Crime Rates and Local Labor Market Opportunities in the United States: 1979-1995¹

July 6, 1998

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Abstract:

The relationship between crime and labor market conditions is typically studied by looking at the unemployment rate. In contrast, this paper argues that wages are a better measure of labor market conditions than the unemployment rate. As the wages of those most likely to commit crime (unskilled men) have been falling in the past few decades, we examine the impact of this trend on the crime rate giving special attention to issues of endogeneity. Wages are found to be a significant determinant of crime and more important than the unemployment rate. As theory would predict, economic factors are more important for property crime than violent crime. These results are robust to various measures of wages, two regression strategies, the inclusion of deterrence variables, and controls for simultaneity.

¹ We appreciate comments from Saul Lach and seminar participants at Hebrew University, Tel Aviv University, University of Georgia, University of Akron, and the 1998 AEA Meetings in Chicago. We also thank the Falk Institute for financial support.

Section I: Introduction

This paper examines the degree to which changes in crime rates for the United States from 1979-1995 can be explained by changes in the labor market opportunities for those most likely to commit crime. From 1980 to 1994, the crime rate in the United States increased despite the aging of the population and a tripling of the prison population (see DiIulio (1996)). Even though most crime is committed by relatively few people who are multiple offenders, Freeman (1996) shows that the propensity to commit crime for those not in jail rose precipitously throughout this period.

Economists usually explain crime rates by examining how the propensity to commit crime responds to the payoffs and punishments of illegal activity (see Becker 1968, Ehrlich (1973), Ehrlich (1996), Levitt (1997)). Most of the existing literature has focused on the likelihood of apprehension and the severity of punishment. These factors represent the direct costs to engaging in crime. This study examines the indirect costs to crime -- the opportunity cost of wages in the legal sector. More specifically, this study estimates the impact of changing labor market opportunities for young, unskilled workers on crime rates. This approach is motivated by two important factors. First, the people who are most likely to commit crime are young and less-educated (see Freeman (1996)). Second, large occupational and industrial shifts during the past few decades, combined with large changes in the wage premiums for education and experience, have affected the types of jobs and wages available to young, unskilled workers (see Bound and Johnson (1992) and Katz and Murphy (1992)). These factors have led researchers to implicate the shifting industrial structure of the economy as a possible explanation for the increasing trends in crime (Wilson (1996)).

So far, the literature that has examined this issue has found moderate, but inconclusive evidence that unemployment rates are positively linked to crime.² This paper differs from the existing literature in two ways. First, instead of concentrating on the

 $^{^{2}}$ See Freeman (1983) for a review of the literature relating crime rates with unemployment and other labor market variables. None of the studies reviewed in his article look

unemployment rate, we prefer to measure the legal market opportunities of potential criminals with wages. Second, the existing literature fails to account for the endogeneity of crime with the observed labor market outcomes. In contrast, we employ a variety of instrumental variable strategies in order to establish the causal relationship from changes in labor market conditions to the changes in crime rates.

As a measure of the labor market prospects for young unskilled men, wages have a number of advantages over the unemployment rate. First, at the individual level, wages are more likely to be exogenous than employment status. Young people move in and out of the labor force and unemployment for many reasons, many of them unrelated to crime. In contrast, the wage represents the price of the worker's skills, and this price is set exogenously by the market. In addition, unemployment is often short-lived and highly cyclical. Given the potentially long-lasting effects of criminal activity, crime should be more responsive to long-term changes in labor market conditions rather than short-term fluctuations. Wages are more likely to capture the exogenous long-term prospects of workers in the legal sector than the unemployment rate, which is dominated by many short-term choices and influences.

While both Freeman (1996) and Wilson (1996) speculate that the declining wages and employment opportunities of unskilled men have contributed to their increasing involvement in crime, to the best of our knowledge, Grogger (1997) is the only paper to examine the role of wages on crime rates. In contrast to Grogger, who estimates a structural model with individual-level data on property crime activity from the NLSY, the present study examines the effects of wages on a variety of individual property and violent crimes. We also perform our analysis on aggregate data. Others have emphasized that the criminal activity of one person affects the criminal activity of others.³ When the propensity to commit crime is a function of the rate at which others engage in illegal

specifically at the wages of unskilled workers or the time period covered in this study. ³ Ehrlich (1981) argues that additional crime by one person could reduce unexploited illegal opportunities for others; Sah (1991) emphasizes the effects of higher crime rates on law enforcement resources; Glaeser, Sacerdote, and Scheinkman (1996) focus on the effects one person's crime on the preferences toward crime of other in the community.

activity, an individual analysis may provide biased estimates of how changing economic conditions influence crime at the aggregate level.

Our empirical approach is to run county-level regressions that control for county fixed-effects and aggregate time trends, in order to explain the within-county changes in crime rates with our measures for the labor market prospects of unskilled men. Crime data come from the Uniform Crime Reports (UCR) and the rest of the data come from the Census Bureau. Two basic regression strategies are employed. First, we perform a panel regression using annual data from 1979-1995 with county and time fixed effects. This approach exploits year-to-year variation in wages in order to explain year-to-year changes in the crime rate.⁴ Second, we perform a ten-year difference (1979-1989) regression at the county level in order to exploit the low frequency variation in the data. Given the long-term consequences of criminal activity, crime should be more responsive to low frequency changes in labor market conditions. In addition, this approach serves to attenuate measurement error problems in panel regression analyses.⁵

Unfortunately, annual wage data are not available at the county level. For our annual regression analysis, we proxy for the wages of unskilled men using the change in the retail wage and the proportion of all workers employed in high-wage industries (Manufacturing, Wholesale Trade, Transportation, Construction) versus low-wage industries (such as Services and Retail). In the ten-year difference regressions, we construct wage and employment status measures for unskilled men from the Census.

The results from both regression strategies indicate that young, unskilled men are responsive to the opportunity costs of crime. The results are consistent with Grogger (1997) who found that youth crime was highly responsive to wages. (Grogger finds that a 10 percent decrease in the potential wages of youths would cause a 10 percent increase in crime.) However, endogeneity is likely to bias estimates of the relationship between crime and labor market conditions. High income individuals or employers may leave areas with

⁴ Because we include fixed county and time effects, identification is coming from the within-county trend deviations from the national trend in wages and crime rates.
⁵ See Griliches and Hausman (1986) and Levitt (1995) for a discussion of advantages of the "long regression" in the presence of measurement error.

higher or increasing crime rates (see Cullen and Levitt (1996) or Willis (1997)). On the other hand, high crime rates may force employers to pay higher wages as a compensating differential to workers.⁶ Consequently, the direction of the bias is not clear.

We control for potential endogeneity with a number of strategies. We use the changes in the proportion of workers in high-wage industries rather than changes in the level of employment in high-wage industries to serve as a proxy for the wage offers of unskilled men. Although it is reasonable to think that employers are driven away from high-crime areas, we do not suspect that employers are being driven away disproportionately in high-wage industries. In fact, the results from Willis (1997) indicate that low-wage employers in the service sector are more likely to relocate due to increasing crime rates, thus biasing the results against our instrument. In addition, we use variables constructed at the state level for the average wage and the average unskilled wage, to proxy for the job prospects of young men at the county level. We believe that high income people or employers may be leaving the county in order to avoid higher crime rates, but think that it is unlikely that they would move out of the state because of higher crime rates within a certain county. If this assumption is correct, a high income person who moves out of the central city to the suburbs should not affect the average wage in the state, thus leaving the state variable exogenous to the county crime level.

Lastly, following the strategy employed by Bartik (1991) and Blanchard and Katz (1992), we use the Census data to generate instruments for the change in labor demand based on the initial industrial composition within the county and the national trends in the industrial composition over the sample period. Using these various methods, the results indicate that endogeneity is not responsible for the negative relationship between the wages of unskilled workers and the various crime rates.

The rest of the paper is organized as follows: Section II presents some general trends in crime rates, wages, and employment. This section also discusses our wage proxies. The literature and the main issues are described in Section III. Sections IV presents the panel regressions using annual data. Section V presents the ten-year (1979-

⁶ See Roback (1982).

1989) difference regression analysis. Section VI concludes the analysis.

Section II: Trends in Crime Rates, Industrial Composition, and Wages

The crime data used throughout this paper come from the Uniform Crime Reports, which are reported to the FBI by local police authorities. Crime rates are defined as reported offenses per 100,000 people and the arrest rates are defined as the ratio of arrests to offenses. Offenses and arrests are reported for the individual violent crimes of murder, rape, robbery, aggravated assault; and for the individual property crimes of burglary, larceny, and auto theft. The violent crime index aggregates the individual violent crimes mentioned above while the property crime index aggregates the individual property crimes. The overall crime index is the aggregation of the seven individual crime classifications. The UCR data is described in more detail in the Appendix.

There are many reasons to be wary of self-reported crime data. First, not every crime is reported to the police. This under-reporting produces measurement error in the offense and arrest rates, which could vary by the type of crime or county of jurisdiction.⁷ In addition, there are variations in the methods of collecting and reporting the data to the FBI by local authorities. Although the accuracy and comparability of self-reported data across counties may be suspect, our inclusion of county fixed-effects eliminates the effects of (time-invariant) cross-county variations in reporting methods. Changes in reporting methods will introduce classical measurement error in our crime measures. However, unless these reporting changes were correlated across counties over time, the data should be revealing real trends in the actual levels of crime.⁸

⁷ In 1994, for example, the National Criminal Victimization Surveys reported that 36.1% of rapes were reported, 40.7% of sexual assaults, 55.4% of robberies, 51.6% of aggravated assaults, 26.8% of personal larcenies without contact, 50.5% of the household burglaries, and 78.2% of motor vehicle thefts and theft attempts. Murder, which has virtually no underreporting, is not subject to this type of bias. See *Sourcebook of Criminal Justice Statistics 1995*, Table 3.38, page 250.

⁸ See Ehrlich (1996) for a discussion of the reporting biases in the crime data. He states that one method of dealing with this problem is to work with the logarithms of the crime

Much has been said about the increasing crime rates in the United States during 1980's and the declining rates during the 1990's. However, many readers will be surprised to learn that the reported crime rates do not match this perception exactly. The standardized log offense rates for the property and violent crime indices for the entire United States are shown in Figure 1. As Figure 1 shows, the two crime indices do not show a steady upward trend throughout the 1980's. The property crime index follows a cyclical pattern which peaks in 1980, declines by 8 percent until 1984, increases by 6 percent until 1991, and then begins to decline all the way through 1995. The global-peak for property crime in 1980 was approximately 3 percent larger than the local-peak in property crime in 1991. So, in terms of property crime, crime was increasing through the later half of the 1980's, but the absolute levels were not extraordinary.

In contrast, the violent crime index exhibits a much clearer trend in Figure 1. Although violent crime still displays a cyclical pattern, the absolute level of violent crime is more than 10 percent larger in 1991 than at the local-peak in 1981. During the whole period, the violent crime index rose by 14 percent until 1991, and then steadily declined by 8 percent as of 1995. Thus, the pattern for violent crime is much more consistent with the common perception of increasing crime trends through the 1980's and declining trends afterwards.⁹

Although the reported violent crime data matches the common perception much more closely than the property crime trend, the overall crime rate looks almost identical to the property crime rate since most crime is property crime. As Figure 2 demonstrates, 87 percent of all crime is composed of property crime. Therefore, any analysis of the overall crime rate will be dominated by whatever is determining the property crime rate. For this reason, our discussion concentrates on the property and violent crime indices as well as the individual crimes within these indices.

As Figure 3 shows, property crime is mostly composed of larceny (67 percent).

rates which are likely to be proportional to the true crime rates. Taking logarithms is the strategy employed in this paper.

