Skill-biased Technological Change, Earnings of Unskilled Workers, and Crime

Naci Mocan
Louisiana State University, NBER and IZA
mocan@lsu.edu

Bulent Unel
Louisiana State University
bunel@lsu.edu

September 2011

PRELIMINARY DRAFT

ABSTRACT

This paper investigates the impact of unskilled workers' wages on crime. Following the literature on wage inequality and skill-biased technological change, we employ CPS data from 1980 to 2005 and create a state-and-year specific measure of skill-biased technological change, which is then used as an instrument for unskilled workers' earnings in crime regressions. Regressions that employ state panels reveal that technology-induced variations in unskilled workers' earnings impact property crime with an elasticity of -1.0. We find that earnings of non-college educated males impact crime, but that earnings of unskilled females have no influence on criminal activity. Estimating a structural crime equation using micro data from NLSY97 and instrumenting real wages of young workers with industry-year-state specific technology shocks, yields elasticities that are in the neighborhood of -1.7 for most types of crime. In both data sets there is evidence for asymmetric impact of unskilled workers earnings on crime. A decline in earnings has a larger effect on crime in comparison to an increase in earnings by the same absolute value.

We thank Deokrye Baek, Elif Filiz and especially Duha Altindag for outstanding research assistance.

Skill-biased Technological Change, Earnings of Unskilled Workers, and Crime

I. Introduction

The United States has experienced a rapid growth in wage inequality since the late 1970s (Autor, Katz and Kearney 2008; Katz and Autor 1999; Bound and Johnson 1992; Katz and Murphy 1992). A large body of research points to skill-biased technological change as a primary driver for this rise in wage inequality. It has been argued that adoption of new technologies was positively correlated with capital intensity and the relative demand for skilled workers (Doms, Dunne and Troske, 1997; Levy and Murnane 1996). While the slowdown in the relative supply of skilled workers contributed to the widening of the wage gap between skilled and unskilled workers (Card and Lemieux 2001), technological change, associated with the development of microcomputers, and the resultant increase in the demand for skill, has been suggested be a major determinant of the rise in wage inequality (Juhn, Murphy and Pierce 1993, Autor, Katz and Krueger 1998, Berman, Bound and Griliches 1994, Katz and Murphy 1992).

In this paper we analyze the extent to which variations in unskilled workers' earnings, induced by skill-based technological change, cause crime. While the impact of legal market earnings on crime is well-determined theoretically since the pioneering work of Becker (1968) and Ehrlich(1973), empirical analyses have been plagued with the difficulty of credibly identifying the impact of wages on crime. Specifically, endogenity of earnings in crime regressions has created a major challenge in identifying the causal impact of legal labor market earnings on crime. We create a theoretically well-defined construct of skill-biased technological change, and employ this measure as an instrument for unskilled workers' earnings.

We analyze two data sets: an annual state panel spanning 1980 to 2005, and a micro data set from NLSY97 covering the years 1997 to 2003. The results show that in state panels, weekly earnings of unskilled workers are significantly related to property crime, with an elasticity of -1.0. Violent crime is not influenced by unskilled workers' earnings. We also find that earnings of unskilled men (but not women) are related to crime, and that the impact of earnings on crime is asymmetric. A decline in real weekly earnings of unskilled workers has a larger impact on crime than an equivalent increase in their earnings. NLSY data generate similar results in that wages impact property crime activity of individuals, and that the impact of wages are asymmetric. The wage elasticities are in the neighborhood of -1.7 for most crimes.

The next section of the paper briefly describes the previous research on wages and crime, and Section III presents a simple theoretical framework. Section IV presents the aggregate crime equation and the asymmetry hypothesis. Section V explains the instrument – skill biased technological change – that is employed in the paper. Section VI describes the data used in the aggregate (state panels) analysis and Section VII displays the results obtained from aggregate data. Section VIII describes the econometric setup of the analysis of micro data, section IX explains the data sets used in this analysis. Section X presents the results obtained from micro data and Section XI is the conclusion.

II. Previous Research

Although economic models of crime predict that legal market opportunities are negatively related to criminal activity (Becker 1968, Ehrlich 1973, Mocan, Billups and Overland 2005) the evidence on the magnitude of the relationship is rather mixed. This is especially true for the impact of wages on crime. In micro data an individual's market wage and his/her unobserved proclivity for criminal activity are likely to be correlated, but it is a major challenge to find instruments that are correlated with individual wages but are exogenous to criminal activity to resolve this endogeneity problem. Grogger (1998) is one of the very few papers that addresses the issue, using cross-sectional data from one year (1980) of the NLSY. An alternative strategy is to use aggregate crime data and to employ aggregate indicators of labor market opportunities under the assumption that they are reasonably exogenous to crime.[1] However, exogeneity of wages is questionable even in aggregate data. For example, local area attributes might be correlated with the level of wages as well as the crime rates. Furthermore, crime rates themselves might impact labor demand and employment at the local level, which would in turn impact wages. Thus, it is desirable to find an instrument that is reasonably correlated with wages at the local level, but not related to crime in the analysis of aggregate data. Gould, Weinberg and Mustard (2002) ran models of county-level crime rates, on state-level wages, where state wages are instrumented with the product of the industrial composition of the state in the beginning of the sample year, the national industrial composition trends in employment in each industry and the change in demographic composition in each industry at the national level.

---

[1] For example, Corman and Mocan (2005) and Hashimoto (1987) used minimum wages. Machin and Meghir (2004) used average area wages to explain crime in England and Wales.

III. Theoretical Framework

Standard theoretical models developed by Becker (1968) and Ehrlich (1973) postulate that optimizing individuals evaluate the expected monetary costs and benefits of participating in the legal labor market and in the market for offenses. Individuals also form expectations about the certainty and severity of punishment and make decisions on their criminal activity and on labor supply to the legal market. In this framework, as the return to legal human capital (wages in the legal labor market) goes up, the propensity to engage in crime goes down. This basic insight can be demonstrated using the simple static model of Grogger (1998), where the individual maximizes a utility function $U(C,L)$, where C stands for consumption and L is leisure time devoted to non-market activity.[2] Total available time T is spent between leisure, the amount of time allocated to the legal labor market T_m, and the amount of time devoted to crime T_c such that $T = L + T_m + T_c$. The budget constraint of the individual is $C = Y + WT_m + R(T_c)$, where Y stands for unearned income, W represents wages faced by the individual in the legal labor market, and R is the returns- to- crime schedule, which is a concave function of T_c. The concavity represents the diminishing marginal returns to crime.

As detailed in Grogger (1998), the marginal rate of substitution (MRS) between consumption and leisure is $MRS(C,L) = F(T_m, Y + R(T_c), L + T_m)$, where T_m and T_c are choice variables. If W_0 stands for the reservation wage of the individual, he/she will work in the labor market if $W > W_0$. Similarly, he will commit crime if $R' = \partial R(T_c)/\partial T_c > W_0$. An individual who allocates time to both crime and the labor market finds the optimal crime

[2] Recent dynamic economic models of propose a richer interplay between investment in human capital and crime, (Mocan, Billups and Overland 2005), but the main insight regarding the impact of returns to human capital is the same. **CITE MORE**

hours where marginal return to an extra hour of crime is equal to the market wage; i.e. where $R' = W$ is satisfied.[3] It is straightforward to show that a decrease in legal wages *W* increases the individuals' optimal allocation of time to crime. The basic theoretical framework described above allows us to estimate an aggregate (state-level) crime equation as well as a crime participation equation using micro data. The analysis of aggregate data is explained in the next section, and the analysis of micro data is provided in Section VIII below.

IV. Analysis of Aggregate Data

The theoretical framework described in the previous section suggests a formulation as depicted by Equation (1) below

(1) $CR=F(W, X, D)$,

where *CR* stands for the extent of criminal activity, *W* represent the relevant market wages, *D* stands for measures of deterrence variables that may capture the cost of crime, and *X* is a vector of variables including unearned income and other attributes that may be correlated with tastes and contextual influences.

Within this framework and following the literature that employs aggregate crime data (Gould, Weinberg and Mustard 2002, Corman and Mocan 2000, Freeman 1999, Levitt 1998, Ehrlich 1996), we estimate the following model

(2) $$CR_{st} = \alpha + \beta W_{st} + X_{st}'\Omega + D_{st}^{b}\Psi + \mu_s + \lambda_t + \varepsilon_{st}$$

where CR_{st} is the crime rate in state *s* and year *t*, which is estimated separately for different types of crime (*e.g.* robbery, burglary, motor vehicle theft) W_{st} stands for the real weekly earnings of unskilled workers in state *s* and year *t*, and X_{st} represents the vector of time-

[3] Note that the expected costs of crime, such as those associated with the certainty and severity of punishment, can be thought of as having been incorporated in to the shape of the returns-to-crime schedule R(Tc).

varying state characteristics. D stands for the arrest rate for crime *c,* and X represents state attributes such as per capita income. To avoid a ratio bias, arrests are deflated by population, rather than by offenses. μ_s stands for unobservable state attributes that influence crime in that state, and λ_t stands for year effects. The details of the variables and the data sources are provided in the data section below.

