magnitude reduces that propensity by 0.15 percentage points, and the difference is statistically significant.[16]

Given the asymmetry in violent crime, we decided to analyze further the specific components of violent crime. The first two columns in the bottom panel of Table 4 report the results where the dependent variable is an indicator if the person committed assault or robbery. In both cases, the impact of unemployment is asymmetric. Given that there is no asymmetry in murder or rape, as shown in the top panel, this suggests that asymmetry in assault and robbery is driving the asymmetry in violent crime. In the bottom panel we also present the results for burglary, theft, and motor-vehicle theft, which are the components of property crime. We cannot reject the hypothesis of the equality of the UR^{+} and UR^{-} coefficients in case of motor-vehicle theft, but there is asymmetry in burglary and theft. Specifically, a one-percentage point increase (decrease) in the unemployment rate generates an increase (decrease) in the probability of committing burglary by 0.11 (0.09) percentage points; and an increase (decrease) in the probability of theft by 0.19 (0.15) percentage points.

Individuals in these panel regressions are in the age range of 13-to-26. When we added a dummy variable to control for the impact of being a juvenile or adult, the same results are obtained. The coefficient of the dummy variable to indicate adulthood was negative and significant in property crime, theft, violent crime and assault regressions.[17]

[16] Using just the unemployment rate instead of UR^{+} and UR^{-} reveals that the estimated coefficient of the unemployment rate is 0.0028 and highly significant in the property crime model as in Table 4. That is, the unemployment effect obtained from a model that assumes symmetry is about 24% smaller in comparison to the effect that entertains asymmetry.

[17] This finding is expected as the punitiveness increases at the age of majority (when age is greater than or equal to 18). Levitt (1998) reports the same result.

As in state-level panel, we investigated the potential nonlinearity in the individual-level panel data by regressing property crime on the same set of controls but replacing UR_t^+ and UR_t^- with total unemployment and unemployment squared. The results provided evidence for a nonlinear relation between crime and unemployment as the coefficients on both the linear and the quadratic unemployment terms were highly significant with *p*-values of zero. To investigate existence of symmetry in the presence of non-linearity, we specified property crime as a nonlinear asymmetric function of unemployment by adding the quadratic terms of UR^+ and UR^- to our original asymmetry specification. The test results indicated that there is economically and statistically significant nonlinearity and asymmetry in the individual-level data, and that the effect of asymmetry on crime was stronger than the effect of nonlinearity. Thus, the results demonstrated the presence of strong asymmetry in individual-level panel data, despite non-linearity.

We also investigated the impact of unemployment on the number of crimes committed by estimating a negative binomial model where the dependent variable is the count of the crimes committed. The results are presented in Table 5. The reported coefficients can be interpreted as elasticities. The results are very similar to those reported in Table 4, with one difference. In this specification we find asymmetry also in motor-vehicle theft where the elasticity of UR^+ is greater than the elasticity of UR^- at the 8.6 percent level.[18]

As an alternative specification, we estimated an ordered probit model where each individual's criminal activity is classified into the following categories for each specific crime: whether the individual did not commit a crime, whether he/she committed one crime, and

[18] We also estimated number of crimes committed using a negative binomial model with individual fixed effects. This specification cannot include the individuals who have never committed a crime, generating smaller sample sizes. Nevertheless, the results are similar. They are reported in the Appendix, Table A1.

whether he/she committed more than one crime. The advantage of this specification is the ability to analyze how an increase in unemployment changes the likelihood of committing no crime, one crime, or more than one crime in a coherent framework. The bulk of the mass is at zero crimes for all crime categories. Table 6 presents the estimated ordered-probit models along with the results of the hypothesis tests that the coefficients of UR^{+} and UR^{-} are equal. The bottom section of each crime column reports the marginal effects of UR^{+} and UR^{-} pertaining to each category. The marginal effects of UR^{+} and UR^{-} are negative for the category of no crime indicating that an increase in these variables decreases the probability of committing no crime. On the other hand, the marginal effects of the unemployment variables are positive for the categories that indicate "one crime" and "more than one crime". Furthermore, the absolute values of the marginal effects of UR^{+} and UR^{-} are very small for the category where crimes are greater than 1, indicating that most of the impact of the unemployment is observed in pulling people in crime, rather than increasing the number of crimes of those who are already committing crimes.

An individual's criminal propensity is expected to be positively related to an increase in the unemployment rate. But also, a higher level of criminal human capital of the individual is expected to raise that propensity. Furthermore, an increased level of criminal human capital would increase the extent of path-dependence in criminal activity (i.e. would make it more difficult to reduce criminal involvement when economic conditions are improving). The individual-level panel allows for a test of this hypothesis. For each person, we know the number as well as the types of crimes committed. Thus, we are able to create a proxy for criminal human capital, which is calculated as the cumulative number of crimes committed until the previous year. We estimated the same models with the addition of this new variable, called *PastCrime* as follows:

$$CR_{it} = \alpha + \beta_1 UR_{it}^{+} + \gamma_1 UR_{it}^{-} + \beta_2 UR_{it}^{+} \times PastCrime_{it} + \gamma_2 UR_{it}^{-} \times PastCrime_{it} + \delta \cdot PastCrime_{it} + X_{it}^{'}\Omega + \mu_i + \Psi_t + \varepsilon_{it}$$

(7)

In this specification the impact of UR_t^{+} on crime is ($\beta_1+\beta_2 PastCrime$), and the impact of UR_t^{-} is ($\gamma_1+\gamma_2 PastCrime$). If a higher level of criminal experience increases the impact of UR_t^{+} on crime, and decreases that of UR_t^{-}, then $(\beta_1 + \beta_2) - (\gamma_1 + \gamma_2)$ should be larger than $(\beta_1 - \gamma_1)$, increasing the wedge between the impacts of UR_t^{+} and UR_t^{-}; i.e., exacerbating the extent of asymmetry.