⁹ Some readers may be surprised that the murder rate hit a global peak in 1980 at 10.2 murders per 100,000 people, and never got above 9.8 which was the second peak in 1991.

Burglary represents 21 percent of property crime while auto theft is only 12 percent. As a consequence, our results for larceny and burglary will determine the results we get for the property crime index as a whole.

The breakdown for violent crime is presented in Figure 4. Violent crime is mostly aggravated assault (62 percent) and robbery (32 percent). Murder (1 percent) and rape (5 percent) occur infrequently and thus have less influence on the overall violent crime index. However, the seriousness of these crimes obviously lends them a disproportionate influence over social welfare and public policy.

The purpose of the preceding few paragraphs was to present the national trends in the two crime indices and show that they are dominated by larceny, burglary, aggravated assault, and robbery. The same features are found in our core sample of counties, which consists of 352 counties which satisfied two criteria: First, their population as of 1989 was over 100,000; Second, they had to have non-missing data for the 17 years from 1979 to 1995. These conditions were set in order to concentrate on large counties where crime rates are the highest and where the data are believed to be the most reliable. The total population covered by our sample as of 1995 is over 142 million people.

The crime trends in our sample are shown in Figure 5. After regressing the log of the crime indices on county and time fixed-effects, the coefficients on the time fixed-effects for property crime and violent crime are plotted in Figure 5. As noted previously, the overall crime trend is dominated by the property crime index. The trends for the property and violent crime indices are very similar to those presented in Figure 1 for the entire United States. Since we are concentrating on large counties, the trends are significantly magnified in our sample.¹⁰ However, the size of our sample and the trends in Figure 5 (in comparison to Figure 1) demonstrate that our sample is representative of the United States as a whole.¹¹

So far we have only looked at the raw crime data with no adjustments for changes in the demographic compositions within each county. Figure 6 plots the property and

¹⁰ See Glaeser and Sacerdote (1995) for an exploration of why crime is more concentrated in highly populated areas.

violent crime time-fixed effects after adjusting for changes in the age distribution (using the percent of the population in five different age groups), the sex composition, the percentage of the population that is black, and the percentage that is neither white nor black. After controlling for these factors, the trends for both types of crime match more closely to the commonly held perceptions. That is, both types of crime rose steadily throughout the 1980's and peaked in the early 1990's. In 1991, the adjusted property crime rate hits a global peak at 15 percent higher than the local-peak in 1980, and 20 percent higher than it was at the beginning of the period in 1979. The upward trend in violent crime found before in Figure 5 is now accentuated as the adjusted rate rises by over 45 percent until 1991 when it begins to decline. After making these demographic adjustments, both crime series indicate a dramatic increase in the incidence of crime, particularly since 1984.

The unadjusted and adjusted crime rates for the individual property crimes are graphed in Figure 7 and Figure 8. They show large declines in burglary throughout the period; auto theft and (to a lesser degree) larceny are increasing. The unadjusted and adjusted rates for the individual violent crimes are shown in Figure 9 and Figure 10. The upward trend in violent crime is seen to be dominated by the upward trends in aggravated assault and robbery (which comprise a total of 94 percent of violent crime in 1995 (see Figure 4)), while there is no distinct trend for murder and rape.

These increasing trends in the adjusted property and violent crime rates occur while the labor market opportunities for young, unskilled men are declining. Annual wage measures for specific demographic groups are not available at the county-level. Consequently, the retail wage is used as one of our proxies for the wages of unskilled men. The retail wage is the lowest of the eight industrial sectors identified in the countylevel data, and based on observable characteristics, employees in the retail sector are generally younger and less skilled than those in other sectors. To test whether the retail wage is a good proxy, we performed a ten-year difference regression (1979-1989) using Census data of the average wages of non-college men on the average retail wage at the

¹¹ See Levitt (1997) for similar trends using the same data with a sample of 59 large cities.

MA level. The regression yielded a point estimate of 0.78 (standard error = 0.04) and an R-squared of 0.71. Therefore, the changes in the retail wage seem to be a powerful proxy for the changes in the wages of non-college men. Figure 11 presents the downward trend in the average retail wage in our county sample over time.¹² From 1979 to 1995, the average retail wage fell by almost 14 percent, but the trend is not steady. The retail wage declined until 1982, increased until 1986, and then continually fell through 1995. As we will see, this pattern is similar to the trend for the wages of non-college men as measured from the CPS at the state level.

Our second proxy for the annual county-level wages of unskilled men is the percent of workers employed in high wage industries. The definition of high-wage industries is determined by dividing the eight major industries into two categories based on their average wage within the industry. Consequently, the average wage in all highwage industries (Manufacturing, Wholesale, Transportation, Construction) is about 50 percent larger than the average wage in low-wage industries (Retail, Services, FIRE, and Government).¹³ As with wages, we do not have county-level industry employment figures for specific demographic groups, but the overall industrial shifts during this period reduced the wages of less-skilled men relative to other groups (Bound and Johnson (1992) and Katz and Murphy (1992)). So given our classification, a shift from high-wage to lowwage industries represents a shift from high-wage to low-wage employment for lessskilled men. Using Census data, a ten-year difference regression (1979-1989) of the average wages of non-college men on the fraction of high-wage employment at the MA level yields a coefficient of 1.91 (standard error = 0.21) and an R-squared of 0.28. So, the percent of high-wage employment appears to be a reasonable instrument for the wages of unskilled men, although less powerful than the retail wage.

The average proportion of all workers employed in high-wage industries in our sample is presented over time in Figure 12. At its peak, employment in high-wage

¹² Retail wages are calculated by taking the total retail income within a county and dividing it by the total employment in the retail sector within the county.

¹³ Average wages for each industry were calculated in the same manner described for the retail wage.

industries was only 35 percent of the workforce, and this percentage is declining over time by over 7 percentage points. This trend may understate the effects on the opportunities for young workers if firms reduce employment by laying-off or reducing hires of young workers. Even ignoring this possibility, employment opportunities in high wage sectors are clearly declining over time.

Using individual-level data from the CPS, the wages of unskilled men are measured more directly. In Figure 13, the standardized average wages of all workers and of non-college, male workers (workers with a high-school degree or less) are plotted over time. The wages of unskilled men are declining throughout the period by over 16 percent. The trend, however, is not steady. Similar to the retail wage, the average wage of non-college men declined quickly from 1979 to 1982, leveled off until 1988, and then declined rapidly throughout the remainder of the sample period. This overall decline represents a significant fall in the opportunity cost of crime in the legal sector, and as Freeman (1996) notes, this decline in wages was not offset by an increase in employment. Consequently, we should expect these trends to lead to increases in the participation of young men in crime, particularly because researchers have found that young, unskilled men are the most likely to commit crime.¹⁴ The timing of these trends seem to support this hypothesis, the goal of this paper is to test whether this relationship is spurious.

Section III: Crime and the Labor Market

The traditional economic approach to crime is to model the decision to commit crime within the context of utility maximization -- a risk averse person decides to commit crime if the expected costs outweigh the expected benefits. The classic papers in this area by Becker (1968) and Ehrlich (1973) focused more on the direct costs to committing crime, measured by the probability of getting caught and the severity of punishment. These direct costs differ by the type of crime committed and are often much easier to

¹⁴ Freeman (1996) reports that two-thirds of prison inmates in 1991 had not graduated from high school.

obtain than the potential benefits to crime. Empirically measuring the effects of these costs on the propensity to commit crime is difficult, since causation can run in either direction.¹⁵ Nevertheless, the economic literature has been mostly concerned with the relationship between deterrence variables and the crime rate.

The least attention is given to the direct benefits to crime, mostly because of the lack of data. The direct gains from crime differ depending on the nature of the crime (Mustard (1998)). Some crimes (such as robbery, larceny, burglary and auto theft) can be used for self-enrichment, whereas other crimes (murder, rape and assault) are much less likely to yield material gains to the offender.¹⁶ Offenders who commit crimes in the latter category are less likely to be motivated by material benefits and more likely to derive benefit from interdependencies in utility with the victim. This notion of interdependence of utility functions between offender and victim for certain crimes is supported by the fact that the crimes of murder, rape, and assault occur frequently between people who have a relationship with each other, whereas the victim and offender have no relationship in the vast majority of property crimes.¹⁷

In addition to the direct costs to crime (the probability and severity of punishment), there are also indirect costs to crime. Engaging in criminal activity jeopardizes one's prospects in the legal labor market. This can occur in direct and indirect ways. Engaging in criminal activity indirectly diverts time and resources away from

¹⁵ See Levitt (1997) for the most recent attempt to untangle the effect of police size as a deterrence to crime.

¹⁶ For example, in 1992 the average monetary loss was \$483, \$840, \$1278 and \$4713 for larceny, robbery, burglary and auto theft, respectively, compared with average monetary losses of \$27 and \$89 for rape and murder. *Crime in the United States 1992*.

¹⁷ For offenses that were committed in 1993 the offenders were classified as nonstrangers to the victims in 74.2% of rapes, 51.9% of assaults, and 19.9% of robberies (*1994 Sourcebook of Criminal Justice Statistics*, p. 235, Table 3.11). Historically statistics on relationships of murder victims to offenders show that the majority of victims knew their offenders (Supplementary Homicide Reports). During the 1990s this relationship has changed, and now slightly less than half of the murder victims know their offenders. For example, in 1993, 47.7% of all murders were committed by people who were known to the victim, 14.0% were committed by strangers, and in 39.3% of the cases the relationship between victim and offender was unknown (*Crime in the United States*)

investing in human capital, thus leading to a loss of potential wages. The time involved in committing crime results in a direct loss of opportunity wages. In addition, the time spent in prison also entails a loss of opportunity wages.

The degree to which the opportunity costs of crime in the legal sector affect the decision to commit crime will also depend on the nature of the crime. For crimes such as burglary or larceny, monetary opportunities in the legal sector should be a greater factor than for crimes like rape and murder where pecuniary considerations are lower. However, holding everything else constant, a reduction in legal opportunities should make one more likely to engage in any form of criminal activity, regardless of motives, due to the forgone earnings during the crime and potentially in jail.

The literature on the effects of labor market opportunities on the crime rates has been summarized by Freeman (1996 and 1994). Most of the literature focuses on explaining the relationship between the unemployment rate and the crime rate. The results are inconclusive, although they generally point to a positive, but small, relationship between the two. Although there have been substantial changes in the structure of earnings during the last few decades, including the declining absolute and relative wages of unskilled men who are most likely to commit crime, there has not been much research looking at the relationship between wages and crime (except for Grogger (1997)).

There are many reasons to believe that wages are a better measure for the legal opportunity costs of crime than unemployment. As Grogger points out, many criminals commit crime while they are employed, so the technology of committing crime does not preclude holding a job. In addition, workers move in-and-out of the work force and unemployment for many different reasons, and most of them are unrelated to the decision to commit crime (Topel and Ward (1992)). Unemployment is also highly cyclical, and for most workers, represents a temporary status that does not measure their long-term prospects in the legal sector. The decision to engage in crime can have long-term consequences, and may not be affected by short-term fluctuations in the unemployment rate. In addition, the decision to be in the labor force and/or to be unemployed can be

1993, p. 20, Table 2.12).

considered a choice variable for the individual, and is therefore endogenous to a host of other factors including the decision to commit crime. Finally, changes in the unemployment rate, at most, will affect only the workers on the margin. That is, it will not have a large effect on the vast majority of people unaffected by a few percentage point changes in the unemployment rate. On the other hand, every worker within a given group is affected by the decline in wages for that group, not just those on the margin. Furthermore, the wages of workers are considered more exogenous to the individual. A worker can be considered a bundle of skills and the labor market rewards him for these skills according to the market price. The individual cannot choose the market price for his skills in the same way he can choose to enter the labor force or look for a job. Therefore, the wages he can receive in the legal sector are exogenous to his choices.¹⁸ For these reasons, in addition to the timing of the crime and wage trends pointed out in Section II, we focus on wages as the primary measure of the opportunity costs of crime in the legal sector.¹⁹

To our knowledge, Grogger's (1997) study of young men using individual level data from the NLSY is the only paper that has focused on declining wages as an explanation for crime. Grogger estimates a structural model of time spent in the criminal sector and the legitimate labor market sector. He finds that the criminal participation of young men in crime is very responsive to their potential wages, explaining "three-quarters of the observed rise in youth crime (page 32)."