As shown by Mocan, Bilups and Overland (2005) and Mocan and Bali (2010), the impact of economic conditions on crime is expected to by asymmetric. A decline in economic opportunity (decline in market wages or increase in the unemployment rate) increases criminal propensity. As participation in crime goes up, legal human capital depreciates and criminal human capital appreciates. This makes it difficult to reduce the extent of criminal activity following the improvement in labor market conditions. Thus, the impact of a deterioration in real weekly earning on crime is expected to be larger in magnitude than the impact of an increase in weekly earnings by the same absolute magnitude. To test this hypothesis we define the crime rate as an asymmetric function of weekly earnings (W), where the conditional mean of the crime rate is specified to follow two different paths depending on the change (increase or decrease) in W as follows.

(3) $$CR_{st} = \alpha + \beta W_{st}^{+} + \gamma W_{st}^{-} + X_{st}'\Omega + D_{st}^{c}\Psi + \mu_s + \lambda_t + \varepsilon_{st}$$

where $$W_{st}^{+} = \begin{cases} W_{st} & \text{if } W_{st} \geq W_{st-1} \\ 0 & \text{if } W_{st} < W_{st-1} \end{cases} \text{ and } W_{st}^{-} = \begin{cases} W_{st} & \text{if } W_{st} < W_{st-1} \\ 0 & \text{if } W_{st} \geq W_{st-1} \end{cases}.$$

This specification allows us to investigate whether an *increase* in weekly earnings has the same impact on crime as a *decrease* in weekly earnings (i.e. whether $\beta=\gamma$ in Equation 3).

As described previously, it is obvious that labor market earnings are an endogenous variable in crime regressions when the unit of observation is the individual. Criminal activity will impact the relevant market wages of the person because participation in the criminal sector deteriorates legal human capital (Mocan, Billups and Overland 2005). In addition, difficult-to-observe characteristics of the individual may be correlated with both the criminal propensity and his/her wages. Similar empirical difficulties exist in aggregate data. For example, unobserved attributes of a state may impact labor market wages as well as criminal activity. Furthermore, as implied by the results of Cullen and Levitt (1999), reverse causality from crime rates to market wages is possible. These authors show that each additional crime in a central city is associated with a net decline of population by one resident. They further show that this net decline in population is due to the out-migration of residents. Movements in the labor demand and labor supply as a result of this crime-induced out-migration may influence market wages.

Because of these concerns, we employ an instrumental variables strategy, where the weekly wages of unskilled workers are instrumented by a measure of skill-biased technological change. Following the framework of Autor, Katz and Krueger (1998) and Autor, Katz and Kearney (2008), we calculate an index of relative demand shifts favoring skilled workers, as detailed in the next section.

V. The Instrument

Consider an extended version of the CES production function in which skilled and unskilled labor are imperfect substitutes. Total output, Y_{st}, produced in state *s* and year *t*, is given by

$$(4) \qquad Y_{st} = \left[\left(A_{Hst} H_{st} \right)^{\rho} + \left(A_{Lst} L_{st} \right)^{\rho} \right]^{\frac{1}{\rho}},$$

where H_{st} and L_{st} stand for quality-adjusted skilled and unskilled labor inputs (employment), respectively. A_{Hst} represents the efficiency of skilled labor (or skilled-labor augmenting technology) in state *s*, time period *t*, while A_{Lst} stands for the efficiency of unskilled labor (unskilled-labor augmenting technology). Variations of this production function have been widely used in similar contexts (Katz and Murphy, 1992; Acemoglu, 1998 and 2002; Ciccone and Peri, 2005; Caselli and Coleman, 2006; Autor, Katz, and Kearney, 2008).[4] The parameter ρ is time-invariant, and the aggregate elasticity of substitution between skilled and unskilled labor is given by $\sigma = 1/(1-\rho)$. Skill-neutral technological improvement raises A_{Hst} and A_{Lst} by the same proportion, while skill-biased technological change increases A_{Hst}/A_{Lst}.

Under the assumption of competitive factor markets and that factors are paid their marginal products, the first order conditions yield the following relationship between the relative wages, W_H/W_L, and relative supply of skills, H/L,

$$(5) \qquad \frac{W_{Hst}}{W_{Lst}} = \left(\frac{A_{Hst}}{A_{Lst}}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{H_{st}}{L_{st}}\right)^{-\frac{1}{\sigma}}.$$

With data on labor supplies and wage earnings, A_{Hst}/A_{Lst} can be backed out for each state and year from equation (5), under the assumption that the parameter σ is known. In our analysis, we set $\sigma = 1.6$, because it is the consensus estimate of the aggregate elasticity of substitution between skilled and unskilled labor (Krusell et al., 2000; Ciccone and Peri, 2005;

[4] The formulation depicted in Equation (5) below remains unchanged even if we assume that the production function has the following general form:

$$Y_{st} = \left[\eta K_{st}^{\alpha} + (1-\eta)[(A_{Hst}H_{st})^{\rho} + (A_{Lst}L_{st})^{\rho}]^{\alpha/\rho}\right]^{1/\alpha},$$

where K_{st} is the capital stock of state *s* in year *t*; α and η are time-invariant parameters.

Autor et al., 2008). As Equation (5) depicts, $\sigma = 1.6$ implies that a 10% increase in the relative supply of skilled labor should lower their relative wage by about 6.3% in the absence of technological change. The relative supply of skilled labor (i.e., college educated workers) has been rising over the last several decades in the U.S., but this rise has been accompanied by a well-documented increase in the relative wages of these workers. These facts imply that, as shown by equation (5), A_H / A_L, has been rising. Put differently, the observed increase in wage inequality in favor of skilled workers in the presence of the sustained increase in the relative supply of skill suggests an increase in (A_H / A_L), which represents skill-biased technological change (Autor, Katz, and Kearney, 2008; Card and DiNardo, 2002).

We employ $\ln(A_H / A_L)$ as an index for skill-biased technological change (Autor, Katz, and Kearney 2008; Autor, Katz, and Krueger 1998).[5] This index of state-and-year specific relative demand shifts in favor of skilled labor is used as an instrument for wages of unskilled labor in each state and year in the analysis of state-level panel data.[6] When we analyze micro data from the NLSY97, we follow the same procedure, but create state-year-and-industry specific measures of relative demand shifts for each industry j, in each state *s,* in each year *t,* $\ln(A_{Hjst} / A_{Ljst})$, where service, manufacturing, and other industries are used as

[5] We use $\ln(A_H / A_L)$ rather than $\ln A_H$ and $\ln A_L$, separately, for two reasons. First, $\ln(A_H / A_L)$ directly measures the of skilled-biased technical change. Second, calculation of $\ln A_H$ and $\ln A_L$ requires exact form of the production function together with the data on capital stocks. If we assume that the production function has the same form as in footnote 4, we need to know parameters α and η, which are not available. Moreover, there are no data on state-level capital stocks.

[6] Note that, it has been suggested that the rise in earnings inequality in the early 1980s was an episodic event, mostly driven by the decline in the real minimum wage (Card and Dinardo 2002). On the other hand, Autor, Katz and Kearney (2008) find limited support for this claim. They argue that the pattern of wage inequality between 1963 and 2005 is explained by a modified version of the skill-biased technological change hypothesis.

three broad industry categories. These measures are matched with workers in the NLSY by the industry of employment. Those who are unemployed are matched with state-wide skill-biased technological change for each year. The details of the micro data analysis are presented in Section VIII and the details of the creation of skill-biased technological change measure are displayed in the Appendix.

VI. Data Used in State Panels

We follow the literature on wage inequality to construct measures of earnings and employment for both skilled and unskilled labor (e.g. Autor, Katz, and Kearney, 2008). Specifically, we use the March Current Population Survey (CPS) from 1980 to 2006 that provide information on prior year's annual earnings and weeks worked. We focus on weekly earnings, which are constructed by dividing total annual earnings (from wages and salaries) in the previous year by the number of weeks worked.[7] Following Gould, Weinberg, and Mustard (2002), we construct average weekly earnings by considering all employed people between 18 and 65 years of age (excluding self-employed workers) and who work on a full-time basis (defined as working 35-plus hours per week). Consistent with our econometric specification and much of the literature, we classify non-college educated individuals (those with 12 or fewer years of schooling) as unskilled labor, and those with at least some college education (13 or more years) are classified as skilled workers. Quality-adjusted earnings (i.e. adjusted for the composition of employment by education, experience and gender) are

[7] Several authors (e.g., Lemieux, 2006; Autor et al., 2008) indicate that the March CPS data are not ideal for analyzing the hourly wage distribution since they lack a point-in-time wage measure, and that the data on usual weekly hours are noisy. This creates substantial measurement error in estimates. Therefore, following much of the literature, we focus on weekly earnings.

deflated by state-specific price deflators from Berry et al. (2000). The appendix provides a complete description of the data sets and construction of aggregate variables.