We estimated a negative binomial model similar to the one reported in Table 5 with the inclusion of the interaction terms as described above. The results are presented in Table 7. The estimated coefficients of the variable *PastCrime* is positive and significant in all crime equations. The coefficients of the interaction terms are negative, but the coefficients of the interaction term between UR_t^{-} and *PastCrime* is more negative in every case, increasing the extent of the asymmetry. As can be seen at the bottom of the table, in case of property crime and theft, the hypothesis of the equality of the coefficients on UR_t^{+} and UR_t^{-} is strongly rejected ($\beta_1=\gamma_1$ in equation 7). The impact of the unemployment rate is symmetric in case of violent crimes. In the table we also report the results of the tests $\beta_1+\beta_2 = \gamma_1+\gamma_2$, which investigate the hypothesis when *PastCrime* is equal to one.[19] As predicted, the extent of asymmetry gets bigger when the number of past crimes committed by the individuals gets larger. In fact, for assault, robbery, burglary and motor-vehicle theft we cannot reject the hypothesis of symmetry for those with no

[19] The overall mean (std) of *PastCrime* is 0.239 (1.125), with the minimum of zero and maximum of 52.

previous crime (the hypothesis of $\beta_1=\gamma_1$ when *PastCrime*=0), but we reject symmetry when *PastCrime* is equal to 1 ($\beta_1+\beta_2 = \gamma_1+\gamma_2$, reported in the last row of Table 7). These findings indicate that the extent of asymmetry is more pronounced for individuals with higher levels criminal human capitals. In other words, the difference between the impacts of an increase and decrease in unemployment gets larger, indicating that a recession pulls the person to crime with more ease, but a recovery does not pull him out as easily.

IV. Summary and Conclusion

In this paper we present evidence of a previously-unnoticed regularity of criminal behavior. The *increase* in property crime during *economic downturns* is greater in magnitude than its *decrease* in *economic recoveries*. Using annual state-level panel data, we find that a one percentage-point increase in state unemployment rate is associated with an additional 3,762 property crimes per year, while a decrease in the unemployment rate by the same absolute magnitude reduces property crime by only 3,143 for a typical state. Violent crime does not react to variations in state unemployment. We illustrate this result in Figure 1. If the level of property crime was steady at 224,000 per year for a state, a one percentage-point increase in the unemployment rate (e.g. from 6% to 7%) would increase the number of property crimes to 227,762 per year. A subsequent decline in the unemployment rate by one percentage point would reduce property crime to 224, 619 per year.[20] The results of this paper indicate that persistence in the level of crime will follow after an increase in criminal activity, and crime will

[20] In Figure 1, the increase in crime is depicted as a quick phenomenon, and the decline is slow because a one percentage point increase in the unemployment rate typically takes 7 months, but a one-point decline on average takes 17 months. Analogous to this, Mocan and Bali (2005) show that increases in crime are sharper over time, and decreases are gradual.

not revert back to its original level. However, this does not imply that crime will increase persistently over time, because the duration of contractions is smaller than the duration of expansions[21], and because policymakers generally react to increased criminal activity by raising the degree of deterrence (see the discussion in Levitt 2002, and Corman and Mocan 2000).

We also analyze the 1958 Philadelphia Birth Cohort, which is a panel of individuals who were born in Philadelphia in 1958, and that contains information about their criminal activity between the ages of 13 and 26. Consistent with the results from the state panel, we find that an increase in the unemployment rate has a larger impact in magnitude than a decrease for all crimes other than murder, rape and motor-vehicle theft. Furthermore, past criminal activity of the individual increases the differential impact of an increase and decrease in unemployment. Employing the same data sets but estimating models that assume a symmetric impact of unemployment generates coefficients that are substantially smaller than the ones obtained from the specifications that allow for asymmetry. This finding may help explain the mixed results obtained by previous research that assumed symmetry.

A number of factors may cause an increase in crime such as reduced certainty and severity of punishment, increased joblessness, demographic shifts, changes in risk aversion and time preferences. A model of human capital formation (e.g. Mocan, Billups and Overland 2005) can generate the asymmetric dynamics of criminal activity as was identified in this paper. In addition, recent theoretical models present mechanisms that can generate asymmetries in crime. Examples include the model which incorporates social interaction within peers (Harris and Gonzales-Valcarcel 2008) and the model of Calvo-Armegol, Verdier and Zenou (2007) where the existence of personal networks is the driving mechanism of the asymmetry. Given that the

[21] During the period of 1945-2001, the U.S. economy experienced 8 cycles, where the average contraction was 10 months, and the average expansion was 52 months as reported by the NBER.

social cost of crime is substantial[22], the findings of this paper suggest that it may be cost effective to implement measures and mechanisms that will prevent crime commission rates from rising in the first place. Furthermore, the findings are also important because they suggest that it is conceivable that a number of other behaviors exhibit asymmetric responses to their determinants. For example, as mentioned by Harris and Gonzales-Valcarcel (2008) the positive impact of a high-performing classmate could be different in absolute value from the negative impact of a low-performing classmate, which has implication for education policies such as ability-tracking. Another example is the influence of income on health, where an increase in joblessness or income by a particular amount may impact health outcomes differently than a decrease by the same amount.