This paper is the first to study this issue at a more aggregated level with a nonstructural approach. While both approaches have their advantages and disadvantages in terms of their reliance on untested assumptions and data with their own sets of problems, we believe that both approaches are useful complements to each other in the examination

¹⁸ Endogeneity problems will arise if his choice of working affects the level of his skills by affecting his investment in human capital. For this reason, we use wage residuals in the empirical section in order to abstract from changes in observed levels of skills, and therefore measure the changes in the structure of skill prices. Although the results for the levels are not presented, the results are similar either way.

¹⁹ Lott (1992) also argues that reputational sanctions are positively correlated with the wage.

this issue. Both studies rely on self-reported data (although at different levels of aggregation), however, we use a fuller set of crime categories than in Grogger's study. His data are limited to property crime while we are able to examine property and violent crime as well as the individual types of crime within these broad categories.

Performing the analysis at the aggregate level may have further advantages. The recent crime literature has emphasized the external effects of one person's crime activity on the level of activity of his peers (Glaeser, Sacerdote, and Scheinkman (1996)). If the psychic costs to crime are lower when others are committing more crimes (i.e. people have less shame when others are doing it), the crime decision of one person can affect the level of crime of others.²⁰ Since an individual-level analysis is limited to a selected sample, this external effect may not be captured within the sample. An aggregate level analysis will capture both the direct affect of an individual's decision to commit crime as well as the external effect, although it will not separately identify the two effects.

An aggregate analysis will also capture other environmental determinants of the decision to commit crime. Since most criminals are young men, the age and sex distribution will be important contributing factors, which may be magnified or attenuated by any external effects they have when they are concentrated together.²¹ Different age and gender groups may also be characterized as easier targets of crime. Thus, as we saw in Section II which showed the large differences between the adjusted and unadjusted crime trends, it is important to control for demographic changes in order to identify the affects of the changes in wages.

Some aggregate characteristics will have ambiguous effects on the level of crime. For example, a decline in the standard of living could be considered as a decline in the labor market opportunities of the workers in that area, and therefore, lead to greater crime. However, general economic welfare may affect the opportunities for property crime. If

²⁰ In increase in aggregate crime can also affect the decision of the individual in a more indirect way if it leads to reduction in the likelihood of apprehension. See Sah (1991).
²¹ Economists have not explored why most crime it committed by men. Concerning the age issue, Grogger (1997) contends that crime declines as age increases because age is a proxy for the wage.

there is less material wealth to steal, then the crime rate may decline if general economic conditions deteriorate. Our empirical strategy will seek to isolate the effect of the changes in wages of those most likely to commit crime -- unskilled men -- after controlling for the changes in the general economic prosperity of the area.

The crime rate in a particular area could be affected by the whole range of income distribution within the area. However, isolating all these effects introduces a variety of problems establishing the direction of causality. Although high income people have more material wealth to steal (leading to higher crime), they also have the resources to self-protect themselves with garages, alarms, guards, and other measures (leading to lower crime). They also have the resources to move out of high crime areas, thus leading to a reduction in the observed average wage in the area in response to crime (Cullen and Levitt (1996)). If employers leave areas in response to increasing crime rates, this could be another mechanism that leads higher crime rates to cause a decrease in wages (Willis (1997). However, if remaining employers have to raise wages in high crime areas as a form of compensating differential, then higher crime rates could cause wages to rise, even in the face of an out-migration of workers (Roback (1982)).

In order to identify whether the declining wages of unskilled men are enticing them into criminal activity, the empirical strategy must seek to establish the direction of causality. To do this, instruments are needed that are correlated with the changes in crime within an area only through changes in the wages within the area. In the next section, we develop an empirical framework to control for the demographic changes, isolate the effects of the declining wages of unskilled men on crime, and control for any potential endogeneity which leads to a reverse causality.

Section IV: Analysis Using Annual Data, 1979-1995

This section provides an empirical analysis of the preceding discussion at the county-level of aggregation. The analysis uses 17 years of panel data (1979-1995) for 352 counties described in Section II. In each regression specification, county fixed-effects control for much of the cross-sectional variation as we try to explain the within-county

trends in the crime rates over this period. Yearly fixed-effects are also included to take out the national trends. We expect that the labor market variables of interest can help explain the national trends, but we seek to identify the effects of these variables from the within-county deviations from the national trends in order to abstract from any spurious correlation at the national level.²² Because demographic changes will alter the costs and benefits to crime as described in Section III, each specification also controls for changes in the age distribution, sex composition, the percentage of the population that is black, and the percentage of the population that is non-white and non-black.

The empirical strategy is to identify the importance of the labor market opportunity costs for those individuals that are most likely to commit crime. As most crime is committed by young, unskilled men, two variables are used to directly proxy for their opportunity wages, since direct measures for the wages of unskilled men are not available at the county-level on an annual basis. We concentrate on wages rather than the employment rate for reasons discussed in the previous section. As discussed in Section II, the wage proxies for young, unskilled men at the county level are the retail wage and the percent of all workers employed in high-wage industries. In order to control for the general level of prosperity in the county, log income per capita is also included in most specifications. As discussed in Section III, the aggregate income level has opposing effects on the rewards to crime and the costs of crime.

After controlling for the changes in the demographics, the coefficient estimates for various combinations of the labor market variables are displayed in Table 1. The purpose of presenting each combination is to show how sensitive the labor market proxies are to each other, so that the effect of each one is clearly identified. The first specification for each of the two index crimes (columns 1 and 6) shows that each crime index is very responsive to the retail wage when it is isolated without any other labor market controls. The coefficient for property crime (-0.429) is a bit larger than the estimate for violent crime (-0.301), and both are statistically significant. Since the retail wage declined on

²² The labor market variables explain a greater portion of the time series variation in crime rates when time fixed-effects are excluded from the models.

average by 13.6 percent, these coefficient estimates would predict a 5.9 percent (-13.6 multiplied by -0.429) rise in the property crime rate and a 4.1 percent rise in violent crime due to the decline in the retail wage. These "predicted" effects, evaluated at the average change in the independent variables between 1979 and 1995, are reported below each coefficient in brackets (the standard errors are directly below the coefficients in parentheses).

The second specification in Table 1 (columns 2 and 7) shows the effect of the retail wage on crime after controlling for the overall level of welfare in the county as proxied by the income per capita of the county. For property crime, the retail wage effect is reduced somewhat by the income per capita variable as it falls from -0.429 to -0.313, but it still remains statistically significant. The coefficient on income per capita is also significant at -0.249. The negative coefficient on income per capita could mean that the costs of property crime represented by this variable are stronger than the potential benefits it also represents. However, if the retail wage measures the wages of unskilled workers imperfectly, per capita income may be picking up some of the variation in the wages of just those workers who are most likely to commit crime. Another possibility, addressed later in this section, is whether this result stems from endogeneity.

For violent crime, adding the income per capita variable does not affect the retail wage coefficient (it changes from -0.301 to -0.295). Unlike the result for property crime, the coefficient for income per capita is not significant for the violent crime index, thus suggesting that the overall welfare of the county is not an important determinant of the violent crime rate. Like property crime, violent crime is significantly affected by the retail wage which is proxying for the wage level offered to those most likely to commit crime.

Since the retail wage is not a perfect measure of the wages of young, unskilled workers, we now experiment with our second proxy for their wages -- the percent of workers in high-wage industries. Columns 3 and 8 in Table 1 present the effect of this variable when the other labor market variables are excluded. The next columns (4 and 9) show what happens when income per capita is then added to the specification. This wage proxy is inversely related to property crime and positively related to violent crime. For both indices, the addition of the income per capita measure has no effect, although the

income per capita measure itself is significantly negative now for both crime indices (before it was only significant for property crime). The positive effect of this wage proxy for unskilled men for violent crime is contrary to the hypothesis that declining wages entice unskilled workers into a life of crime, but as we will see in the next table, this result is not robust when we look at the individual violent crimes.

The last specification for each crime index in Table 1 uses all three labor market variables together -- income per capita, the retail wage, and the percent of high-wage workers. The coefficient estimates for each of the variables are not very affected by the inclusion of the other variables. For property crime, the coefficient on the percent of high-wage workers is virtually identical to when the retail wage was excluded, and the retail wage coefficient actually gets a bit larger in magnitude. Both of these variables as well as the negative coefficient on income per capita are statistically significant. The results for violent crime follow a similar pattern. Both proxies for the wages of unskilled workers seem unaffected by the inclusion of the other.

These results suggest that our two wage proxies are picking up potentially important, but different aspects of our targeted variable -- the opportunity labor market cost of crime for unskilled workers. These results could stem from the fact that both are imperfect measures, or we could think of the retail wage as picking up the current opportunity wage and the percent of high-wage workers as proxying more for the longterm opportunity wage. Since they are unaffected by the inclusion of the other, we use the combination of both of them together to be our "core" specification. However, the reader should keep in mind that either variable can be excluded with little effect on the other coefficients.

Table 2 presents the "core" specification for each crime classification within each crime index. This table shows that the retail wage is significant statistically and economically for each individual property and violent crime. Counties with a larger than average drop in the retail wage experience higher than average increases in each type of crime, with an elasticity response of roughly 0.30 percent for both the property and violent crime indices. Within property crime, the biggest effect is on burglary (-0.593) and larceny (-0.299). The coefficient on auto theft is significantly negative (-0.172), but is

small and is counter-acted by the positive coefficient estimate on the percent of workers in high-wage industries (0.018). The overall effect of both wage proxies, evaluated at their average change between 1979 and 1995, is to increase burglary by 12.7 percent (8.1 percent from the retail wage and 4.6 percent from the percent of high wage workers), increase larceny by 10.2 percent, and decrease auto theft by 11.4 percent. Although the results for auto theft run counter to the proposed hypothesis, the fact that burglary and larceny compose 88 percent of property crime means that these variables are very significant factors for property crime as a whole. Since the coefficient estimates on both proxies are similar when they are specified alone rather than together, the results for auto theft suggest that the retail wage and the percent of workers in high wage industries are picking-up very different phenomena for this particular crime.

As for violent crime in Table 2, the coefficient for the retail wage is significantly negative for all the individual crimes while the percent of workers in high wage industries is not significant at all. The combined effects of both variables, evaluated at their mean changes over time, is to increase aggravated assault by 3.1 percent, increase murder by 7.4 percent, increase robbery by 5.4 percent, and increase rape by 8.8 percent. All of these numbers would be stronger if we only looked at the effect of the retail wage since the coefficient on the percent of workers in high-wage industries, although not significant, is generally positive and therefore working to decrease violent crime.