Uniform Crime Reports data, pertaining to specific FBI index crimes (burglary, larceny, motor vehicle theft, robbery, murder, rape and aggravated assault) are obtained from the Bureau of Justice Statistics. Arrests for each specific crime type are compiled from hardcopies of the uniform crime reports. In calculating the arrest rates, arrests are divided by the state population covered by police agencies reporting to the FBI, also obtained from the Uniform Crime Reports. The percentage of state population living in urban areas, percentage black, and percentage aged 15 to 24 are based on the Census information. Per capita personal disposable income in the state is obtained from the Bureau of Economic Analysis, and the unemployment rate data are provided by the Bureau of Labor Statistics. Per capita beer consumption data (which are obtained from the National Institutes of Health) is used as a proxy for alcohol consumption in each state. The descriptive statistics of the data are provided in Table 1.

Figure 1 presents the behavior of U.S. property crime rate (the sum of burglaries, larcenies and motor vehicle thefts per 100,000 population) and the overall crime rate in the sample period of this study. Property crime went up between 1984 and 1991, and declined steadily since that time. Total crime, which consists of both property and violent crime, has the same pattern as the property crime, because property crime constitutes the majority of total crime.

Figures 2A-7A display the crime rates of unskilled workers in a sample of states from different regions of the country. There is significant heterogeneity in the behavior of the crime rates. For example, over the sample period of 1980 to 2005, Louisiana’s crime rate went up rather steadily between 1980 and 1996, and started declining afterwards. On the other hand, the crime rate in Texas reached its peak in 1988, and the crime rate in Maine has declined since 1980 with some jumps in late 1980s and mid 1990s. The crime rate in California declined in the early 1980s, then remained steady for a decade, and dropped significantly between 1993 and 1999. In contrast, crime went up between early 1980s and early 1990s in Massachusetts before started declining, and the crime in West Virginia went up, rather than decline, between early1980s and 2005.

Figures 2B-7B present the quality-adjusted real weekly earnings of unskilled workers in the same states.[8] In some states, there is a visible negative correlation between crime and real weekly earnings of unskilled workers. For example, in Louisiana, earnings of unskilled workers went down between 1980 and 1991, and they bounced and started going up after 1991. Crime in Louisiana increased between 1980 and 1996, and declined afterwards. In Maine and West Virginia, real weekly earnings of unskilled workers were going up between 1980 and 2005 when crime was declining. Real earnings steadily declined in Texas between 1980 and 1992, and they started increasing afterwards. Crime in Texas exhibits the reverse pattern. On the other hand, the correlation between crime and earnings of unskilled workers is not strong in Massachusetts and in California.[9] Note that Figures 2B-7B display quality-adjusted real weekly earnings of unskilled workers (see the Appendix for the construction). The level of simple weekly earnings (unadjusted for education, experience or gender composition) are higher, but the two follow the same time-series pattern in a state.

[8] The average weekly earnings for each year are calculated using weighted individual weekly earnings.

[9] These particular states are not anomalies in any sense. Analysis of other states shows that the behavior of the crime rate is quite different between the states. For example, the crime rate in Florida increased steadily between 1984 and 2005, while Michigan exhibited a continuous decline in crime. Similarly, there is heterogeneity between states regarding the simple correlation between the crime rate and earnings of unskilled workers. For example, the two variables move in opposite direction in Mississippi over time, while the relationship is less clear in Indiana.

VII. Estimation Results of State-level Panel Data

Tables 2A and 2B present the instrumental variables results where aggregate property crime, aggregate violent crime, and their components (i.e. burglary, larceny, murder, and so on) are regressed on unskilled workers' real earnings, arrests rates for the corresponding crimes and other time-varying state attributes. Earnings of unskilled workers are instrumented with $\ln(A_H / A_L)$ from Equation (5). The instrument is powerful in each case, and the F-statistic of the instrument in the first stage regressions is about 28. Regressions also control for state and time fixed-effects and a common time-trend; the standard errors are clustered at the state level. Following Levitt (1998), Corman and Mocan (2000), and Katz, Levitt, and Shustorovich (2003), arrest rates are lagged once to minimize the impact of simultaneity between crime and deterrence.

Column (1) of Table 2A shows that the IV-estimate of the coefficient of unskilled (non-college) workers' weekly earnings is about -10 in the total property crime regression and it is highly significant. The estimate suggests that a \$20 increase in weekly real earnings of unskilled workers (which corresponds to a 5 % increase at the sample mean) reduces property crime rate by 200 (or about 10,500 fewer property crimes in a state in a year), which corresponds to a 4.8 % decline. This suggests an elasticity of property crime with respect to real weekly earnings of -0.96. Columns (2) and (3) show that an increase in weekly earnings of unskilled workers reduces two components of property crime: burglary and larceny, but it has no impact on motor-vehicle theft. A \$20 increase in weekly earnings of unskilled workers generates a decline in the burglary rate by about 60, or 6%, which translates into 3,160 fewer burglaries. The same increase in earnings brings about a decline in the larceny rate by 160, (5.7%). This suggests that the elasticity of burglary and larceny with respect of the earnings of unskilled workers is in the range of -1.1 to -1.2. The coefficient of unskilled workers' earnings is not significantly different from zero in violent crime regressions.[10]

Table 2A also shows that state alcohol consumption is positively related to crime and that the arrest rate has a negative impact on most crimes and the impact is estimated with precision in case of burglary, larceny, and total property crime. Lagging the arrest rate twice or omitting it from the models did not alter the estimated coefficients of weekly earnings.[11] Per capita state income has a negative impact on motor vehicle thefts and robberies.

Table 2B displays the results of the instrumental variables regressions which include *Weekly Earnings*$^{+}$ and *Weekly Earnings*$^{--}$ as two separate regressors. The first stage regression of this specification uses $\ln(A_H/A_L)^{+}$ and $\ln(A_H/A_L)^{-}$ as instruments, which are constructed the same way as *Weekly Earnings*$^{+}$ and *Weekly Earnings*$^{--}$. Column (1) of Table 2B shows that a decrease in unskilled workers' weekly earnings has a larger impact on total property crime than an increase in earnings by the same magnitude. That is, the coefficient of *Weekly Earnings*$^{--}$ is larger in absolute value than that of *Weekly Earnings*$^{+}$, and the difference is statistically different from zero at the eight percent level. Specifically, if real weekly earnings of unskilled workers *go down* by $10, the property crime rate goes up by about 176, which corresponds to *an increase* in the number of property crimes by about

[10] Estimating the models using OLS, by treating the weekly earnings of unskilled workers as exogenous, provided estimates of earnings that were mostly positive and sometimes statistically different from zero. At its face, this would suggest that an increase in weekly earning of non-college workers would increase crime, and it underlines the importance of addressing endogeneity.

[11] In models that omitted the deterrence variables, estimated coefficients of weekly earnings were larger in absolute value in most cases.

9,275.[12] On the other hand, if weekly earnings *increase* by $10, the property crime rate goes down by only 168, which translates into a *decline* in the number of property crimes by 8,854. The same asymmetry is detected in the impact of weekly earnings of unskilled workers on burglary and larceny. In both cases, a decline in real weekly earnings has a larger impact on criminal activity than an increase in weekly earnings by the same magnitude, although the difference is not significantly different from zero in case of burglary (p=0.15).

Tables 3A and 3B present the results of similar analyses with one difference. In these specifications, we employ real weekly earnings of *unskilled men* as opposed to all unskilled workers. The results indicate that weekly earnings of unskilled men have a negative impact on burglaries, larcenies and on overall property crime. Table 3B demonstrates that, consistent with earlier results, a decline in weekly earnings of unskilled men generates a larger impact on property crime than an increase by the same amount. (The coefficients of *Weekly Earnings*$^{-}$ are larger in absolute value than the coefficients of *Weekly Earnings*$^{+}$, and the difference between the estimated coefficients is different from zero in case of larceny and it is borderline significant for total property crimes).

The framework of the skill-biased technological change depicted by Equations (4) and (5) and the literature on wage inequality assume that wages are determined on inelastic relative supply of the skill groups (Acemoglu and Autor 2010; Autor, Katz and Kearney, 2008; Autor, Katz, Krueger 1998). Deviations from full-employment are implicitly ruled out, but they can take place idiosyncratically because of cyclical conditions. This suggests that one can incorporate unemployment to this analysis as an exogenous variable as was done in the analysis of wage inequality (e.g. Autor, Katz and Kearney 2008). Tables 4A-5B display

[12] The coefficients of *Weekly Earnings*$^{+}$ and *Weekly Earnings*$^{-}$ are larger in comparison to the coeffiients of *Weekly Earnings* reported in table 2B because the mean values of *Weekly Earnings*$^{+}$ and *Weekly Earnings*$^{-}$ *are* smaller than *Weekly Earnings* by construction (see Equation 3).

the results of the models that include state unemployment rate as an additional explanatory variable. A comparison with Tables 2A-3B shows that inclusion of the unemployment rate does not alter the magnitudes of other coefficients appreciably and that unemployment has an independent and positive effect on total property crime, and well as on burglaries and larcenies. An increase in unemployment also increases robberies: a violent crime that has a monetary motive. Tables 4A and 4B imply that a one-percentage point increase in the state unemployment rate increases property crime rate by 74-103, (which translates into an increase in property crimes by 2%), which generates 3,636 to 4,954 additional property crimes per year. This magnitude is remarkably similar to the ones reported by recent research. The same one-percentage point increase in the unemployment rate generates a 3.8% increase in robberies. Consistent with earlier results, Tables 4B shows that the impact of weekly earnings of low-skilled workers on crime is larger when earnings are declining.