[22] The estimates range from $300 billion to $1 trillion (Miller et al. 1995, Anderson 1999).

Table 1
The Impact of Recessions and Recoveries on Crime Using State-level Panel Data
(1978 to 2004)

	Property Crime Rate		Violent Crime Rate	
	(1)	(2)	(3)	(4)
Recession (UR_t^+)	97.437***	72.990***	3.267*	0.115
	(17.506)	(14.288)	(1.739)	(1.664)
Recovery (UR_t^-)	86.035***	61.428***	1.057	-2.012
	(19.745)	(16.039)	(1.923)	(1.853)
Prisoners/Population		-257428***		-3962.51
		(42178.490)		(3919.739)
% White		-1037.320**		-115.286***
		(463.502)		(36.956)
% Black		706.327		-74.822
		(827.340)		(90.952)
% Hispanic		-2809.710**		-19.205
		(1311.221)		(133.412)
% Urban Pop.		-592.543		99.202
		(1221.002)		(151.750)
Alcohol consumption		-17.772		-0.255
		(21.954)		(2.131)
% 15-19 year olds		229.822***		20.009***
		(49.562)		(6.633)
% 20-24 year olds		-26.120		8.835
		(41.762)		(5.579)
% 25-34 year olds		179.698***		17.819***
		(26.261)		(2.572)
% 35-44 year olds		-200.946***		-34.065***
		(48.007)		(5.319)
% 45-54 year olds		105.310**		1.609
		(52.953)		(5.299)
N	1,377	1,373	1,377	1,373

The models include state fixed effects, time fixed effects and state-specific time trends. The numbers in parentheses are robust standard errors. *, **, or *** signify statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 1 (continued)

	Burglary	Theft	Motor Vehicle Theft
Recession (UR_t^+)	29.375***	38.150***	5.465*
	(4.923)	(8.320)	(3.173)
Recovery (UR_t^-)	27.972***	31.911***	1.545
	(5.374)	(9.331)	(3.421)
Prisoners/Population	-88003.300***	-130498.100***	-38926.300***
	(13632.110)	(23366.500)	(9232.599)
% White	-47.140	-456.059*	-534.116***
	(118.047)	(256.867)	(142.653)
% Black	647.337**	823.995	-765.004***
	(274.994)	(502.287)	(217.868)
% Hispanic	-720.016*	-2241.836***	152.146
	(413.968)	(718.739)	(431.319)
% Urban Pop.	-1507.240***	680.391	234.305
	(431.666)	(715.601)	(351.010)
Alcohol consumption	-7.876	-10.307	0.412
	(6.978)	(13.065)	(5.030)
% 15-19 year olds	57.605***	116.219***	55.998***
	(15.530)	(31.025)	(11.722)
% 20-24 year olds	-64.045***	-9.909	47.833***
	(13.448)	(25.876)	(12.946)
% 25-34 year olds	43.629***	85.635***	50.433***
	(8.569)	(16.370)	(6.376)
% 35-44 year olds	-72.588***	-50.057*	-78.302***
	(15.445)	(28.472)	(12.714)
% 45-54 year olds	23.083	98.397***	-16.171
	(14.998)	(34.099)	(12.940)
N	1373	1373	1373

The models include state fixed effects, time fixed effects and state-specific time trends. The numbers in parentheses are robust standard errors. *, **, or *** signify statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2

The Impact of Differential Current and Past Unemployment on Crime Rates of Cohorts

Cohorts 2 Years Apart
with UR Impacting Crime with a 4 Year Lag (i=2, k=4)

	15 to 17	18 to 19	20 to 24	25 to 29	30 to 34	35 to 39
$\Delta^i UR_t$	71.793	90.444***	60.370***	39.110***	24.826***	14.741**
	(54.070)	(29.283)	(15.077)	(12.405)	(9.395)	(6.268)
$\Delta^i UR_{t-k}$	74.936*	78.583***	28.350**	10.682	5.822	2.989
	(38.830)	(24.910)	(12.728)	(10.851)	(6.341)	(6.341)

Cohorts 3 Years Apart
with UR Impacting Crime with a 4 Year Lag (i=3, k=4)

	15 to 17	18 to 19	20 to 24	25 to 29	30 to 34	35 to 39
$\Delta^i UR_t$	60.323	78.437*	56.047***	37.484***	23.940***	14.287**
	(62.443)	(39.480)	(17.472)	(12.317)	(9.129)	(5.920)
$\Delta^i UR_{t-k}$	7.565	44.706	30.408*	16.123	9.056	6.202
	(47.672)	(31.214)	(16.369)	(13.019)	(10.179)	(7.356)

Cohorts 2 Years Apart
with UR Impacting Crime with a 5 Year Lag (i=2, k=5)

	15 to 17	18 to 19	20 to 24	25 to 29	30 to 34	35 to 39
$\Delta^i UR_t$	78.754	93.226***	61.929***	42.388**	26.365*	15.115
	(64.528)	(35.638)	(18.440)	(17.558)	(14.567)	(9.705)
$\Delta^i UR_{t-k}$	81.379*	82.948***	34.006**	18.736	10.470	5.795
	(47.119)	(31.040)	(15.769)	(13.808)	(11.633)	(8.260)