Table 3 re-runs the regressions in Table 2 but includes the arrest rates as independent variables. Missing values for arrest rates are more numerous than for offense rates, so the sample is reduced to 245 counties. The inclusion of the arrest rates does not meaningfully alter the coefficient estimates on the labor market variables. The magnitude and statistical significance of the retail wage variable for all the individual property and violent crimes are comparable to Table 2. The same is true for the percent of workers in high wage industries. The arrest rates have a large and significantly negative effect for every classification of crime. Because the numerator of the dependent variable appears in the denominator of the arrest rate (the arrest rate is defined as the ratio of total arrests to total offenses), measurement error in the offense rate leads to a downward bias in the

coefficient estimates of the arrest rates ("division bias").²³ However, the results indicate that the labor market coefficients are robust to the usual inclusion of the arrest rates, as well as the decrease in the number of counties. To work with the broadest sample possible, the remaining specifications exclude the arrest rates.²⁴

Up to now, our results may be contaminated by the endogeneity of crime and observed wages at the county level. An increase in crime within a county may lead employers to relocate, thus reducing labor demand and wages within the county (Willis (1997)). Similarly, if avoiding crime is a normal good, an increase in crime will cause high-wage individuals to move out of the county (Cullen and Levitt (1996)). However, it seems likely that crime-induced migration will occur mostly across county lines within states rather than across states. That is, high-wage earners may be leaving the county because of increases in the crime rate, but their decision to leave the state is exogenous to increases in the crime rate. Under this assumption, higher crime rates will likely reduce (measured) county-level wages, but they should have little impact on wages at the state level. Therefore, to control for the endogeneity between county level wages and crime rates, we use the average wage for all workers in the state as a substitute for income per capita for the county, and substitute the average wage for non-college men in the state for the retail wage in the county. Another advantage of this procedure is that it is possible to estimate the annual wages of specific demographic groups at the state level using the CPS, whereas before we had to proxy for the wages of unskilled men at the county level. Although we could use a two-step IV approach with these state-wide variables, we prefer to substitute them straight into the equation as independent variables because the retail

²³ See Levitt (1995) for an analysis of this issue and why the relationship between arrest rates and offense rates are so strong.

²⁴ Ideally we would like to incorporate additional deterrence variables into the regression analysis. Unfortunately, conviction and sentencing data are only available at the county level for four states. However, we do not believe that the exclusion of these deterrence variables biases our results for the economic variables, because they are likely to be uncorrelated, as the results in Table 3 demonstrate with the arrest rates. The use of further deterrence variables will also open up a variety of endogeneity issues which are beyond the scope of this study (see Levitt (1997) for a study of the endogeneity of crime and police force size).

wage itself was only a proxy measure of the variable of interest.

Endogeneity should be less of a problem with our second proxy for the countylevel wages of unskilled men -- the percent of all workers employed in high-wage industries. Although increases in crime rates will certainly cause existing employers to relocate and new employers to locate elsewhere, we believe this will alter the level of employment but not necessarily the share of employment in high-wage industries. That is, unless increases in crime are driving-out high-wage employment disproportionately, then the percent of employment in high wage industries should be exogenous to the crime rate. In fact, the results in Willis (1997) suggest that employment is unrelated to property crime and that violent crime drives out low-wage employment in services much more than in high-wage industries.²⁵ Thus, using the percent of workers in high-wage industries may bias our results against finding significant negative effects for this variable -- which might be the explanation for why the estimated coefficient on this variable is frequently positive (although not significant) in Tables 2 and 3 for violent crime.

Table 4 presents the regression results using the state-wide wage variables and the county-level percent of workers in high-wage industries. Our wage measures are actually the residuals from regressing individual wages from the CPS on education, experience, experience squared, and controls for race and marital status. The construction of these variables is described in detail in the Appendix. Using the residuals allows us to abstract from wage changes due to changes in observable characteristics of workers, and thus more accurately reflect changes in the structure of wages. We also believe that using residuals should attenuate any remaining endogeneity issues which involve the county crime rate affecting the state-level composition of workers. It should be noted, however, that very similar results are obtained by using the state wages themselves rather than the residuals.

Comparing the coefficient estimate for the non-college wage in the state in Table 4

²⁵ Using data from neighborhoods in Los Angeles, Willis (1997) reports that an increase of violent crime is associated with an decrease of 14 jobs per square mile. Broken down by industry, 9 of those jobs are lost in services and "all other" employment, 2 are lost in manufacturing, and one each in wholesale and transportation.

to the coefficient on the retail wage for the county in Table 2, the coefficient estimates are larger and still significant for both of the crime indices. For the property index as a whole, the retail wage coefficient was -0.333 in Table 2 while the non-college state wage is -0.483 in Table 4 (both are significant). For the violent crime index, the comparable estimates are -0.282 in Table 2 compared to -0.460 in Table 4. The state wage for non-college workers seems to be considerably stronger than the county retail wage for auto theft, burglary, aggravated assault, and robbery. The coefficient flips signs for murder and rape but is insignificant for murder. This result suggests that endogeneity may be a larger issue for murder and rape, or it may be the case that for all crimes, the state-level wages capture different aspects of the wages of unskilled men at the county-level than the county-level retail wage.

The results for the percent of workers in high wage industries are very similar to those in Table 2. Again, it is worth noting that excluding this variable does not affect the coefficient estimates on the state wage variables in any significant way. The state wage for all workers has a small effect for most crimes, which suggests that the negative effect found for property crimes using the county-level income per capita variable in Tables 1 and 3 may be due to the endogenous outmigration of high income individuals from high crime areas instead of the imperfect nature of the retail wage as a proxy for the wages of unskilled men.

The combined effect of both proxies for the wages of unskilled workers in Table 4 predict a 10 percent increase in property crime and a 3.6 percent increase in violent crime, when evaluated at their average within-county change over the sample period. Since the adjusted index for all property crime increased by only 16.5 percent over the sample period, the predicted increase in property crime from the two wage proxies explains about 60 percent of the increase. For violent crime, the two variables explain roughly 8.8 percent of the 41 percent increase in the adjusted series.

For the individual crimes, the combined effects are the largest for burglary (predicting a 14.1 percent increase), larceny (8.8 percent increase), aggravated assault (5.3 percent increase), and robbery (8.0 percent increase). Apart from auto theft, these are the crimes that typically have an economic motive behind them, in contrast to rape or murder.

Therefore, we expect our wage proxies to be stronger factors in these crimes than for rape or murder. The auto theft result for the percent of high-wage industries is a bit of a puzzle, but as noted before, the wage measure of unskilled men in Table 4 and the retail wage (from earlier tables) have the expected signs and continue to do so after excluding the percent of high wage workers.

Table 4 basically tells the same story as the previous tables. For the most common crimes in each category (burglary, larceny, aggravated assault, and robbery), the wage proxies of unskilled men are important factors. The similarity of the results for the retail wage and the state wage of non-college men suggest that endogeneity is not responsible for the negative relationship between the wages of less skilled workers and the increase in crime. In fact, the results are more negative with the state wages, which is the opposite direction of the bias predicted by the endogeneity argument. This suggests that the state level wages for unskilled workers are actually better measures for the wages of unskilled workers within the county than the county-level retail wage.

Although the point estimates are comparable in magnitude for violent crime and property crime as a whole, violent crime increased more dramatically than property crime during this period. Therefore, the decline in the wages for unskilled men explain up to 60 percent of the increase in adjusted property crime and only 8 percent of the increase in adjusted violent crime.²⁶ The findings for the individual crimes are consistent with the hypothesis that economic (monetary) incentives play a larger role for economically motivated crimes such as burglary and robbery in comparison to crimes like murder and rape. Furthermore, these results have been shown to be robust to the inclusion of the arrest rates, a decrease in sample size, and several experiments with the specification of our labor market proxies.

²⁶ Note that we are comparing the predicted change in crime to the "adjusted" increase in crime after controlling for changes in demographics. As noted in Section II, the "adjusted" crime indexes grew much faster than the unadjusted.

Section V: Analysis of 10 Year Differences, 1979-1989

This section studies the relationship between economic conditions and crime rates using ten-year differences. The use of ten-year differences has a number of implications. First, it emphasizes low-frequency variations in economic conditions. The previous analysis was based on annual data and thus was trying to explain changes in crime rates within a given year with the contemporaneous change in our wage proxies. Given measurement error in our independent variables, long-term changes may suffer less from attenuation bias than estimates based on annual data (Griliches and Hausman (1986) and Levitt (1995)). Also, given the long-term consequences of criminal activity, crime should be more responsive to low frequency changes in labor market conditions. The model estimated in the previous section was conservative in the sense that it did not try to estimate the full effect of lagged changes in wages on the current changes in crime. The "long regression" strategy employed here is less demanding on the identification of the full effects of changes in our wage measures on crime, even in the absence of measurement error.

The use of two Census years (1979 and 1989) for our beginning and ending points has two further advantages. First, it is possible to construct detailed measures of labor market conditions for specific demographic groups, which we were unable to do on an annual basis with county-level data. Second, we are better able to link each county to the appropriate local labor market in which it resides. In most cases the relevant labor market exceeds the county of residence. Therefore, labor market conditions in each county are measured using labor market variables for the SMSA/CMSA in which it lies. Consequently, the sample in this analysis is restricted to those which lie within metropolitan areas.²⁷

²⁷We have also constructed labor market variables at the county group level. Unfortunately, due to changes in the way the Census identified counties in both years, the 1980 and 1990 sample of county groups are not comparable, introducing considerable noise in our measures. The sample in this section differs from that in the previous section in that it (1) excludes counties which are not in MA's (or are in MA's which are not identified on both the 1980 and 1990 PUMS 5% samples); (2) it includes counties with

To measure the labor market prospects of potential criminals, we compute the log wage of non-college men after controlling for observable characteristics, and the employment rate of non-college men. To control for the effects of changes in the standard of living on criminal opportunities, we include the mean log household income in the MA. The construction of these variables is discussed in the data appendix. In addition to these variables, our regressions control for the same set of demographic changes employed in the previous section. The estimates presented here are for the tenyear differences of the dependent variables on similar differences in the independent variables. Thus, analogous to the previous section, our estimates are based on cross-county variations in the changes in economic conditions after eliminating fixed-county effects and aggregate time-series effects. Cross-sectional models not reported here yield similar estimates. Table 5 presents descriptive statistics.

Table 6 presents weighted least squares results for the crime indices and for individual crimes²⁸. We focus on property crimes before considering violent crimes. The estimates indicate a strong positive effect of household income on crime rates. This effect is consistent with household income as a measure of criminal opportunities. The wages of non-college men have a large negative effect on property crimes. The estimated elasticities range from -0.785 for larceny to -2.282 for auto theft. The 13.7% drop in wages for non-college men between 1979 and 1989 is associated with a 13.9% increase in overall property crimes. The unemployment rate among non-college men has a large positive effect on property crimes. Previous researchers have often found a weak relationship between crime and unemployment rates (see Freeman (1994) for a survey of the literature). Including wage measures tends to reduce the estimated effects of unemployment range between 2.2 and 2.5. However, unemployment increased by only 0.6 percent over this period so changes in unemployment rates are responsible for small changes in crime rates (between 1 and 2 log points). Given the large variations in crime

fewer than 100,000 residents which are within MA's.

²⁸ Similar regressions which include the fraction of households with female heads and the

(see Glaeser, Sacerdote, and Scheinkman (1996)), the economic variables explain a reasonable amount of the variations in crime.

Turning to violent crime, the estimates for aggravated assault and robbery are quite similar to those for the property crimes. Given the pecuniary motives for robbery, this similarity is to be expected and is similar to the results in the previous section. Some assaults may occur in the course of property crimes, leading them to share some of the characteristics of property crimes. Taken together, assault and robbery constitute 94% of violent crimes (Figure 4), thus the violent crime index follows the same pattern. The crimes with the weakest pecuniary motive are murder and rape. As expected, the relationship between the economic variables and these crimes is quite weak. None of the variables is significant in the murder equation. The negative relationship between household income and rape indicates that rape declines with income. In general, the weak relationship between our economic variables and murder and rape suggests that our estimated relationships are not due to a spurious correlation between economic conditions and crime rates generally.