These results also underline the importance of addressing endogeneity of earnings, as OLS regressions (not reported) of crime on earnings revealed positive and insignificant coefficients of earnings.

VIII. Analysis of Micro Data

Based on the theoretical framework summarized in Section III above, and following Grogger (1998), in this section we estimate a structural crime participation equation using data from NLSY97. Specifically, consider equations (6) and (7) below

$$\ln W_{it} = X_{it}\Omega + \varepsilon_{it}\,, \tag{6}$$

$$\ln[R'(T_{cit})] = X_{it}\Phi + D_{it}\Psi + \lambda T_{cit} + \mu_{it}\,, \tag{7}$$

where (6) is a standard Mincerian equation for market wages *W,* and equation (7) specifies the marginal returns to crime, where T_c represents time spent committing crime*, and* $R'(T_c) = \partial R / \partial T_c$ stands for the returns to committing crime. *X* stands for the vector of personal attributes and *D* stands for state characteristics, including deterrence variables.

As described in section III, if the person is engaged in crime, it should be the case that $\ln[R'(T_{cit} > 0)] > \ln W$. This indicates that the probability of committing crime [Pr(CR=1)] can be depicted as $\Pr(CR = 1) = \Pr(X\Phi + D\Psi + \mu - \ln W > 0)$) or

(8) $$\Pr(CR = 1) = \Pr(\mu > \ln W - X_{it}\Phi - D_{it}\Psi).$$

Equation (8) can be estimated by maximum likelihood probit, but two complications exist. First, market wages W are not observed for those who don't work in the labor market, and estimating Equation (8) using only those who work could produce sample selection bias. Second, ε and μ in Equations (6) and (7) are likely to be correlated. That is, unobserved factors that influence labor market productivity may be correlated with unobservables that impact productivity in the criminal sector, which constitutes a potential source of endogeneity of wages. To address the first issue, we specify a selection equation that classifies individuals into worker vs. non-worker groups and estimates it along with the wage equation using full maximum likelihood. Identification is achieved by including unearned income in the selection equation and excluding it from the wage equation. Alternative identification restrictions, such as including indicators of marijuana use and gun ownership in addition to household income, provided the same results. This selectivity-corrected wage equation is used to impute the market wages of non-workers.

To address the endogeneity of wages, we instrument wages with skill-biased technological change index as explained in section V. Because each worker's *sector* of work is known in the data, we classified workers into three groups as working in the service sector, in the manufacturing sector, or in other sectors (which consists of agriculture, mining and construction). We calculated the index of skill-biased technology for each state, year, and sector using the algorithm described in the Appendix. More specifically, we specified production functions for the manufacturing sector, the sector, service sector and the residual (all other) sectors which depend on skilled and unskilled labor as before and recovered the index for the skill-biased technology using equation (5).

We then matched each worker in each state, year and sector with the corresponding sector-state-and year specific skill-biased technology index. Because the sector affiliation is unknown for non-workers, we matched them by year, with the state-and-year specific skill-biased technology index—the one that is used in the state-panel analysis of the paper.

In this framework we estimate Equation (9) where CR_{ijt} stands for an indicator of various types of criminal activity (e.g. theft, stealing cars, drug sales) for person *i* who resides in state *j* in time *t*, and the vector X stands for personal attributes of the person. D represents a vector of time-varying state characteristics which includes aggregate measures of deterrence, such as the arrest rates for specific crimes. $\ln W_{ijt}$ is the logarithm of the market wages of worker *i,* in state *j* and time *t*, instrumented with skill-biased technological change; and υ stands for the error term:

$$(9) \qquad CR^{c}_{ijt} = \beta \ln W_{ijt} + X_{ijt}{}'\Phi + D_{jt}{}'\Psi + \varepsilon_i + \theta t + \upsilon_{ijt}.$$

IX. Micro Data from the NLSY97

We use confidential geo-coded National Longitudinal Survey of Youth 1997 cohort (NLSY97). The main data set is constructed using information from the 1997 - 2003 waves of the NLSY97, which contains a nationally representative sample of 8,984 youths who were aged 12 to 16 as of December 31st 1996. The respondents have been followed annually since the survey was initiated. We limit the sample to 1997-2003 waves because everyone who took the survey between these years was asked of question on criminal activity. After 2003 crime questions were asked to those who had reported to have been arrested in previous waves in addition to a small group of not-arrested respondents.

We employ seven different indicators of delinquency. They are robbery, which is a violent crime, and six categories of property crimes such as whether the person committed burglary, whether he/she stole a car, whether he/she sold or helped selling hard drugs like cocaine, and whether he/she sold any drugs. Other crime measures include stealing a purse, a wallet, or stealing something from a store (Larceny); and Other Property Crimes such as whether the person received, possessed or sold stolen property, embezzlement, and fraud. We also employ a variable to indicate if the person committed Larceny, Car Theft or Robbery. [13]

In each wave, individuals are asked about the jobs they have taken since the last interview. Respondents report up to 11 different jobs as well as the hourly compensation they have received in each job. Highest hourly compensation reported for the year is used as

[13] These outcome variables are constructed based on a series of questions in the following form "Have you done XXX since the last interview?" where XXX stands for various crimes mentioned in the text. From 1998-2003 all crime questions were asked in that form. In the first wave in 1997, the question was "Have you ever done XXX?" followed by "How many times have you committed XXX in the last 12 months?" or "How old were you when you last did XXX?" Thus, we used these variables to construct the outcome variables for the first wave.

the relevant wage (Finlay 2009). To eliminate outliers, above the 95th percentile of the wage distribution are omitted. Finally, the wage rate is deflated by the State-level CPI.

Some of the individuals in our sample reported that they have not worked since the date of last interview. Their market wages are predicted by estimating jointly a labor force participation and equation and a wage equation as shown by Equations (8) and (9). The exclusion restriction for the selection equation is to omit conventional non-labor income from the wage equation. Non-labor income is defined as the difference between individual's total household income and his/her personal labor income. As a result, our non-labor income measure includes the following income types: child support, interest from bank accounts, dividends from stocks or mutual funds, rental income, income received from the parents, and from other sources (except own farms/businesses or salaries).

NLSY97 includes information about the industry classifications of individuals' jobs. We used the 2002 Census definitions of the industries.[14] After matching individuals with their industries, we used the technology shocks as an instrumental variable. Obviously, those individuals who reported not having worked since the date of the last interview do not belong to an industry. Consequently, we modified our instrumental variable such that the non-working people are matched with the overall technology shocks.

Individual control variables employed includes whether the individual has carried a gun in the last year, individual's age, an indicator for whether the individual has at least a high school degree (including GED), individual's household income (income from all sources in the family) and household size, indicators for marital status, number of biological children the individual has (regardless of whether they live in individual's household), an indicator for whether the individual lives in an urban area, and the number of days in the last month the

[14] The Census Bureau has re-classified some of the jobs in 2002. We utilized this new classification.

individual has consumed more than 5 alcoholic beverages and used marijuana.[15] In addition, we use aggregate level control variables. These controls are the per capita personal income in individual's state, share of the population aged between fifteen and twenty four and share of the population that is black in the state. Moreover, we matched the individuals in our sample with the relevant arrest rates by their county and according to the crime they have committed and whether they are older or younger than 18 years of age. For example, somebody who is younger than 18 is matched with juvenile arrest rates and those with age greater than or equal to 18 are matched with adult arrest rate in the county with the specific crimes.

County-level arrest data are obtained Uniform Crime Reporting Program (County-Level Detailed Arrest and Offense Data sets for years between 1997 and 2004). These data provide the number of juvenile and adult arrests in each county for several crime categories including the Index I crimes and minor crimes such as drug sale, fraud, embezzlement, vandalism and so on. Using the population of each county, we calculated per capita (times 100,000) adult and juvenile arrests for motor vehicle theft, robbery, larceny, and burglary. For hard drugs, we used the arrests pertaining to the sale and manufacturing of cocaine and opium; and for any drug we used the arrests pertaining to the sale and manufacturing of nay narcotics. For *Other property crime*, we used the arrest rates for forgery, fraud, embezzlement and buying/receiving/possessing stolen property. For *Any Property Crime*, we used the sum of the property crime arrests and robbery arrests.

[15] Urban classification has been changed in 2003 by the NLSY (because the Census classification was changed in 2000). We employed the definition as reported in the NLSY.