Cohorts 3 Years Apart
with UR Impacting Crime with a 5 Year Lag (i=3, k=5)

	15 to 17	18 to 19	20 to 24	25 to 29	30 to 34	35 to 39
$\Delta^i UR_t$	58.493	75.908	56.622***	39.922**	25.067**	14.518*
	(72.812)	(45.656)	(20.865)	(15.726)	(12.292)	(8.013)
$\Delta^i UR_{t-k}$	32.843	65.028**	43.632**	28.376**	16.618	10.349
	(50.635)	(31.579)	(17.756)	(13.491)	(10.836)	(7.686)

Table 3
The Impact of Unemployment on Crime at
Different Ages

Arrest rate of individuals who are	UR_t^+	UR_t^-	$UR_t^- = UR_t^-$
15 to 17	61.293	42.508	2.00
	(46.617)	(36.165)	[0.167]
18 to 19	54.805*	40.392	3.37
	(31.400)	(26.675)	[0.076]
20 to 24	36.446**	27.632*	5.29
	(16.213)	(14.042)	[0.028]
25 to 29	25.469**	19.922**	4.40
	(9.659)	(8.504)	[0.044]
30 to 34	17.574***	14.501**	2.43
	(5.538)	(5.334)	[0.129]
35 to 39	10.117**	8.296**	2.07
	(4.220)	(3.804)	[0.160]

The values in parentheses are standard errors adjusted for serial correlation up to lag 8. *, **, or *** signify statistical significance at the 10%, 5%, and 1% levels, respectively. The values in the last column report the F-statistics for the null hypothesis of the equality of the coefficients of UR_t^+ and UR_t^-. The marginal significance levels are reported in square brackets.

Table 4
The Impact of Recessions and Recoveries on Crime Using Individual-level Panel Data
Dichotomous Dependent Variable

	Property Crime	Violent Crime	Murder	Rape
Recession (UR^{+})	0.0037***	0.0018***	0.00002	0.00002
	(0.0004)	(0.0004)	(0.00006)	(0.00009)
Recovery (UR^{-})	0.0032***	0.0015***	0.00003	0.00003
	(0.0004)	(0.0004)	(0.00006)	(0.00008)
% White	0.0004***	0.0002***	0.000006	-0.000001
	(0.00003)	(0.00003)	(0.000004)	(0.000006)
% Black	0.0151***	0.0084***	0.0002	0.00002
	(0.0010)	(0.0009)	(0.0002)	(0.0002)
% Urban	-0.0211***	-0.0112***	-0.0002	-0.0008
	(0.0035)	(0.0032)	(0.0005)	(0.0007)
Police	-0.0187***	-0.0050*	-0.0001	0.0010
	(0.0032)	(.0028)	(0.0005)	(0.0007)
Pennsylvania Population	-0.0497***	-0.0274***	0.0002	-0.0012
	(0.0040)	(0.0036)	(0.0005)	(0.0008)
Real Income	-0.0011***	-0.0010***	-0.00008**	-0.00005
	(0.0002)	(0.0002)	(0.00003)	(0.00004)
N	380,240	380,240	380,240	380,240
F (1, 27159)	55.42	13.99	1.07	0.65
	[p = 0.000]	[p = 0.000]	[p = 0.301]	[p = 0.420]

	Assault	Robbery	Burglary	Theft	Motor Vehicle Theft
Recession (UR^{+})	0.0011***	0.0011***	0.0011***	0.0019***	0.0111***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Recovery (UR^{-})	0.0009***	0.0009***	0.0009***	0.0015***	0.0111***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0002)
% White	0.0001***	0.0001***	0.0001***	0.0002***	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
% Black	0.0039***	0.0059***	0.0043***	0.0089***	0.0031***
	(0.0007)	(0.0007)	(0.0007)	0.0008	(0.0004)
% Urban	-0.0074***	-0.0057**	-0.0057**	-0.0084***	-0.0102***
	(0.0024)	(0.0023)	(0.0023)	(0.0027)	(0.0017)
Police	-0.0041**	-0.0045**	-0.0039*	-0.0079***	-0.0075***
	(0.0021)	(0.0020)	(0.0020)	(0.0025)	(0.0015)
Pennsylvania Population	-0.0154***	-0.0154***	-0.0134***	-0.0237***	-0.0164***
	(0.0027)	(0.0025)	(0.0025)	(0.0030)	(0.0019)
Real Income	-0.0004***	-0.0006***	-0.0003***	-0.0008***	-0.00006
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.00009)
N	380,240	380,240	380,240	380,240	380,240
F (1, 27159)	7.54	14.95	9.15	37.39	2.07
	[p = 0.006]	[p = 0.000]	[p = 0.002]	[p = 0.000]	[p = 0.150]

The numbers in parentheses are clustered standard errors that correct for heteroscedasticity and contemporaneous cross-correlations in the residuals. *, **, or *** signify statistical significance at the 10%, 5%, and 1% levels, respectively. *F* statistic tests for the hypothesis of the equality of the coefficients on UR^{+} and UR^{-}. The values in square brackets contain the *p*-values for the *F* statistic.