As discussed previously, we are concerned that our results may be biased upward or downward by causality running from criminal activity to labor market conditions. To address the direction of causality we employ an instrumental variables strategy. Following Bartik (1991) and Blanchard and Katz (1992), we develop instruments for the change in labor demand which exploit cross-MA variations in industrial composition interacted with variations in industrial growth rates. In contrast to those authors, we are interested in instrumenting for labor market conditions of specific demographic groups. Therefore, we also exploit cross-industry variations in the changes in industrial shares of 4 demographic groups (gender interacted with educational attainment).

A formal derivation of the instruments is provided in the Appendix. An example with two industries provides the intuition behind the instruments. Consider the auto and computer industries. Autos (computers) constitute a large share of employment in Detroit (San Francisco). The national employment trends in these industries are markedly

fraction beneath the poverty line yield similar results.

different. Therefore, the decline in the auto industry's share of national employment will adversely affect the demand for labor in Detroit much more than in San Francisco. Conversely, the increasing share of hi-tech workers at the national level would translate into a much larger positive effect on the demand for labor in San Francisco than in Detroit. In addition, if the biased technological change causes the auto industry to reduce its employment of unskilled men, this will affect the demand for unskilled labor in Detroit more than in San Francisco.

Since the trends in the national industrial shares and national demographic shares within industries are likely to be exogenous to any local crime trends, we impute the change in labor demand in each labor market by using their initial industrial and demographic composition and extrapolating what the trend should be by using the national trends. In this way, variations in the initial industrial and demographic composition can generate exogenous cross-MA variations in labor demand. By performing these extrapolations for different demographic groups within each MA, we obtain eight instruments which are used to identify exogenous variation in the three labor market variables. After controlling for our demographic variables, the partial R² between our set of instruments and the three labor market variables range from 0.242 to 0.327.²⁹

The IV estimates in Table 7 show no effect of household income on crime whereas the WLS estimates showed a strong relationship between household income and crime. These IV estimates are similar to those from the annual sample in the previous section. One explanation for the difference between the IV and WLS estimates is that high crime rates may force employers to raise wages causing the WLS estimates to be biased upwards. Only in the case of auto theft does mean household income remain positive and significant. Mean household income may measure auto theft opportunities better than the opportunities for other crimes. The IV estimates of the wage and unemployment rates of non-college men are quite similar to the WLS estimates, indicating that reverse causality is not responsible for these effects.

²⁹ We feel that this instrument strategy is more appropriate for identifying long-term changes in labor demand rather than picking up year-to-year variation.

Among the violent crimes, the IV estimates for aggravated assault, murder, and rape are generally smaller and estimated imprecisely. As before, robbery follows the same pattern as the property crimes. High income levels appear to reduce rape although higher wages for non-college men are associated with higher rape rates.

To summarize this section, the use of ten-year changes enables us to exploit the low-frequency relation between wages and crime. It also allows us to use direct measures for the wages and unemployment rates of unskilled workers calculated from the Census. Increases in the unemployment of non-college men are found to increase property crime while increases in their wages reduce property crime. Violent crimes are less sensitive to economic conditions than property crimes. Our estimates for property crime exceed those from annual data, which is consistent with a greater impact of long term economic changes on crime or measurement error in our independent variables. Using IV to control for reverse causality has little effect on the relationship between the wages and unemployment rates for less skilled men and crime rates. Our estimates imply that declines in labor market opportunities of less skilled men were responsible for substantial increases in property crime.

Section VI: Conclusion

The existing economic literature on crime emphasizes the effects of deterrence measures. Studies which examine the effects of labor market conditions typically do so using the unemployment rate. Such studies frequently find a weak positive relationship between crime and unemployment. To the best of our knowledge, no work controls for the potential endogeneity between crime and labor market conditions.

We study the effects of economic conditions on crime by using the wages and unemployment of the group that is most likely to commit crime -- young, unskilled men. Wages are shown to be theoretically and empirically a better measure for the opportunity cost of crime than the unemployment rate, which can help explain why previous studies have found mixed results for explaining crime rates with labor market variables. We also

employ a number of strategies to control for endogeneity.

The empirical strategy uses time-series variation within a geographic area (after controlling for national trends) to identify the effect of various measures for the opportunity cost of crime for young, unskilled men. Our results indicate that economic conditions are important determinants of crime. After controlling for endogeneity, our IV estimates from the "long regression" indicate that the wage declines of unskilled men have contributed to a 13.5 percent increase in burglary, 7.1 percent increase in larceny, 9.2 percent increase in aggravated assault, and an 18 percent increase in robbery. Similar results were obtained from panel regressions with annual data. These four categories represent 88 percent of all property crime and 94 percent of all violent crime. Although the unemployment rate is found to be a significant factor, the average increase in unemployment was very small. Therefore, the "predicted" increase in most crimes due to the increase in unemployment is in the 1 to 2 percent range. As expected, economic conditions have a larger impact on crimes with a pecuniary motive than crimes such as rape and murder where monetary considerations are smaller. These findings are shown to be robust to various measures for the opportunity costs of crime, the inclusion of arrest rates, controls for endogeneity, and both the short and long time period regression strategies.

References

Bartik, Timothy J. *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W. E. Upjohn Institute for Employment Research, 1991.

Becker, Gary. "Crime and Punishment: An Economic Approach," *Journal of Political Economy*, 1968, 76:2, 169-217.

Bound, John; and Johnson, George. "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations." *American Economic Review*, 1992, 82:3, 371-392.

Blanchard, Oliver Jean; and Katz, Lawrence F. "Regional Evolutions." *Brookings Papers on Economic Activity*, 1992, 0:1, 1-69.

Cullen, Julie Berry; and Levitt, Steven D. "Crime, Urban Flight, and the Consequences for Cities," NBER Working Paper #5737. September 1996.

DiIulio, John, Jr. "Help Wanted: Economists, Crime and Public Policy," *Journal* of Economic Perspectives, Winter 1996.

Ehrlich, Isaac. "Crime, Punishment, and the Market for Offenses." *Journal of Economic Perspectives*, Winter 1996.

Ehrlich, Isaac. "On the Usefulness of Controlling Individuals: An Economic Analysis of Rehabilitation, Incapacitation, and Deterrence." *American Economic Review*, June 1981, 307-322.

Ehrlich, Isaac. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation." *Journal of Political Economy*, 1973, 81:3, 521-565.

Freeman, Richard B. "Why Do So Many Young American Men Commit Crimes and What Might We Do About It?" *Journal of Economic Perspectives*, Winter 1996.

Freeman, Richard B. "The Labor Market." In <u>Crime</u>, edited by James Q. Wilson and Joan Petersilia, Institute for Contemporary Studies, 1995, 171-191.

Freeman, Richard B. "Crime and the Job Market." NBER Working Paper #4910, 1994.

Freeman, Richard B. "Crime and the Employment of Disadvantaged Youths." In <u>Urban Labor Markets and Job Opportunity</u>, edited by George Peterson and Wayne Vroman, Urban Institute, 1992, 201-237. (Also NBER #3875, 1991)

Freeman, Richard B. "Crime and Unemployment." In Crime and Public Policy,

edited by James Q. Wilson, 1983.

Glaeser, Edward; and Sacerdote, Bruce. "Why Is There More Crime in Cities?" Working Paper, November 1995.

Glaeser, Edward; Sacerdote, Bruce; and Scheinkman, Jose. "Crime and Social Interactions," *Quarterly Journal of Economics*, 1996, 507-548.

Griliches, Zvi; and Hausman, Jerry. "Errors in Variables in Panel Data," *Journal of Econometrics*, 1986, 93-118.

Grogger, Jeff. "Market Wages and Youth Crime," NBER Working Paper #5983, March 1997.

Hashimoto, Masanori. "The Minimum Wage Law and Youth Crimes: Time Series Evidence." *Journal of Law and Economics*, 1987, 443-464.

Levitt, Steven. "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime," *American Economic Review*, June 1997, 270-290.

Levitt, Steven. "Why Do Increased Arrest Rates Appear to Reduce Crime: Deterrence, Incapacitation, or Measurement Error?" NBER Working Paper #5268, 1995.

Lott, John R. Jr. "An Attempt at Measuring the Total Monetary Penalty from Drug Convictions: the Importance of an Individual's Reputation." *Journal of Legal Studies* 21 (January 1992): 159-187.

Katz, Lawrence F.; and Murphy, Kevin M. "Changes in Relative Wages, 1965-1987: Supply and Demand Factors." *Quarterly Journal of Economics* 107 (February 1992): 35-78.

Mustard, David. "Re-examining Deterrence: The Importance of Omitted Variable Bias." Working paper, 1998.

Roback, Jennifer. "Wages, Rents, and the Quality of Life," *Journal of political Economy*, 1982, 90:6, 1257-78.

Sah, Raaj. "Social Osmosis and Patterns of Crime," *Journal of Political Economy*, 1991, 99:6, 1272-95.

Topel, Robert H.; and Ward, Michael P. "Job Mobility and the Careers of Young Men," *Quarterly Journal of Economics*, 1992, 107:2, 439-79.

Uniform Crime Reports, Federal Bureau of Investigation. Washington, DC.

Willis, Michael. "The Relationship Between Crime and Jobs," University of California--Santa Barbara, Working Paper, May 1997.

Wilson, William Julius. <u>When Work Disappears: The World of the New</u> <u>Urban Poor</u>, Alfred A. Knopf, New York: 1996.

Wilson, James Q. and Richard J. Herrnstein, <u>Crime and Human Nature</u>, Simon & Schuster, New York: 1985.

<u>Appendix</u>

Appendix I. Description of the UCR Crime Data

The number of arrests and offenses from 1977-1995 were obtained from the Federal Bureau of Investigation's Uniform Crime Reporting Program, which is a cooperative statistical effort of over 16,000 city, county, and state law enforcement agencies. These agencies voluntarily report the offenses and arrests in their respective jurisdictions. For each instance of crime, the agencies only record the most serious offense during the crime. For instance, if a murder is committed in the middle of a bank robbery, only the murder is recorded. The list of individual crimes and their definitions follow.

I. Violent Crime -- includes murder, rape, robbery and aggravated assault.

A. Murder and Non-negligent Homicide -- is the willful (non-negligent) killing of one human being by another and is based on police investigations, rather than the determination of a medical examiner or judicial body. Deaths caused by negligence, attempts to kill, assaults to kill, suicides, accidental deaths, and justifiable homicides are excluded. Justifiable homicides are limited to: (1) the killing of a felon by a law enforcement officer in the line of duty; and (2) the killing of a felon by a private citizen.

B. Forcible Rape -- is the carnal knowledge of a female forcibly and against her will. Included are rapes by force and attempts or assaults to rape. Statutory offenses (where no force was used and the victim is under age of consent) are excluded.

C. Robbery -- is the stealing, taking, or attempting to take anything of value from the care, custody, or control of a person or persons by force, threat of force or violence, and/or by putting the victim in fear. Robbery includes attempted robbery and is divided into seven sub-classifications: street and highway, commercial house, residence, convenience store, gas or service station, bank, and miscellaneous.

D. Aggravated Assault -- is the unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault is usually accompanied by the use of a weapon or by means likely to produce death or great bodily

harm. Simple assaults are excluded. It includes assault with intent to kill.