Table 5 presents the descriptive statistics. The regressions include the individuals who have contributed at least two observations to the sample. The reported descriptive statistics pertain to our largest sample – regressions for the ANY CRIME outcome. [16]

X. Estimation Results using Micro Data

Table 6 presents the results obtained from estimation of the selection equation and the market wage equation. The two equations are estimated jointly using maximum likelihood. The results are consistent with those obtained from typical wage studies where having at least a high school degree and being male have a positive impact on wages, but being Black has a negative impact on wages in comparison to whites. State income and living in urban areas are positively correlated with wages. Nonlabor income has a negative impact on the propensity to work in the legal labor market; the same is true for state income and the unemployment rate. Higher education makes the person more likely to participate in the legal labor market. Blacks and Hispanic have lower propensities to participate.

Table 7A presents the crime regressions that employ the NLSY data. Potential market wages of non-workers are imputed using the selection-corrected wage equation

[16] The means of the county level arrest rates are smaller in comparison to the means of the state level arrest rates (reported in Table 1). This is because of three reasons. First, the sample includes individuals from small counties in which there are very few arrests for some crime types. This pulls the sample average down. Secondly, when calculating the arrest rates, we deflated the total number of arrests for each specific crime for both juveniles and adults with the total number of people in the jurisdiction covered by the agencies in the county. In other words, to calculate the juvenile (adult) arrest rate for, say, larceny, we divided the number of juvenile (adult) larceny arrests by the total population. Ideally, we would use the number of juveniles in the county to calculate the juvenile arrest rates and the number of adults to calculate the adult arrest rates. However, such information is not provided by the FBI. As a result, although our measures of the county arrest rates are good proxies for juvenile and adult arrests, they are lower than their true value. Thirdly and most importantly, our sample is mostly made up of young individuals. The average age is below eighteen. Consequently, the juvenile arrest rate has a greater weight in the means reported in Table 5. The juvenile arrests make up only a small portion of total arrests. For example, in 2004, only 16% of all arrests involved a juvenile in the US. Therefore, it is natural to have smaller means for the arrest rates in the individual level analysis.

displayed in Table 6 and wages are instrumented by state-year-sector specific skill-biased technology parameters. Because non-workers'sector of work does not exist, we assigned them the state-and-year specific skill-biased technology index.

Real wages have no significant impact on robbery or burglary,[17] but they impact all other crime categories. The results indicate that a 1-percent increase in real wages decreases the propensity to steal something from a store or a purse or wallet (column 2) by about 16 percentage points. The same increase in wages generates a decline in the propensity to steal a car by 4 percentage points. Similarly, wages have a negative impact on participating in other crimes (possession of stolen property, etc.), selling any drugs, as well as selling hard drugs. The implied elasticies are about -1.7 for most crime categories.

Arrests reduce criminal proclivity with statistically significant impacts in case of larceny, selling hard drugs, burglary and the indicator that identifies whether the person committed larceny, robbery or car theft. Heavy drinking, marijuana use and carrying a gun are positively related to criminal activity.

Table 7B displays the model which includes $Wage^{+}$ and $Wage^{-}$ as explanatory variables. Similar to the results obtained from state panels (see Table 2B), the coefficients of $Wage^{-}$ are generally larger in absolute value than those of $Wage^{+}$ indicating that the impact on the propensity to commit crime of a given decrease in wages is larger than the increase in wages of the same magnitude. The difference in the coefficients of $Wage^{+}$ and $Wage^{-}$ is significantly different from zero in the models that explains selling hard drugs (column 6), and where larceny+robbery+motor vehicle theft is the dependent variable (column 1). The difference is marginally significant (p=0.12) in case of other crime (column 5).

[17] Robbery is a violent crime, where the perpetrator takes or attempts to take something valuable from the victim by using a weapon or by the threat of violence. Burglary involves entering into a structure, such as a house, to commit theft.

The results obtained from estimating the models for men are presented in Tables 8A and 8B. Wages have a negative and statistically significant impact on all crimes with the exception of robbery and burglary. Table 8B shows that the impact of $Wage^{-}$ is larger than that of $Wage^{+}$ as before ,and that the difference in the impact is significantly different from zero in case of larceny (column 2) and larceny-robbery-motor vehicle theft (column 1).

XI. Conclusion

Although formal economic models of crime were developed more than four decades ago, empirical issues have created substantial obstacles regarding reliable inference about the magnitudes of the relationships between economic variables and criminal activity. Inconsistent estimates reported in the literature prompted some analysts to argue that there is little evidence to support the hypothesis that economic conditions impact crime and that there is a disconnect between theory and empirical evidence (Piehl 1998). In this paper we investigate the impact of unskilled (non-college educated) workers earnings in crime. Using the framework employed in the literature on wage inequality, and using the March CPS data, we create a state-and-year specific measure of skill-biased technological change and use it as an instrument for unskilled workers' earnings in state panels.

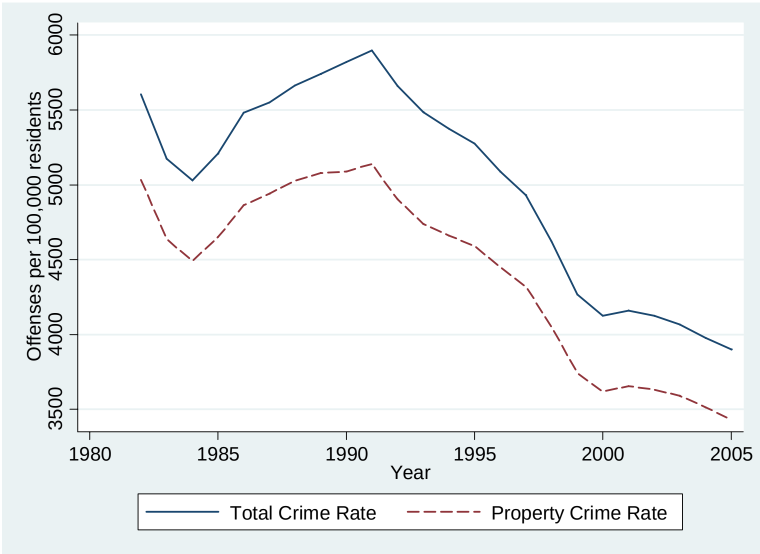
Estimation of crime regressions using state panels from 1980 to 2005 demonstrate that a decrease in unskilled workers real weekly earnings, induced by skilled-biased technological change, is negatively elated to state property crime with an elasticity of -1.0 Violent crime is not influenced by weekly earnings of unskilled workers. We also detect asymmetry in the impact of unskilled workers earnings on crime. A deterioration in earnings has a larger effect on crime in magnitude in comparison to an increase in earnings by the same absolute amount. We find that the earnings of non-college educated males are related to crime, but the earnings of unskilled females have no impact on criminal activity.

We also employ micro data from the geocoded confidential version of the NLSY97 to estimate models of criminal participation. The NLSY97 data contain detailed measures of individuals' criminal activity as well as personal and household attributes and wages. Goecodes allow us to identify the location of the individual and merge them with the relevant county arrest rates. The data set consists of young and mostly unskilled workers. For those who have not participated in the legal labor market, we impute wages by jointly estimating a labor force participation equation and a wage equation. We create state-year-industry specific measures of skill-biased technological change for three broad industry categories (manufacturing, service, other) and match workers with the relevant skill-biased technological change indicators, by their industry.[18] We instrument market wages with state-year-industry specific technology shocks and find wage elasticities in the range of -1.7 for property crimes such as larceny and car theft. The asymmetric impact of wages on crime is also detected in micro data.

The results indicate that individual crime decisions respond to labor market incentives as predicted by theory, and that an increase in wages of unskilled workers has a significant impact on criminal activity.

[18] Those who have not worked in the labor market in a given year, are matched the with state-wide technology shock in that year.