Table 5
The Impact of Recessions and Recoveries on Crime Using Individual-level Panel Data
Negative Binomial Regressions
Dependent Variable: Count of Crimes

	Property Crime	Violent Crime	Murder	Rape
Recession (UR_t^+)	0.3161***	0.2195***	-0.0027	0.0492
	(0.0354)	(0.0380)	(0.2268)	(0.1717)
Recovery (UR_t^-)	0.2867***	0.2012***	0.0462	0.0670
	(0.0336)	(0.0362)	(0.2219)	(0.1665)
% White	0.0286***	0.0236***	0.0197	0.0053
	(0.0024)	(0.0029)	(0.0191)	(0.0129)
% Black	0.6915***	0.6822***	0.2840	0.0864
	(0.1091)	(0.0951)	(0.4890)	(0.3885)
% Urban	-2.6051***	-1.7589***	-0.4717	-1.4038
	(0.3259)	(0.3594)	(2.1506)	(1.5763)
Police	-1.3047***	-0.7892***	0.1776	1.4439
	(0.2536)	(0.2727)	(1.7715)	(1.2542)
Pennsylvania Population	-3.3466***	-2.7915***	1.0777	-1.6637
	(0.3224)	(0.3786)	(2.1717)	(1.6452)
Real Income	-0.0221	-0.0663***	-0.2270**	-0.0834
	(0.0158)	(0.0174)	(0.1083)	(0.0704)
Year	-0.7585***	-0.3870***	0.4670	-0.0532
	(0.1118)	(0.1296)	(0.8122)	(0.5763)
N	380240	380240	380240	380240
Equality of the coeff. of	18.79	6.76	2.11	0.42
UR^+ and UR^- $\chi^2(1)$	[p=0.000]	[p=0.009]	[p=0.147]	[p= 0.515]

	Assault	Robbery	Burglary	Theft	Motor Vehicle Theft
Recession (UR_t^+)	0.2234***	0.2500***	0.2756***	0.2970***	0.4894***
	(0.0520)	(0.0582)	(0.0572)	(0.0446)	(0.0850)
Recovery (UR_t^-)	0.2041***	0.2260***	0.2537***	0.2609***	0.4609***
	(0.0496)	(0.0555)	(0.0543)	(0.0427)	(0.0798)
% White	0.0194***	0.0308***	0.0228***	0.0246***	0.0582***
	(0.0035)	(0.0047)	(0.0039)	(0.0031)	(0.0063)
% Black	0.4877***	0.9529***	0.5034***	0.7494***	0.9983***
	(0.1329)	(0.1395)	(0.1564)	(0.1287)	(0.2945)
% Urban	-1.7638***	-1.8306***	-2.0304***	-2.4075***	-4.6193***
	(0.4776)	(0.5674)	(0.5199)	(0.4293)	(0.7701)
Police	-0.7368**	-1.1188***	-0.7953*	-1.1385***	-3.0488***
	(0.3627)	(0.4230)	(0.4070)	(0.3200)	(0.5915)
Pennsylvania Population	-2.6783***	-3.2383***	-2.8026***	-2.9923***	-5.7591***
	(0.4864)	(0.6059)	(0.5239)	(0.4044)	(0.7904)
Real Income	-0.0456*	-0.0745***	-0.0126	-0.0407**	0.0098
	(0.0236)	(0.0267)	(0.0256)	(0.0207)	(0.0365)
Year	-0.4563***	-0.3993*	-0.6217***	-0.6375***	-1.4563***
	(0.1697)	(0.2046)	(0.1844)	(0.1481)	(0.2566)
N	380240	380240	380240	380240	380240
Equality of the coeff. of	3.69	5.13	4.18	17.04	2.96
UR^+ and UR^- $\chi^2(1)$	[p=0.055]	[p=0.024]	[p=0.041]	[p=0.000]	[p=0.086]

Table 6
The Impact of Recessions and Recoveries on Crime Using Individual-level Panel Data
Ordered Probit Regressions

	Property Crime	Violent Crime	Murder	Rape
Recession (UR^+)	0.1182***	0.0687***	0.0029	0.0216
	(0.012)	(0.0128)	(0.0610)	(0.0473)
Recovery (UR^-)	0.1059***	0.0621***	0.0164	0.0271
	(0.011)	(0.0122)	(0.0594)	(0.0456)
% White	0.0114***	0.0074***	0.0054	0.0015
	(0.0008)	(0.0009)	(0.0050)	(0.0035)
% Black	0.3266***	0.2290***	0.0930	0.0224
	(0.0306)	(0.0312)	(0.1318)	(0.1080)
% Urban	-0.8256***	-0.5018***	-0.1412	-0.4732
	(0.1056)	(0.1164)	(0.5743)	(0.4318)
Police	-0.5441***	-0.2100**	0.0179	0.3756
	(0.0803)	(0.0898)	(0.4685)	(0.3475)
Pennsylvania Population	-1.3136**	-0.8831***	0.2494	-0.5884
	(0.1034)	(0.1200)	(0.5821)	(0.4501)
Real Income	-0.0123***	-0.0242***	-0.0613**	-0.0200
	(0.0053)	(0.0058)	(0.0289)	(0.0199)
N	380240	380240	380240	380240
Equality of the coeff. of UR^+ and UR^- $\chi^2(1)$	30.10	7.70	2.08	0.50
	[p=0.000]	[p=0.006]	[p=0.149]	[p=0.478]
Marginal Effect (on Crime = 0)				
Marginal Effect (UR^+)	-0.0036	-0.0019	-0.000003	-0.00004
Marginal Effect (UR^-)	-0.0032	-0.0017	-0.000018	-0.0001
Marginal Effect (on Crime = 1)				
Marginal Effect (UR^+)	0.0027	0.0016	0.000003	0.00004
Marginal Effect (UR^-)	0.0025	0.0014	0.000018	0.0001
Marginal Effects (on Crime > 1)				
Marginal Effect (UR^+)	0.0008	0.0003	0.0000000	0.000002
Marginal Effect (UR^-)	0.0007	0.0003	0.0000002	0.000003