II. Property Crime -- includes Burglary, Larceny, and Auto Theft

A. Burglary -- is the unlawful entry of a structure to commit a felony or a theft. Burglary is categorized into three subclassifications: forcible entry, unlawful entry where no force is used, and attempted forcible entry.

B. Larceny (except motor vehicle theft) -- is the unlawful taking, carrying, leading, or riding away of property or articles of value from the possession or constructive possession of another. Larceny is not committed by force, violence, or fraud. Attempted larcenies are included. Embezzlement, "con" games, forgery, worthless checks, etc., are excluded. Larceny is subdivided into a number of smaller classifications: from motor vehicles, shoplifting, motor vehicle accessories, from buildings, bicycles, pocket picking, purse snatching, coin operated vending machines, and all others.

C. Motor vehicle theft -- is the theft or attempted theft of a motor vehicle. A motor vehicle is self-propelled and runs on the surface and not on rails. Motor vehicle theft includes all cases where vehicles are driven away and abandoned, but excludes vehicles taken for temporary use and returned by the taker. Specifically excluded from this category are motorboats, construction equipment, airplanes, and farming equipment.

When zero crimes were reported for a given crime type, the crime rate was changed to 0.1 before taking the natural log of the crime rate. Since 1985, some counties have shown zeros for all their offense and arrest categories, even though they should have been recorded as missing. This occurred because the ICPSR has been unable to distinguish the FBI's legitimate values of 0 and from values of 0 that should be missing. To address this concern, when the number of index offenses and arrests were all 0 for a given county in a given year, that county was assigned missing values for all offense and arrest rates. If an individual offense or arrest category had a value of 0 and that county had non-zero values for other crime categories, then the raw data were untouched. This rule was followed because the FBI and ICPSR indicated that law enforcement agencies normally report the data for all crimes and do not selectively send data for some types of

crimes and not for others.

Appendix II. The Annual County Income, Employment, and Population Data

The data for county-level per capita income and total income and employment by industry are taken from the Regional Economic Information System (REIS), a component of the Bureau of Commerce. Workers were categorized into eight industries: Manufacturing, Wholesale, Transportation, Construction, Retail, Services, FIRE, and Government. Due to missing values, Agriculture was excluded. Average wages for a given sector were calculated by dividing the total sectoral income by the total employment in that sector. Population data for age, race and gender were taken from the US Census Bureau's annual estimates.

Appendix III. Construction of the State-level Wage Residuals from the CPS

This section describes the construction of the CPS data set. We use the merged outgoing rotation groups for 1979-1995. The data on each survey correspond to the week prior to the survey. We employed these data rather than the March CPS given the need to estimate wages for individual states - the outgoing rotation groups contain approximately three times as many observations as the March CPS. Unlike the March CPS, non-labor income is not available on the outgoing rotation groups surveys.

We use the log weekly wages of non-college men and of all workers after controlling for observable characteristics. Non-college is defined as not having attended more than 12 years of school (individuals who completed 12 years of school and attended part of their 13th year are considered to have some college). Wages were estimated for workers who worked or who held a job in the week prior to the survey. The sample was restricted to those who usually work 35 or more hours a week, were between 18 and 65, and were working in the private sector (non self-employed) or for government (the universe for the earnings questions). To estimate weekly wages, the edited earnings per week were used for workers paid weekly, the product of usual weekly hours and the hourly wage was used for those paid hourly. Individuals with top-coded weekly earnings were assumed to have earnings 1.5 times the top-code value. All earnings figures were

deflated using the CPI-U to 1982-1984=100. Workers whose earnings were beneath \$35 per week in 1982-1984 terms were deleted from the sample as were those with imputed values for the earnings questions.

To control for changes in the human capital stock of the workforce, we control for observable worker characteristics when estimating wages. We employ a two-step procedure. Let w_{cti}^{g} denote the log weekly wage of individual *i* in demographic group *g* in area *c* at time *t* and let x_{cti}^{g} denote his characteristics. In the first stage, log weekly wages are regressed upon individual worker characteristics,

$$w_{cti}^g = \boldsymbol{b}_t^g x_{cti}^g + \boldsymbol{e}_{cti}^g$$

Our controls include years of completed schooling, a quartic in potential experience, and dummy variables for Hispanic, black, and marital status. A separate model is estimated for each gender and education group and each year. This specification permits the effects of each explanatory variable to vary across the four gender-education groups and to change over time. The mean log wage of non-college men in area c at time t is the mean log wage residual for the non-college male workers in the area,

$$W_{ct}^{HS,M} = \frac{1}{n_{ct}^{HS,M}} \sum_{i} e_{cti}^{HS,M} .$$

Where $n_{ct}^{HS,M}$ denotes the number of non-college male workers in area *c* in the sample in year *t*. The wage of all workers in the area is estimated as the mean log wage residual over all workers in the area,

$$W_{ct} = \frac{1}{n_{ct}} \sum_{g,i} \mathbf{e}_{cti}^{g}$$

Where n_{ct} denotes the number of workers in area c in the sample in year t.

Appendix IV. Description of the Census Data

The census was used to estimate the mean log weekly wages of noncollege men, the unemployment rate among non-college men, and the mean log household income in each MA for 1979 and 1989. The census was also used to estimate industry employment shares at the national and MA levels and the employment shares for each gender-education group within each industry which were used to construct the industrial composition instruments. We employed the 5% sample of the 1980 and 1990 Censuses.

Wage information comes from the wage and salary income in the year prior to the survey. For 1980, we restrict the sample to persons between 18 and 65 who worked at least one week, were in the labor force for 40 or more weeks and usually worked 35 or more hours per week. The 1990 census does not provide data on weeks unemployed. To generate an equivalent sample of high labor force attachment individuals, we restrict the sample to people who worked 20 or more weeks in 1989 and who usually worked 35 or more hours per week. People currently enrolled in school were eliminated from the sample in both years. Individuals with positive farm or non-farm self-employment income were excluded from the sample. People who earned less than \$40 per week in 1979 dollars were excluded from the sample as were people whose weekly earnings exceeded \$2,500 per week. In the 1980 census, people with top-coded earnings were assumed to have earnings 1.45 times the top-coded value. The 1990 census imputes individuals with top-coded earnings to the median value for those with top-coded earnings in the state. These values were used. Individuals with imputed earnings (non top-coded), labor force status, or individual characteristics were excluded from the sample. The procedures used to control for individual characteristics in the CPS were also used for the census data.³⁰

The mean log household income was estimated using the income reported for the year prior to the survey for persons not living in group quarters. Individuals with imputed values for any of the earnings categories were dropped from the sample. We estimated household income by taking the sum across all income categories (negative values included) for each person in the household and then summing over all individuals. This method yields the same income for households beneath the top-coded value, but typically provides more accurate measurements for top-coded households -- the top-coded value

³⁰ The 1990 census categorizes schooling according to the degree earned. Dummy variables were included for each educational category.

for household income is beneath the sum of the top-codes for each income category.

We estimate the employment status of non-college men using the current employment status because the 1990 census provides no information about weeks unemployed in 1989. The sample is restricted to people between 18 and 65 not currently enrolled in school. The unemployment rate was constructed as the number of unemployed people divided by the number of people in the labor force.

The industry composition instruments require industry employment shares at the national and MA level and the employment shares of each gender-education group within each industry. These were estimated from the census. The sample included all persons between 18 and 65 not currently enrolled in school who resided in MA's. Individuals with imputed industry affiliations were dropped from the sample. Our classification has 69 industries at roughly the 2-digit level of the SIC. Individuals were weighted using the person weight in the 1990 census. The 1980 census is a flat sample.

Appendix V. Construction of the MA Level Instruments from the Census

This section outlines the construction of the instruments for labor demand. We exploit inter-city variations in industrial composition interacted with industrial differences in growth and technological change favoring particular groups to construct instruments for the change in demand for labor of all workers and workers in particular groups at the city (MA) level.

Let $f_{i|ct}$ denote industry *i*'s share of the employment at time *t* in city *c*. This expression can be read as the employment share of industry *i* conditional on the city and time period. Let $f_{i|t}$ denote industry *i*'s share of the employment at time *t* for the nation. The growth in industry *i*'s employment nationally is given by,

$$GROW_i \equiv \frac{f_{i|1}}{f_{i|o}} - 1$$

Our instrument for the change in total labor demand in city c is,

 $GROW \ TOTAL_c \equiv \sum_i f_{i|c0} GROW_i \ .$

We estimate the growth in total labor demand in city c by taking the weighted average of the national industry growth rates. The weights for each city correspond to the initial industry employment shares in the city. These instruments are analogous to those in Bartik (1991) and Blanchard and Katz (1992).

The empirical work uses a number of measures of labor market conditions. In order to capture variations in these measures we construct instruments for the change in demand for labor in four demographic groups. Our groups are defined on the basis of gender and education (non-college educated -- those with no more than 12 years of completed school or a high school diploma; and college educated -- those with some college including completion and post-graduate schooling). Let $f_{g|cti}$ denote demographic group g's share of the employment in industry i at time t in city c ($f_{g|t}$ for the whole nation). Group g's share of the employment in city c at time t is given by,

$$f_{g|ct} \equiv \sum_{i} f_{g|cti} f_{i|ct} \, .$$

The change in group g's share of employment can be decomposed as,

$$f_{g|c1} - f_{g|c0} \equiv \sum_{i} f_{g|c0i} \left(f_{i|c1} - f_{i|c0} \right) - \sum_{i} \left(f_{g|c1i} - f_{g|c0i} \right) f_{i|c1}$$

The first term reflects the effects of industry growth rates. The second term reflects changes in each group's share of employment within industries. The latter can be thought of as arising from industrial differences in biased technological change.

In estimating each term, we replace the MA-specific variables with analogues constructed from national data. All cross-MA variation in the instruments are due to cross-MA variations in initial industry employment shares. In estimating the effects of industry growth the demand for labor of each group, we replace the MA-specific employment shares ($f_{g|c0i}$) with national employment shares ($f_{g|0i}$). We also replace the actual end of period shares ($f_{i|c1}$) with estimates ($\hat{f}_{i|c1}$). Our estimate of the growth term is,

$$GROW_{gc} \equiv \sum_{i} f_{g|0i} \left(\hat{f}_{i|c1} - f_{i|c0} \right).$$

The date 1 industry employment shares for each MA are estimated using the industry's initial employment share in the MA and the industry's employment growth nationally.

$$\hat{f}_{g|c1} = \frac{f_{i|c0} GROW_i}{\sum_j f_{j|c0} GROW_j} \,.$$

To estimate the effects of biased technology change, we take the weighted average of the changes in each group's national employment share,

$$TECH_{gc} \equiv \sum_{i} \left(f_{g|1i} - f_{g|0i} \right) f_{i|c0} .$$

The weights correspond to the industry's initial share of employment in the MA.

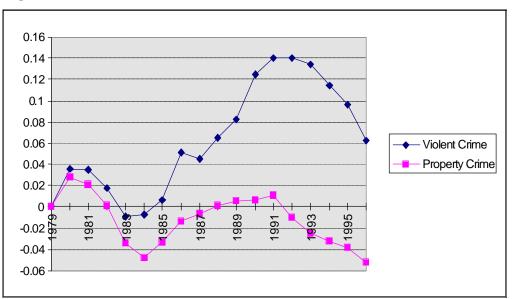


Figure 1: United States National Trends in Crime Indices

Plotted values are the log offense rate (offenses per 100,000 people) relative to the year 1979. The Property Crime Index is the sum of Auto Theft, Burglary, and Larceny. The Violent Crime Index is the sum of Aggravated Assault, Robbery, Murder, and Rape.