Figure 1
U.S. Crime




Louisiana
Figure 2A
Crime Rate
7000
6000
5000
4000
1980
1985
1990
1995
2000
2005
Year
Figure 2B
Real Weekly Unskilled Earnings
550
500
450
400
1980
1985
1990
1995
2000
2005
Year
Texas
Figure 3A
Crime Rate
8000
7000
6000
5000
1980
1985
1990
1995
2000
2005
Year
Figure 3B
Real Weekly Unskilled Earnings
540
520
500
480
460
440
1980
1985
1990
1995
2000
2005
Year
Maine
Figure 4A
Crime Rate
4500
4000
3500
3000
2500
1980
1985
1990
1995
2000
2005
Year
Figure 4B
Real Weekly Unskilled Earnings
400
380
360
340
1980
1985
1990
1995
2000
2005
Year

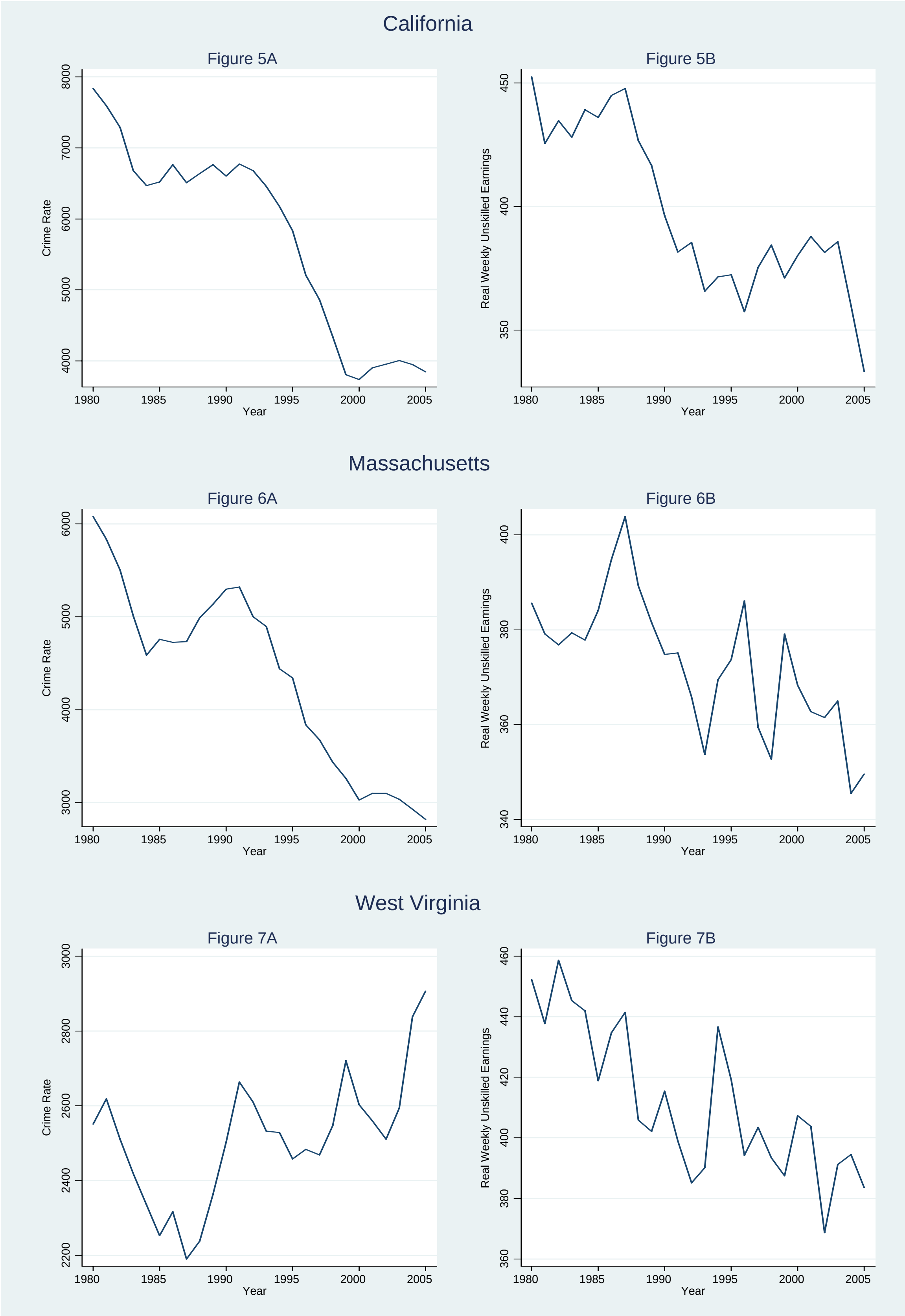

California
Figure 5A
Crime Rate
4000
5000
6000
7000
8000
1980
1985
1990
1995
2000
2005
Year
Figure 5B
Real Weekly Unskilled Earnings
350
400
450
1980
1985
1990
1995
2000
2005
Year
Massachusetts
Figure 6A
Crime Rate
3000
4000
5000
6000
1980
1985
1990
1995
2000
2005
Year
Figure 6B
Real Weekly Unskilled Earnings
340
360
380
400
1980
1985
1990
1995
2000
2005
Year
West Virginia
Figure 7A
Crime Rate
2200
2400
2600
2800
3000
1980
1985
1990
1995
2000
2005
Year
Figure 7B
Real Weekly Unskilled Earnings
360
380
400
420
440
460
1980
1985
1990
1995
2000
2005
Year

Table 1: Descriptive Statistics

(State Panels, 1980-2005)

Variable	Mean	Std. Dev.
Weekly Earnings-Unskilled		
Simple Average		
All Unskilled Workers	679.9	(63.9)
Male Unskilled Workers	778.6	(81.7)
Quality Adjusted		
All Unskilled Workers	410.1	(41.8)
Male Unskilled Workers	408.1	(44.8)
Crime Rates		
Property	4,149.5	(1,102.2)
Burglary	949.3	(359.5)
Larceny	2,796.3	(699.6)
Motor Vehicle Theft	404.0	(210.6)
Violent	470.3	(238.0)
Murder	6.0	(3.4)
Rape	36.0	(13.8)
Robbery	133.6	(96.4)
Assault	294.6	(154.5)
Arrest Rates		
Property	14.57	(227.28)
Burglary	2.27	(30.3)
Larceny	11.5	(188.6)
Motor Vehicle Theft	0.8	(8.4)
Violent	2.63	(20.9)
Murder	0.08	(0.8)
Rape	0.26	(4.2)
Robbery	0.56	(5.4)
Assault	1.7	(10.5)
Income Per Capita	22,085.1	(7,161.5)
Unemployment Rate	5.7	(1.9)
Percent 15-24 Year Olds	14.9	(1.5)
Percent Black	10.0	(9.4)
Percent Urban Population	71.2	(14.7)
Alcohol Consumption	2,324.4	(389.9)

Notes: The crime rates are per 100,000 state population covered by the police agencies that report to FBI. Arrest rate is calculated as the number of arrests per 1,000 population. Criminal Justice Expenditures is total justice expenditures (state and local) per 100,000 population. Alcohol consumption is volume of beer consumption (in 1,000 gallons) per 100,000 population.

Table 2A
Instrumental Variable State Panel Regressions
The Impact of Unskilled Weekly Earnings on Crime

	Property				**Violent**				
	Total	Burglary	Larceny	MV Theft	**Total**	Murder	Rape	Robbery	Assault
	I	II	III	IV	V	VI	VII	VIII	IX
Weekly Earnings-Unskilled	-9.933**	-3.018**	-8.090***	1.171	-0.284	-0.002	-0.056	-0.100	-0.136
	(3.983)	(1.429)	(2.660)	(1.084)	(0.504)	(0.009)	(0.060)	(0.264)	(0.330)
Income Per Capita	-0.047	-0.010	-0.003	-0.034***	-0.009	0.000	0.000	-0.006**	-0.002
	(0.034)	(0.010)	(0.021)	(0.011)	(0.006)	(0.000)	(0.000)	(0.003)	(0.004)
Arrest Rate (-1)	-0.089***	-0.188***	-0.072***	-0.031	-0.029	-0.002	0.015	0.016	-0.024
	(0.018)	(0.055)	(0.014)	(0.155)	(0.034)	(0.016)	(0.014)	(0.102)	(0.062)
Percent 15-24 Year Olds	-41.409	-10.188	-53.929**	22.739**	0.450	0.256***	1.170**	-1.071	0.145
	(44.037)	(15.605)	(26.738)	(11.414)	(6.647)	(0.065)	(0.575)	(2.761)	(6.188)
Percent Black	97.790	18.051	58.560	21.205	12.731	0.469**	-1.369	2.298	11.471
	(82.820)	(30.568)	(48.324)	(19.881)	(16.820)	(0.203)	(1.318)	(7.891)	(10.091)
Alcohol Consumption	1.634***	0.476***	1.060***	0.099	0.190***	0.002***	0.013***	0.082***	0.093***
	(0.312)	(0.102)	(0.197)	(0.080)	(0.047)	(0.001)	(0.004)	(0.024)	(0.033)
Observations	1111	1111	1111	1111	1111	1111	1111	1109	1111

Robust Standard errors, clustered at the state level are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. The dependent variable for each regression is the crime rate per 100,000 state population covered by the police agencies that report to FBI. Arrest rate is calculated as the number of arrests per 1,000 population. Alcohol consumption is volume of beer consumption (in 1,000 gallons) per 100,000 population. The regression also includes percent urban population.