Table 6 (continued)

	Assault	Robbery	Burglary	Theft	Motor Vehicle Theft
Recession (UR^+)	0.0753***	0.0756***	0.0819***	0.1023***	0.1467***
	(0.0173)	(0.0173)	(0.0173)	(0.0150)	(0.0236)
Recovery (UR^-)	0.0685***	0.0663***	0.0733***	0.0890***	0.1430***
	(0.0166)	(0.0166)	(0.0164)	(0.0143)	(0.0222)
% White	0.0067***	0.0093***	0.0076***	0.0090***	0.0187***
	(0.0012)	(0.0012)	(0.0012)	(0.0010)	(0.0017)
% Black	0.1789***	0.3149***	0.2220***	0.3048***	0.3350***
	(0.0437)	(0.0413)	(0.0449)	(0.0387)	(0.0654)
% Urban	-0.5765***	-0.4797***	-0.5651***	-0.7007***	-1.3380***
	(0.1590)	(0.1581)	(0.1569)	(0.1424)	(0.2218)
Police	-0.2689**	-0.3251***	-0.2830**	-0.3987***	-0.9351***
	(0.1231)	(0.1218)	(0.1221)	(0.1065)	(0.1645)
Pennsylvania Population	-0.9125***	-0.9425***	-0.8715***	-1.0736***	-1.8514***
	(0.1623)	(0.1642)	(0.1564)	(0.1359)	(0.2180)
Real Income	-0.0161**	-0.0241***	-0.0083	-0.0177**	-0.0018
	(0.0079)	(0.0078)	(0.0079)	(0.0070)	(0.0109)
N	380240	380240	380240	380240	380240
Equality of the coeff. of UR^+ and UR^- $\chi^2(1)$	4.13	8.41	6.48	21.23	0.58
	[p=0.042]	[p=0.004]	[p=0.011]	[p=0.000]	[p=0.445]
Marginal Effect (on Crime = 0)					
Marginal Effect (UR^+)	-0.0011	-0.0011	-0.0011	-0.0019	-0.0009
Marginal Effect (UR^-)	-0.0010	-0.0009	-0.0010	-0.0016	-0.0008
Marginal Effect (on Crime = 1)					
Marginal Effect (UR^+)	0.0010	0.0009	0.0009	0.0016	0.0008
Marginal Effect (UR^-)	0.0009	0.0008	0.0008	0.0014	0.0007
Marginal Effect (on Crime > 1)					
Marginal Effect (UR^+)	0.0001	0.0001	0.0002	0.0002	0.0001
Marginal Effect (UR^-)	0.0001	0.0001	0.0001	0.0002	0.0001

The values in parentheses are standard errors clustered at the individual level that correct for heteroscedasticity and contemporaneous cross-correlations in the residuals. *, **, or *** signify statistical significance at the 10%, 5%, and 1% levels, respectively.

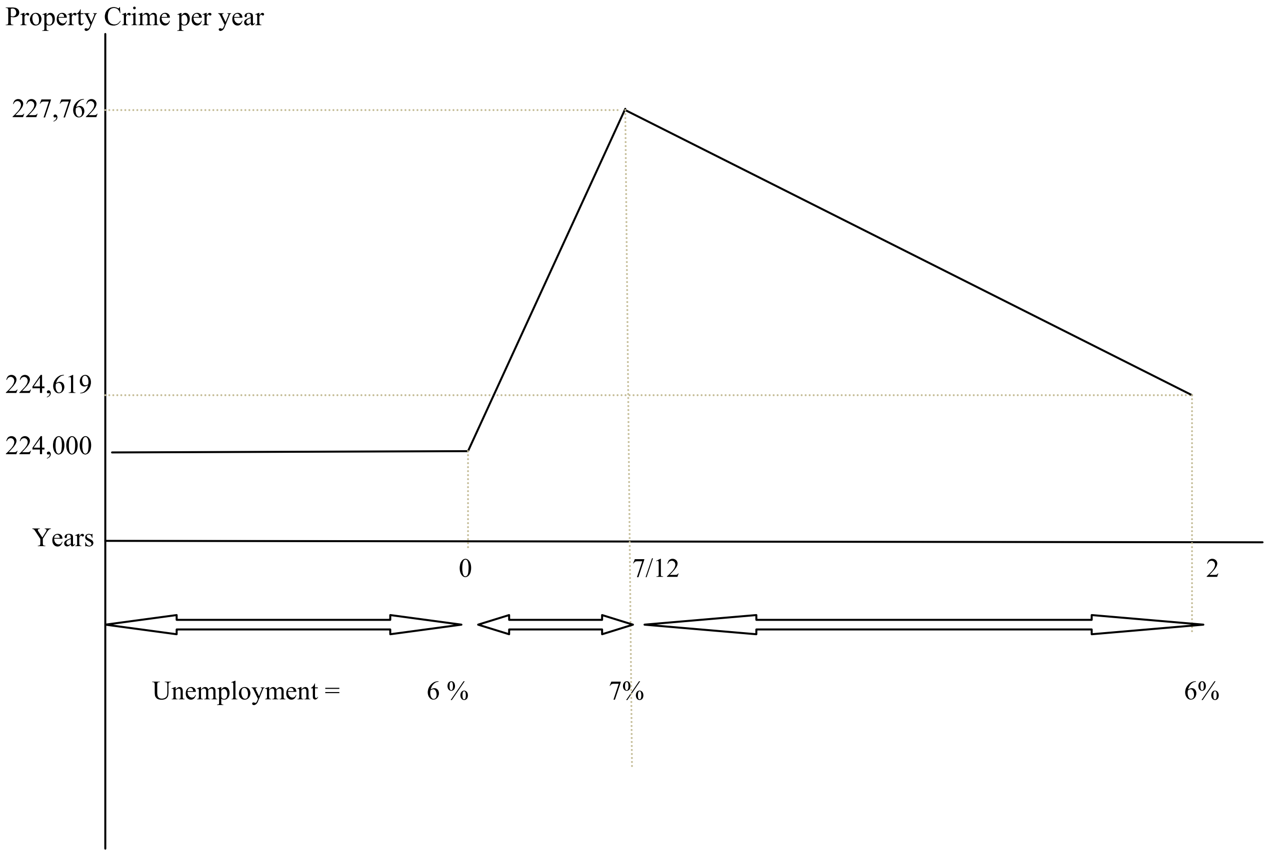
Table 7
The Impact of Recessions and Recoveries on the Number of Crimes
Negative Binomial Regressions