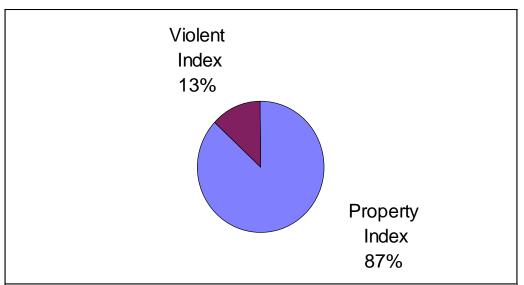


Figure 2: Composition of the Overall Crime Index in 1995 for the Whole U.S.

Sourcebook of Criminal Justice Statistics, Federal Bureau of Investigation.

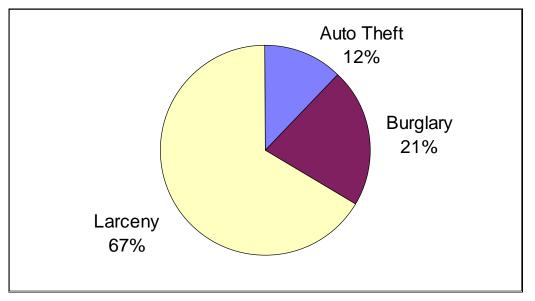


Figure 3: Composition of Property Crime Index in 1995 for the Whole U.S.

Sourcebook of Criminal Justice Statistics, Federal Bureau of Investigation.

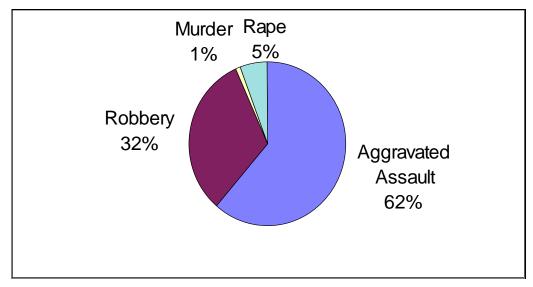


Figure 4: Composition of Violent Crime Index in 1995 for the Whole U.S.

Sourcebook of Criminal Justice Statistics, Federal Bureau of Investigation.

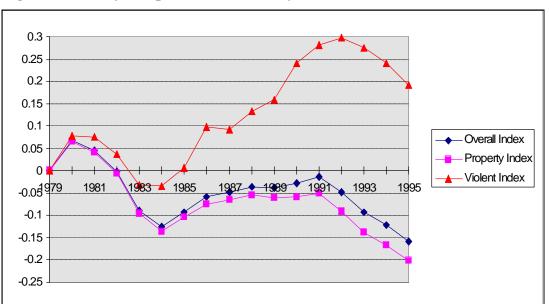


Figure 5: County Sample Trends in Unadjusted Crime Indices

Plotted values are the coefficients on the time dummies from regressions of the log offense rates on time dummies and county fixed effects for 352 counties with population over 100,000. Population was also used as weights.

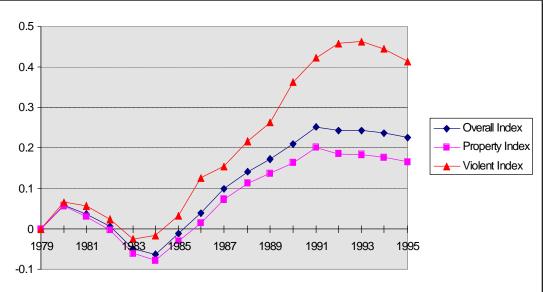


Figure 6: County Sample Trends in Adjusted Crime Indices

Plotted values are the coefficients on the time dummies of regressions of the log offense rates on time dummies, county fixed effects, and controls for age, sex, and racial compositions for 352 counties with population over 100,000. Population was also used as weights.

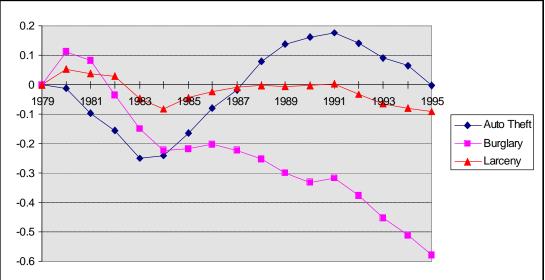


Figure 7: County Sample Trends in Unadjusted Property Crimes

Plotted values are the coefficients on the time dummies of regressions of the log offense rates on time dummies and county fixed effects for 352 counties with population over 100,000. Population was also used as weights.

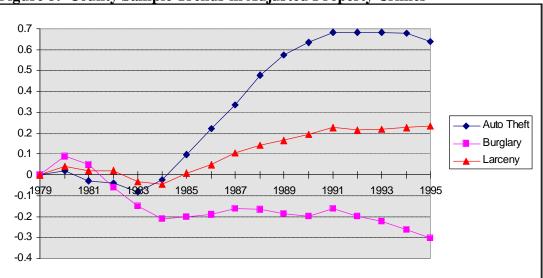


Figure 8: County Sample Trends in Adjusted Property Crimes

Plotted values are the coefficients on the time dummies of regressions of the log offense rates on time dummies, county fixed effects, and controls for age, sex, and racial compositions for 352 counties with population over 100,000. Population was also used as weights.

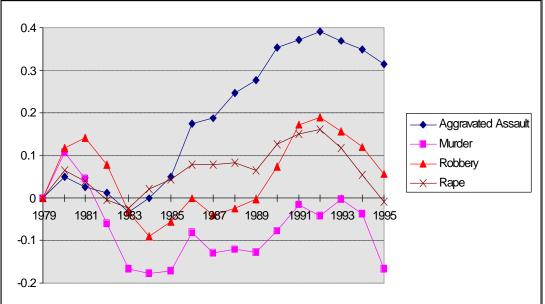


Figure 9: County Sample Trends in Unadjusted Violent Crimes

Plotted values are the coefficients on the time dummies of regressions of the log offense rates on time dummies and county fixed effects for 352 counties with population over 100,000. Population was also used as weights.

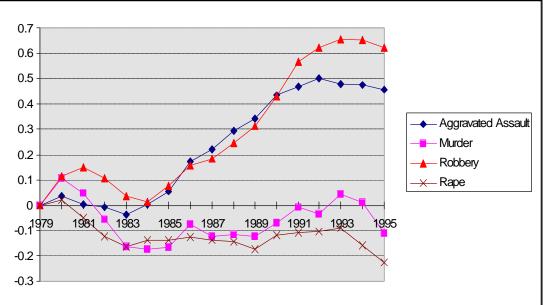


Figure 10: County Sample Trends in Adjusted Violent Crimes

Plotted values are the coefficients on the time dummies of regressions of the log offense rates on time dummies, county fixed effects, and controls for age, sex, and racial compositions for 352 counties with population over 100,000. Population was also used as weights.

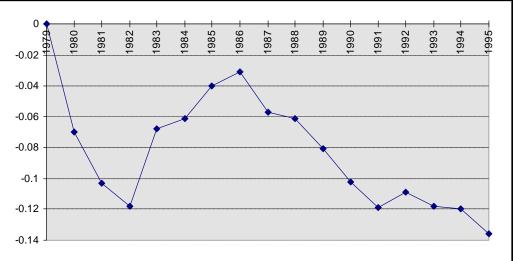


Figure 11: Log of Retail Income Per Retail Worker Over Time

Each point represents the coefficients from a county-level weighted regression of log retail income per retail worker on time dummy variables with average population for the county used as weights.

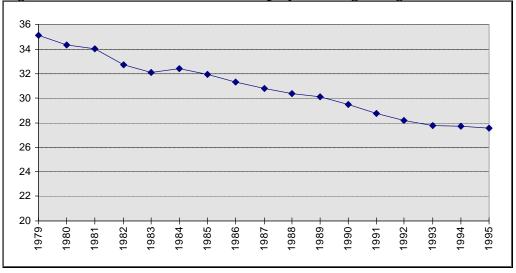


Figure 12: Percent of All Workers Employed In High-Wage Industries

High Wage industries include manufacturing, wholesale, transportation, and construction. Low wage industries include retail, services, FIRE, and government. Agriculture has been excluded due to missing values. Percentages were calculated by taking a weighted average of the county-level observations using the average county population as weights.

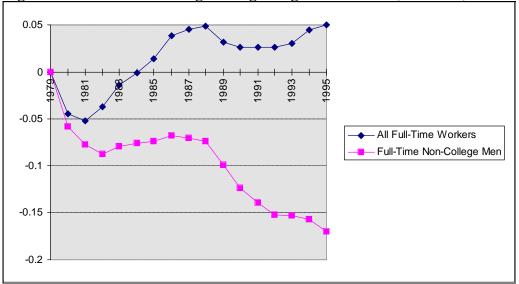


Figure 13: Standardized Log Average Wages Over Time (CPS data)

Plotted values are the coefficients of regressing log wages on year-specific dummy variables.

Table 1: County Level Regressions for Property and Violent Crime Offense Rate Indexes, 1979-1995										
	Property	Property	Property	Property	Property	Violent	Violent	Violent	Violent	Violent
	Crime	Crime	Crime	Crime						
	Index	Index	Index	Index						
Log Income Per		-0.249**		-0.377**	-0.206**		-0.013		-0.185**	-0.040
Capita		(0.051)		(0.046)	(0.052)		(0.075)		(0.067)	(0.076)
		[-5.1]		[-7.7]	[-4.2]		[-0.3]		[-3.8]	[-0.8]
Log Retail Income	-0.429**	-0.313**			-0.333**	-0.301**	-0.295**			-0.282**
Per Retail Worker	(0.044)	(0.050)			(0.050)	(0.063)	(0.072)			(0.073)
	[5.9]	[4.3]			[4.5]	[4.1]	[4.0]			[3.8]
Percent of All			-0.005**	-0.004**	-0.004**			0.003*	0.003**	0.003*
Workers in High			(0.001)	(0.001)	(0.001)			(0.001)	(0.001)	(0.002)
Wage Industries			[3.8]	[3.0]	[3.0]			[-2.3]	[-2.3]	[-2.3]
Observations	5984	5984	5984	5984	5984	5984	5984	5984	5984	5984
Partial R ²	0.016	0.020	0.004	0.015	0.023	0.004	0.004	0.001	0.002	0.004

** indicates significance at the 5% level. * indicates significance at the 10% level. Standard errors in parentheses. Numbers in brackets represent the "predicted" percent increase of the crime rate due to the mean change in the independent variable, computed by multiplying the coefficient estimate by the mean change in the independent variable between 1979-1995 (multiplied by 100). Observations are for 352 counties for 17 years. Regressions include county and time fixed effects and demographic controls (percent of population age 10-19, age 20-29, age 30-39, age 40-49, age 50-64, and age 65 and over, percent male, percent black, and percent non-black and non-white). Regressions weighted by mean of population size of each county. Partial R² are after controlling for county and time fixed effects, and demographic controls.