Table 2B

Instrumental Variable State Panel Regressions
The Impact of Unskilled Weekly Earnings (Increase and Decrease) on Crime

	Property				**Violent**				
	Total	Burglary	Larceny	MV Theft	**Total**	Murder	Rape	Robbery	Assault
	I	II	III	IV	V	VI	VII	VIII	IX
Weekly Earnings-Unskilled(+)	-16.822**	-5.162*	-14.758***	3.092	0.222	-0.011	-0.065	0.335	-0.036
	(7.863)	(2.832)	(5.710)	(2.296)	(0.992)	(0.020)	(0.128)	(0.492)	(0.680)
Weekly Earnings-Unskilled(-)	-17.627**	-5.413*	-15.537**	3.317	0.282	-0.013	-0.066	0.386	-0.024
	(8.289)	(2.985)	(6.037)	(2.442)	(1.062)	(0.022)	(0.136)	(0.527)	(0.726)
Income Per Capita	-0.022	-0.002	0.021	-0.041***	-0.010	0.000	0.000	-0.008**	-0.003
	(0.045)	(0.014)	(0.031)	(0.013)	(0.008)	(0.000)	(0.001)	(0.004)	(0.004)
Arrest Rate (-1)	-0.086***	-0.181***	-0.068***	-0.055	-0.031	-0.001	0.015	0.005	-0.024
	(0.020)	(0.058)	(0.016)	(0.149)	(0.033)	(0.016)	(0.012)	(0.096)	(0.061)
Percent 15-24 Year Olds	-58.860	-15.620	-70.821*	27.609**	1.734	0.231***	1.147*	0.030	0.399
	(53.950)	(18.937)	(36.590)	(13.473)	(7.181)	(0.086)	(0.652)	(3.094)	(6.630)
Percent Black	116.533	23.884	76.703	15.977	11.352	0.495**	-1.344	1.113	11.198
	(95.336)	(34.645)	(63.567)	(23.115)	(15.635)	(0.226)	(1.459)	(7.203)	(9.799)
Alcohol Consumption	1.789***	0.524***	1.209***	0.056	0.178***	0.002**	0.014***	0.072***	0.091**
	(0.399)	(0.131)	(0.274)	(0.094)	(0.049)	(0.001)	(0.005)	(0.024)	(0.037)
Observations	1111	1111	1111	1111	1111	1111	1111	1109	1111

Robust Standard errors, clustered at the state level are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. The dependent variable for each regression is the crime rate per 100,000 state population covered by the police agencies that report to FBI. Arrest rate is calculated as the number of arrests per 1,000 population. Alcohol consumption is volume of beer consumption (in 1,000 gallons) per 100,000 population. The regression also includes percent urban population.

Table 3A
Instrumental Variable State Panel Regressions
The Impact of Male Unskilled Weekly Earnings on Crime

	Property				Violent				
	Total I	Burglary II	Larceny III	MV Theft IV	**Total** V	Murder VI	Rape VII	Robbery VIII	Assault IX
Weekly Earnings-Unskilled	-8.452**	-2.568**	-6.883***	0.996	-0.242	-0.001	-0.047	-0.085	-0.116
	(3.347)	(1.223)	(2.234)	(0.934)	(0.423)	(0.008)	(0.050)	(0.223)	(0.278)
Income Per Capita	-0.047	-0.010	-0.003	-0.034***	-0.009	0.000	0.000	-0.006**	-0.002
	(0.033)	(0.010)	(0.021)	(0.011)	(0.006)	(0.000)	(0.000)	(0.003)	(0.004)
Arrest Rate (-1)	-0.098***	-0.208***	-0.080***	-0.003	-0.031	-0.003	0.012	0.013	-0.026
	(0.021)	(0.062)	(0.016)	(0.181)	(0.037)	(0.017)	(0.016)	(0.104)	(0.064)
Percent 15-24 Year Olds	-37.277	-8.932	-50.564*	22.252**	0.568	0.257***	1.193**	-1.030	0.201
	(43.575)	(15.457)	(26.270)	(11.192)	(6.586)	(0.064)	(0.557)	(2.762)	(6.112)
Percent Black	89.333	15.481	51.672	22.203	12.489	0.467**	-1.416	2.208	11.355
	(79.946)	(29.376)	(47.219)	(19.984)	(16.745)	(0.201)	(1.283)	(7.852)	(10.063)
Alcohol Consumption	1.619***	0.471***	1.047***	0.101	0.189***	0.002***	0.013***	0.082***	0.093***
	(0.303)	(0.100)	(0.193)	(0.080)	(0.046)	(0.001)	(0.004)	(0.024)	(0.032)
Observations	1111	1111	1111	1111	1111	1111	1111	1109	1111

Robust Standard errors, clustered at the state level are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. The dependent variable for each regression is the crime rate per 100,000 state population covered by the police agencies that report to FBI. Arrest rate is calculated as the number of arrests per 1,000 population. Alcohol consumption is volume of beer consumption (in 1,000 gallons) per 100,000 population. The regression also includes percent urban population.

Table 3B
Instrumental Variable State Panel Regressions
The Impact of Unskilled Male Weekly Earnings (Increase and Decrease) on Crime

	Property				Violent				
	Total I	Burglary II	Larceny III	MV Theft IV	**Total** V	Murder VI	Rape VII	Robbery VIII	Assault IX
Weekly Earnings-Unskilled(+)	-12.653**	-3.882*	-11.094***	2.319	0.163	-0.009	-0.049	0.250	-0.028
	(5.750)	(2.092)	(4.106)	(1.679)	(0.770)	(0.015)	(0.095)	(0.386)	(0.512)
Weekly Earnings-Unskilled(-)	-13.366**	-4.106*	-11.809***	2.543	0.232	-0.010	-0.049	0.307	-0.013
	(6.151)	(2.238)	(4.408)	(1.814)	(0.842)	(0.016)	(0.103)	(0.424)	(0.558)
Income Per Capita	-0.033	-0.006	0.011	-0.038***	-0.010	0.000	0.000	-0.007**	-0.003
	(0.038)	(0.011)	(0.026)	(0.012)	(0.007)	(0.000)	(0.000)	(0.004)	(0.004)
Arrest Rate (-1)	-0.100***	-0.213***	-0.083***	0.014	-0.029	-0.004	0.012	0.019	-0.025
	(0.023)	(0.069)	(0.019)	(0.186)	(0.039)	(0.019)	(0.017)	(0.106)	(0.066)
Percent 15-24 Year Olds	-55.258	-14.558	-68.586**	27.913**	2.301	0.226***	1.186*	0.406	0.577
	(51.972)	(18.108)	(34.125)	(12.552)	(7.226)	(0.087)	(0.634)	(3.174)	(6.597)
Percent Black	102.580	19.626	64.950	18.033	11.213	0.490**	-1.411	1.167	11.078
	(86.446)	(30.881)	(57.073)	(22.171)	(16.667)	(0.217)	(1.387)	(7.943)	(9.989)
Alcohol Consumption	1.738***	0.508***	1.166***	0.063	0.178***	0.002***	0.013***	0.073***	0.090**
	(0.355)	(0.119)	(0.238)	(0.092)	(0.048)	(0.001)	(0.005)	(0.024)	(0.036)
Observations	1111	1111	1111	1111	1111	1111	1111	1109	1111

Robust Standard errors, clustered at the state level are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. The dependent variable for each regression is the crime rate per 100,000 state population covered by the police agencies that report to FBI. Arrest rate is calculated as the number of arrests per 1,000 population. Alcohol consumption is volume of beer consumption (in 1,000 gallons) per 100,000 population. The regression also includes percent urban population.

Table 4A
Instrumental Variable State Panel Regressions
The Impact of Unskilled Weekly Earnings on Crime; Model with the Unemployment Rate

	Property				**Violent**				
	Total I	Burglary II	Larceny III	MV Theft IV	**Total** V	Murder VI	Rape VII	Robbery VIII	Assault IX
Weekly Earnings-Unskilled	-9.849**	-2.991**	-8.039***	1.176	-0.279	-0.002	-0.055	-0.094	-0.137
	(3.885)	(1.408)	(2.604)	(1.077)	(0.499)	(0.009)	(0.059)	(0.256)	(0.329)
Income Per Capita	-0.043	-0.009	-0.000	-0.033***	-0.008	0.000	0.000	-0.006**	-0.003
	(0.034)	(0.010)	(0.021)	(0.011)	(0.006)	(0.000)	(0.000)	(0.003)	(0.004)
Arrest Rate (-1)	-0.088***	-0.186***	-0.071***	-0.029	-0.028	-0.002	0.015	0.018	-0.024
	(0.018)	(0.053)	(0.013)	(0.153)	(0.034)	(0.016)	(0.013)	(0.100)	(0.061)
Unemployment	74.090***	24.408***	44.765**	4.926	4.482	-0.003	0.187	5.243***	-0.910
	(27.973)	(9.098)	(17.465)	(6.053)	(3.956)	(0.074)	(0.369)	(1.799)	(2.798)
Percent 15-24 Year Olds	-25.051	-4.800	-44.046*	23.827**	1.440	0.255***	1.211**	0.085	-0.056
	(41.814)	(14.792)	(25.305)	(10.975)	(6.671)	(0.069)	(0.576)	(2.650)	(6.032)
Percent Black	94.751	17.050	56.723	21.003	12.547	0.469**	-1.376	2.084	11.508
	(78.522)	(29.520)	(46.326)	(19.486)	(16.468)	(0.203)	(1.315)	(7.480)	(10.135)
Alcohol Consumption	1.767***	0.520***	1.140***	0.108	0.198***	0.002***	0.014***	0.092***	0.091***
	(0.324)	(0.105)	(0.206)	(0.086)	(0.050)	(0.001)	(0.004)	(0.026)	(0.035)
Observations	1111	1111	1111	1111	1111	1111	1111	1109	1111

Robust Standard errors, clustered at the state level are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. The dependent variable for each regression is the crime rate per 100,000 state population covered by the police agencies that report to FBI. Arrest rate is calculated as the number of arrests per 1,000 population. Alcohol consumption is volume of beer consumption (in 1,000 gallons) per 100,000 population. The regression also includes percent urban population.