	Property Crime	Violent Crime	Murder	Rape
Recession (UR^+)	0.3469***	0.2010***	-0.0381	0.1158
	(0.0399)	(0.0422)	(0.2496)	(0.1827)
Recovery (UR^-)	0.3299***	0.2029***	0.0446	0.1384
	(0.0372)	(0.0400)	(0.2382)	(0.1752)
Pastcrime	1.3641***	1.0733***	0.6664**	0.9226***
	(0.0771)	(0.0871)	(0.3299)	(0.1901)
$UR^+ \times Pastcrime$	-0.0773***	-0.0459***	-0.0120	-0.0555**
	(0.0096)	(0.0107)	(0.0394)	(0.0231)
$UR^- \times Pastcrime$	-0.0972***	-0.0681***	-0.0313	-0.0638***
	(0.0099)	(0.0110)	(0.0432)	(0.0239)
% White	0.0287***	0.0224***	0.0224	0.0056
	(0.0026)	(0.0028)	(0.0191)	(0.0131)
% Black	0.7064***	0.6925***	0.4544	0.0281
	(0.1412)	(0.1043)	(0.5324)	(0.4260)
% Urban	-2.4451***	-1.1187***	-0.0884	-1.3122
	(0.3939)	(0.3752)	(2.3379)	(1.7018)
Police	-1.3443***	-0.7253**	0.0751	1.3788
	(0.2698)	(0.2856)	(1.8314)	(1.2893)
Pennsylvania Population	-3.4635***	-2.5479***	1.0289	-1.8736
	(0.3450)	(0.3728)	(2.3534)	(1.7417)
Real Income	-0.0262	-0.0737***	-0.2611**	-0.0664
	(0.0190)	(0.0195)	(0.1187)	(0.0745)
Year	-0.8122***	-0.3044**	0.5512	-0.1629
	(0.1312)	(0.1363)	(0.8747)	(0.6096)
N	380240	380240	380240	380240
$\chi^2(1)$	4.2	0.06	4.89	0.6
	[p=0.0403]	[p=0.8007]	[p=0.027]	[p=0.4384]
$\chi^2(1)$	22.17	7	3.04	0.24
	[p=0.000]	[p=0.0081]	[p=0.0814]	[p=0.6224]

Table 7 (continued)

	Assault	Robbery	Burglary	Theft	Motor Vehicle Theft
Recession (UR^+)	0.1893***	0.2475***	0.3117***	0.3248***	0.4784***
	(0.0557)	(0.0666)	(0.0643)	(0.0497)	(0.0878)
Recovery (UR^-)	0.1884***	0.2467***	0.3100***	0.2987***	0.4719***
	(0.0527)	(0.0630)	(0.0591)	(0.0465)	(0.0833)
Pastcrime	0.8697***	1.1211***	1.3249***	1.0707***	1.2699***
	(0.0891)	(0.1415)	(0.1092)	(0.0938)	(0.1346)
$UR^+ \times Pastcrime$	-0.0372***	-0.0460***	-0.0741***	-0.0567***	-0.0740***
	(0.0110)	(0.0165)	(0.0135)	(0.0115)	(0.0165)
$UR^- \times Pastcrime$	-0.0562***	-0.0696***	-0.0943***	-0.0728***	-0.0975***
	(0.0114)	(0.0173)	(0.0143)	(0.0121)	(0.0174)
% White	0.0182***	0.0305***	0.0215***	0.0259***	0.0562***
	(0.0035)	(0.0043)	(0.0039)	(0.0032)	(0.0067)
% Black	0.5417***	0.9816***	0.4913***	0.7551***	0.9953**
	(0.1439)	(0.1527)	(0.1638)	(0.1549)	(0.3901)
% Urban	-1.0291**	-1.3636**	-1.6374***	-2.4987***	-4.1402***
	(0.5026)	(0.5881)	(0.5797)	(0.4984)	(0.9134)
Police	-0.5979	-1.1717***	-0.6383	-1.2207***	-2.9596***
	(0.3759)	(0.4343)	(0.4146)	(0.3361)	(0.6048)
Pennsylvania Population	-2.3350***	-3.1579***	-3.0036***	-3.1023***	-5.5283***
	(0.4999)	(0.5808)	(0.5527)	(0.4287)	(0.7874)
Real Income	-0.0632**	-0.0797**	-0.0193	-0.0472**	-0.0009
	(0.0251)	(0.0312)	(0.0302)	(0.0237)	(0.0412)
Year	-0.3004*	-0.3874*	-0.6254***	-0.7353***	-1.3967***
	(0.1784)	(0.2163)	(0.2035)	(0.1677)	(0.2940)
N	380240	380240	380240	380240	380240
$\chi^2(1)$	0.01	0.00	0.02	6.74	0.12
	[p=0.9296]	[p=0.9478]	[p=0.8933]	[p=0.0094]	[p=0.7266]
$\chi^2(1)$	3.56	4.39	3.16	19.13	2.81
	[p=0.0593]	[p=0.0362]	[p=0.0754]	[p=0.000]	[p=0.0935]