Table 2: County Level Regressions for Various Offense Rates, 1979-1995										
	Overall	Property	Auto	Burglary	Larceny	Violent	Aggravated	Murder	Robbery	Rape
	Crime	Crime	Theft			Crime	Assault			
	Index	Index				Index				
Log Income Per	-0.178**	-0.206**	-0.347**	-0.240**	-0.156**	-0.040	0.197**	0.494**	-0.158*	0.315
Capita	(0.051)	(0.052)	(0.092)	(0.064)	(0.052)	(0.076)	(0.096)	(0.195)	(0.096)	(0.104)
	[-3.7]	[-4.2]	[-7.1]	[-4.9]	[-3.2]	[-0.8]	[4.0]	[10.1]	[-3.2]	[6.5]
Log Retail Income	-0.346**	-0.333**	-0.172**	-0.593**	-0.299**	-0.282**	-0.227**	-0.759**	-0.393**	-0.597**
Per Retail Worker	(0.049)	(0.050)	(0.088)	(0.064)	(0.050)	(0.073)	(0.092)	(0.186)	(0.092)	(0.099)
	[4.7]	[4.5]	[2.3]	[8.1]	[4.1]	[3.8]	[3.1]	[10.4]	[5.4]	[8.1]
Percent of All	-0.005**	-0.004**	0.018**	-0.006**	-0.008**	0.003*	-0.000	0.004	-0.000	-0.001
Workers in High	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)	(0.002)
Wage Industries	[3.8]	[3.0]	[-13.7]	[4.6]	[6.1]	[-2.3]	[0.0]	[-3.0]	[0.0]	[0.7]
Observations	5984	5984	5984	5984	5984	5984	5984	5984	5984	5984
Partial R ²	0.023	0.023	0.020	0.033	0.025	0.004	0.001	0.003	0.006	0.006
See notes to Table 1										

See notes to Table 1.

Table 3: County Level Regressions for Various Offense Rates with Arrest Rates, 1979-1995										
	Overall	Property	Auto	Burglary	Larceny	Violent	Aggravated	Murder	Robbery	Rape
	Crime	Crime	Theft			Crime	Assault			
	Index	Index				Index				
Log Income Per	-0.276**	-0.313**	-0.504**	-0.376**	-0.259**	-0.091	0.211**	0.354**	-0.284**	0.109
Capita	(0.054)	(0.054)	(0.102)	(0.070)	(0.054)	(0.075)	(0.097)	(0.149)	(0.094)	(0.097)
	[-5.7]	[-6.4]	[-10.3]	[-7.7]	[-5.3]	[-1.9]	[4.3]	[7.3]	[-5.8]	[2.2]
Log Retail Income	-0.309**	-0.273**	-0.122	-0.558**	-0.224**	-0.260**	-0.244**	-0.405**	-0.417**	-0.327**
Per Retail Worker	(0.053)	(0.053)	(0.100)	(0.068)	(0.054)	(0.074)	(0.095)	(0.146)	(0.092)	(0.095)
	[4.2]	[3.7]	[1.7]	[7.6]	[3.1]	[3.5]	[3.3]	[5.5]	[5.7]	[4.5]
Percent of All	-0.004**	-0.004**	0.024**	-0.005**	-0.008**	0.005**	0.000	0.015**	0.002	0.002
Workers in High	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Wage Industries	[3.0]	[3.0]	[-18.2]	[3.8]	[6.1]	[-3.8]	[0.0]	[-11.4]	[-1.5]	[-1.5]
Arrests per Offenses	-0.002**	-0.009**	-0.004**	-0.012**	-0.007**	-0.003**	-0.003**	-0.002**	-0.006**	-0.004**
	(0.0003)	(0.001)	(0.0005)	(0.001)	(0.0005)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Observations	4165	4165	4165	4165	4165	4165	4165	4165	4165	4165
Partial R ²	0.047	0.088	0.052	0.112	0.090	0.056	0.047	0.039	0.089	0.086

Sample includes 245 counties for 17 years (1979-1995). See notes to Table 1 for further details.

Table 4: County Level Regressions for Various Offense Rates Using State Variables From the CPS, 1979-1995.										
	Overall	Property	Auto	Burglary	Larceny	Violent	Aggravated	Murder	Robbery	Rape
	Crime	Crime	Theft			Crime	Assault			
	Index	Index				Index				
Log Mean Weekly	-0.086	-0.048	-0.364	0.039*	-0.224	-0.211	-0.431	-1.606**	-0.112	-0.551
Wage of All	(0.161)	(0.163)	(0.283)	(0.213)	(0.163)	(0.237)	(0.299)	(0.608)	(0.301)	(0.325)
Workers in the State	[-0.4]	[-0.2]	[-1.8]	[0.2]	[-1.1]	[-1.1]	[-2.1]	[-8.0]	[-0.6]	[-2.7]
(Residuals)										
Log Mean Weekly	-0.479**	-0.483**	-1.405**	-0.718**	-0.178	-0.460**	-0.408*	0.563	-0.583**	1.113**
Wage of Non-	(0.116)	(0.118)	(0.204)	(0.154)	(0.118)	(0.171)	(0.216)	(0.438)	(0.217)	(0.234)
College Men in the	[5.4]	[5.4]	[15.7]	[8.0]	[2.0]	[5.1]	[4.6]	[-6.3]	[6.5]	[-12.4]
State (Residuals)										
Percent of All	-0.006**	-0.006**	0.014**	-0.008**	-0.009**	0.002	-0.001	0.005	-0.002	0.001
Workers in High	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.002)	(0.002)
Wage Industries in	[4.6]	[4.6]	[-10.6]	[6.1]	[6.8]	[-1.5]	[0.7]	[-3.8]	[1.5]	[-0.8]
the County										
Observations	5984	5984	5984	5984	5984	5984	5984	5984	5984	5984
Partial R ²	0.018	0.017	0.054	0.012	0.017	0.009	0.007	0.002	0.006	0.007

See notes to Tables 1. Residual wages for non-college men were obtained by regressing individual wages on education levels, experience, experience squared, and dummy variables for Hispanic, Black, and marital status.

	Mean	Standard Deviation
Change in Real Mean Log Wages of Non-College Men	137	.091
Change in Real Mean Log Household Income	.087	.118
Change in Unemployment Rate of Non-College Men	.006	.025
Log Changes in Crime Rates (Unadjusted)		
Index Crime	008	.299
Property Crime	028	.304
Auto Theft	.167	.489
Burglary	251	.361
Larceny	.021	.308
Violent Crime	.172	.382
Aggravated Assault	.281	.498
Murder	135	.804
Robbery	.018	.547
Rape	.075	.577

Counties weighted by mean of 1979 and 1989 populations. Sample includes 582 counties that lie within MA's. Counties with missing crime data are excluded from sample as are counties that lie within MA's which are not identified in both the 1980 and 1990 PUMS 5% samples. Changes in crime rates are not adjusted for changes in demographic composition.

Table 6: Effects of Economic Conditions on Crime Rates. Ten Year Differences, 1979-1989. Weighted Least Squares Estimates.										
	Overall	Property	Auto	Burglary	Larceny	Violent	Aggravated	Murder	Robbery	Rape
	Crime	Crime	Theft			Crime	Assault			
	Index	Index				Index				
Change in Mean	0.692**	0.671**	2.088**	0.207	0.566**	0.770**	1.050**	0.679	0.853**	-0.860**
Log Household	(0.187)	(0.190)	(0.300)	(0.221)	(0.195)	(0.266)	(0.346)	(0.578)	(0.378)	(0.399
Income in MA	[6.0]	[5.8]	[18.2]	[1.8]	[4.9]	[6.7]	[9.1]	[5.9]	[7.4]	[-7.5]
Change in Mean	-1.008**	-1.015**	-2.282**	-0.976**	-0.785**	-0.784**	-0.861**	0.065	-1.016**	0.774**
Log Weekly Wage	(0.207)	(0.210)	(0.333)	(0.244)	(0.216)	(0.295)	(0.384)	(0.640)	(0.419)	(0.442)
of Non-College Men	[13.8]	[13.9]	[31.3]	[13.4]	[10.8]	[10.7]	[11.8]	[-0.9]	[13.9]	[-10.6]
in MA (Residuals)										
Unemployment Rate	2.102**	2.226**	2.516**	2.540**	2.160**	0.776	0.694	0.805	2.920**	-1.874*
of Non-College Men	(0.463)	(0.471)	(0.746)	(0.548)	(0.484)	(0.661)	(0.860)	(1.435)	(0.939)	(0.992)
	[1.3]	[1.4]	[1.6]	[1.6]	[1.3]	[0.5]	[0.4]	[0.5]	[1.8]	[-1.2]
Observations	582	582	582	582	582	582	582	582	582	582
Partial R ²	0.074	0.075	0.108	0.072	0.056	0.019	0.017	0.005	0.028	0.014

** indicates significance at the 5% level. * indicates significance at the 10% level. Standard errors in parentheses. Numbers in brackets represent the "predicted" percent increase of the crime rate due to the mean change in the independent variable, computed by multiplying the coefficient estimate by the mean change in the independent variable between 1979-1989 (multiplied by 100). Dependent variable is log change in crime rate from 1979-1989 in county. Sample consists of 582 counties. Regressions include county and time fixed effects and demographic controls (percent of population age 10-19, age 20-29, age 30-39, age 40-49, age 50-64, and age 65 and over, percent male, percent black, and percent non-black and non-white). Regressions weighted by mean of population size of each county. Partial R-squares are after controlling for county and time fixed effects, and demographic controls. Wage residuals control for educational attainment, a quartic in potential experience, Hispanic background, black, and marital status.

Table 7: Effects of Ec	Table 7: Effects of Economic Conditions on Crime Rates. Ten Year Differences, 1979-1989. Instrumental Variables Estimates.										
	Overall	Property	Auto	Burglary	Larceny	Violent	Aggravated	Murder	Robbery	Rape	
	Crime	Crime	Theft			Crime	Assault				
	Index	Index				Index					
Change in Mean	-0.013	-0.035	1.688**	-0.818*	-0.146	-0.167	0.499	0.778	-0.103	-3.192**	
Log Household	(0.382)	(0.389)	(0.608)	(0.459)	(0.399)	(0.543)	(0.701)	(1.166)	(0.772)	(0.828)	
Income in MA	[-0.1]	[-0.3]	[14.7]	[-7.1]	[-1.3]	[-1.5]	[4.3]	[6.8]	[-0.9]	[-27.8]	
Change in Mean	-0.868**	-0.874**	-2.528**	-0.987**	-0.521	-0.406	-0.673	0.684	-1.341*	2.340**	
Log Weekly Wage	(0.364)	(0.370)	(0.579)	(0.467)	(0.379)	(0.517)	(0.667)	(1.110)	(0.735)	(0.789)	
of Non-College Men	[11.9]	[12.0]	[34.6]	[13.5]	[7.1]	[5.6]	[9.2]	[-9.4]	[18.4]	[-32.1]	
in MA (Residuals)											
Unemployment Rate	2.54**	2.777**	2.991*	3.019**	2.707**	1.441	2.089	-0.139	3.359*	-1.453	
of Non-College Men	(1.004)	(1.021)	(1.596)	(1.204)	(1.046)	(1.425)	(1.841)	(3.061)	(2.026)	(2.175)	
	[1.6]	[1.7]	[1.9]	[1.9]	[1.7]	[0.9]	[1.3]	[-0.1]	[2.1]	[-0.9]	
Observations	582	582	582	582	582	582	582	582	582	582	

** indicates the coefficient is significant at the 5% significance level. * indicates significance at the 10% level. Standard errors in parentheses. Numbers in brackets represent the "predicted" percent increase of the crime rate due to the mean change in the independent variable, computed by multiplying the coefficient estimate by the mean change in the independent variable between 1979-1989 (multiplied by 100). Dependent variable is log change in crime rate from 1979-1989 in county. Sample consists of 582 counties. Regressions include county and time fixed effects and demographic controls (percent of population age 10-19, age 20-29, age 30-39, age 40-49, age 50-64, and age 65 and over, percent male, percent black, and percent non-black and non-white). Regressions weighted by mean of population size of each county. Wage residuals control for educational attainment, a quartic in potential experience, Hispanic background, black, and marital status. Instruments are augmented Bartik-Blanchard-Katz instruments for the change in total labor demand, and in labor demand for four gender-education groups.