The χ^2 test in the second-to-last row in the table pertains to the test of ($\beta_1 = \gamma_1$) in Equation (7). The χ^2 test in the last row in the table pertains to the test of ($\beta_1+\beta_2 = \gamma_1+\gamma_2$) in Equation (7). *, **, or *** signify statistical significance at the 10%, 5%, and 1% levels, respectively.



Property Crime per year
227,762
224,619
224,000
Years
0
7/12
2
Unemployment =
6 %
7%
6%

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Appendix Table-A1
Negative Binomial Regressions with Individual Fixed Effects

	Property Crime	Violent Crime	Murder	Rape
Recession (UR^+)	0.3314***	0.1987***	0.0037	0.0782
	(0.0340)	(0.0369)	(0.2389)	(0.1736)
Recovery (UR^-)	0.2992***	0.1809***	0.0529	0.0979
	(0.0318)	(0.0352)	(0.2314)	(0.1674)
% White	0.0310***	0.0211***	0.0205	0.0059
	(0.0021)	(0.0025)	(0.0181)	(0.0122)
% Black	0.8686***	0.6477***	0.3310	0.0731
	(0.0854)	(0.0867)	(0.4920)	(0.3660)
% Urban	-2.3646***	-1.4754***	-0.4879	-1.6762
	(0.3142)	(0.3360)	(2.1995)	(1.5950)
Police	-1.5165***	-0.6343**	0.0977	1.3210
	(0.2251)	(0.2577)	(1.7516)	(1.2143)
Pennsylvania Population	-3.5791***	-2.5218***	0.9862	-2.0536
	(0.3027)	(0.3416)	(2.2881)	(1.6607)
Real Income	-0.0280*	-0.0670***	-0.2277**	-0.0704
	(0.0158)	(0.0165)	(0.1082)	(0.0715)
Year	-0.716	-0.305	0.460	-0.163
	(0.109)	(0.120)	(0.821)	(0. 578)
N	41482	35490	1722	3080
$\chi^2(1)$	23.06	6.92	1.89	0.50
	[p=0.000]	[p=0.009]	[p=0.169]	[p=0.477]

	Assault	Robbery	Burglary	Theft	Motor Vehicle Theft
Recession (UR^+)	0.2226***	0.2300***	0.2495***	0.2990***	0.4733***
	(0.0525)	(0.0543)	(0.0548)	(0.0459)	0.0826
Recovery (UR^-)	0.2046***	0.2026***	0.2250***	0.2626***	0.4616***
	(0.0499)	(0.0515)	(0.0513)	(0.0430)	0.0771
% White	0.0194***	0.0285***	0.0229***	0.0254***	0.0603***
	(0.0034)	(0.0037)	(0.0035)	(0.0029)	0.0056
% Black	0.5008***	0.9491***	0.6510***	0.8415***	1.0739***
	(0.1276)	(0.1255)	(0.1325)	(0.1125)	0.2169
% Urban	-1.7251***	-1.4931***	-1.7764***	-2.1350***	-4.2979***
	(0.4767)	(0.4941)	(0.5030)	(0.4302)	0.7524
Police	-0.7671**	-1.0082***	-0.8639**	-1.1703***	-3.0134***
	(0.3656)	(0.3748)	(0.3671)	(0.3073)	0.5336
Pennsylvania Population	-2.6772***	-2.8663***	-2.6384***	-3.0571***	-5.8530***
	(0.4810)	(0.5037)	(0.4915)	(0.4113)	0.7444
Real Income	-0.0463**	-0.0716***	-0.0226	-0.0452**	-0.0052
	(0.0237)	(0.0242)	(0.0252)	(0.0214)	0.0370
Year	-0.448	-0.305	-0.520	-0.576	-1.361
	(0.169)	(0.176)	(0.177)	(0.151)	(0.257)
N	22260	18536	18690	28294	9800
$\chi^2(1)$	3.24	7.83	5.33	16.92	0.5200
	[p = 0.072]	[p = 0.005]	[p = 0.021]	[p = 0.000]	[p = 0.471]