Table 4B
Instrumental Variable State Panel Regressions
The Impact of Unskilled Weekly Earnings (Increase and Decrease) on Crime
Model with the Unemployment Rate

	Property				Violent				
	Total	Burglary	Larceny	MV Theft	**Total**	Murder	Rape	Robbery	Assault
	I	II	III	IV	V	VI	VII	VIII	IX
Weekly Earnings-Unskilled(+)	-16.349**	-5.009*	-14.422***	3.076	0.233	-0.011	-0.064	0.351	-0.042
	(7.407)	(2.706)	(5.388)	(2.255)	(0.971)	(0.020)	(0.125)	(0.478)	(0.669)
Weekly Earnings-Unskilled(-)	-17.113**	-5.246*	-15.172***	3.299	0.293	-0.012	-0.065	0.403	-0.031
	(7.804)	(2.850)	(5.695)	(2.397)	(1.039)	(0.021)	(0.133)	(0.513)	(0.714)
Income Per Capita	-0.017	-0.001	0.024	-0.041***	-0.010	0.000	0.000	-0.008**	-0.003
	(0.042)	(0.013)	(0.030)	(0.013)	(0.008)	(0.000)	(0.001)	(0.004)	(0.005)
Arrest Rate (-1)	-0.084***	-0.178***	-0.067***	-0.056	-0.031	-0.001	0.015	0.005	-0.025
	(0.019)	(0.055)	(0.015)	(0.146)	(0.033)	(0.016)	(0.012)	(0.095)	(0.061)
Unemployment	103.029***	33.394***	73.185***	-3.532	2.203	0.040	0.224	3.262	-1.334
	(37.337)	(12.450)	(25.024)	(10.076)	(5.333)	(0.092)	(0.568)	(2.335)	(3.642)
Percent 15-24 Year Olds	-35.210	-7.955	-54.021*	26.798**	2.240	0.240***	1.198*	0.778	0.093
	(48.385)	(16.856)	(32.387)	(12.170)	(6.892)	(0.082)	(0.611)	(2.866)	(6.256)
Percent Black	111.336	22.199	73.011	16.155	11.241	0.493**	-1.355	0.949	11.265
	(88.100)	(32.794)	(58.791)	(22.982)	(15.474)	(0.224)	(1.444)	(6.974)	(9.868)
Alcohol Consumption	1.966***	0.581***	1.335***	0.050	0.182***	0.002**	0.014**	0.078***	0.088**
	(0.415)	(0.136)	(0.283)	(0.106)	(0.054)	(0.001)	(0.006)	(0.026)	(0.041)
Observations	1111	1111	1111	1111	1111	1111	1111	1109	1111

Robust Standard errors, clustered at the state level are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. The dependent variable for each regression is the crime rate per 100,000 state population covered by the police agencies that report to FBI. Arrest rate is calculated as the number of arrests per 1,000 population. Alcohol consumption is volume of beer consumption (in 1,000 gallons) per 100,000 population. The regression also includes percent urban population.

Table 5: Descriptive Statistics: NLSY97 Data

	Definition	Mean	(STD)
Crime Variables			
Larceny/CarTheft/Robbery	=1 if stole something (property crimes and robberies), =0 otherwise	0.099	(0.299)
Larceny	=1 if stole something from a store or stole a purse/wallet, =0 otherwise	0.088	(0.283)
Car Theft	=1 if stole something from a store, =0 otherwise	0.007	(0.086)
Other Crime	=1 if possessed stolen goods, committed fraud, embezzlement ,etc. =0 otherwise	0.030	(0.171)
Selling Drug	=1 if sold any kind of drugs, =0 otherwise	0.058	(0.235)
Selling Hard Drug	=1 if sold hard drugs like cocaine, =0 otherwise	0.021	(0.144)
Burglary	=1 if went into a house or building to steal something, =0 otherwise	0.012	(0.110)
Robbery	=1 if used or threatened to use a weapon to get something from someone else, =0 otherwise	0.004	(0.062)
Personal Variables			
Wage	Real weekly wage in cents	949.753	(346.412)
High School+	=1 if the respondent completed at least high school, =0 otherwise	0.390	(0.488)
Household Income	Annual household income in 1,000 dollars	26.416	(45.079)
Non-labor Income	Non-labor income in dollars in 100 dollars	5.093	(168.970)
Household Size	The number of individuals in the respondent's household	4.145	(1.674)
Age	Age of the respondent	17.710	(2.583)
Gun	=1 if the respondent has carried a gun since the last interview, =0 otherwise	0.050	(0.218)
Heavy Drinking	The number of days in the last month that the respondent has consumed 5+ alcoholic beverages	1.079	(3.075)
Marijuana Use	The number of days in the last month that the respondent has used Marijuana	1.703	(5.884)
Urban	=1 if the respondent lives in an urban area, =0 otherwise	0.739	(0.439)
Married	=1 if married, =0 otherwise	0.037	(0.189)
Separated	=1 if separated, =0 otherwise	0.002	(0.045)
Children	The number of children of the respondent	0.133	(0.435)
County Variables			
Arrest:Larceny/CarTheft/Robbery	The number of arrests of relevant age group (juveniles or adults) for stealing (property crimes and robberies) per 1,000 people in respondent's county	3.024	(2.042)
Arrest: Larceny	The number of arrests of relevant age group (juveniles or adults) for larceny per 1,000 people in the respondent's county	2.214	(1.618)
Arrest: Car Theft	The number of arrests of relevant age group (juveniles or adults) for stealing a	0.270	(0.280)

	car per 1,000 people in the respondent's county		

(Table 1 concluded)

Arrest: Stolen Property etc.	The number of arrests of relevant age group (juveniles or adults) for committing other property crimes per 1,000 people in the respondent's county	7.901	(16.828)
Arrest: Selling Drugs	The number of arrests of relevant age group (juveniles or adults) for selling drugs per 1,000 people in the respondent's county	0.543	(1.007)
Arrest: Selling Hard Drug	The number of arrests of relevant age group (juveniles or adults) for selling hard drugs like cocaine per 1,000 people in the respondent's county	0.284	(0.805)
Arrest: Burglary	The number of arrests of relevant age group (juveniles or adults) burglary per 100,000 people in the respondent's county	0.539	(0.428)
Arrest: Robbery	The number of arrests of relevant age group (juveniles or adults) for robbery per 100,000 people in the respondent's country	0.223	(0.241)
State Variables			
State Per Capita Income	State Per Capita Income in 1,000 dollars	29.088	(4.415)
Share of Population aged 15-24	Share of the Population for aged 15 to 24	14.041	(0.911)
Share of Black population	Share of Black population	13.403	(8.512)

Table 6
NLSY Data; Selection into Labor Force and Market Wages

	Selection Equation	Wage Equation
Non Labor Income	-0.0001**	
	(0.00005)	
Household Size	-0.001	-0.007***
	(0.005)	(0.002)
High/College	0.089***	0.071***
	(0.022)	(0.007)
Male	0.014	0.047***
	(0.016)	(0.006)
Black	-0.272***	-0.022***
	(0.022)	(0.008)
Hispanic	-0.131***	-0.009
	(0.024)	(0.008)
Age	0.181***	0.023***
	(0.008)	(0.003)
Urban	-0.017	0.029***
	(0.020)	(0.007)
Married	-0.235***	0.072***
	(0.044)	(0.014)
Separated	-0.076	-0.073
	(0.155)	(0.075)
Divorced	-0.345**	0.025
	(0.146)	(0.041)
Children	-0.160***	0.013*
	(0.022)	(0.007)
State Per Capita Income	-0.026	0.016**
	(0.017)	(0.007)
Unemployment	-0.040**	0.009
	(0.019)	(0.007)
Share of Population aged 15-24	-0.081**	0.034**
	(0.035)	(0.013)
Share of Black population	-0.059*	0.030*
	(0.035)	(0.015)
Observations	55,037	
rho	-0.811	

Robust standard errors, clustered at the individual level, are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. State alcohol consumption, state and year dummies are included in all regressions.

Table 7A: NLSY Data. Instrumental Variables Regressions.

	Larceny/ Car Theft/ Robbery (1)	Larceny (2)	Car Theft (3)	Stolen Property etc. (4)	Selling Drugs (5)	Selling Hard Drug (6)	Burglary (7)	Robbery (8)
Log Wage	-0.179***	-0.160***	-0.041***	-0.086***	-0.101**	-0.058**	-0.019	0.011
	(0.048)	(0.047)	(0.016)	(0.031)	(0.040)	(0.023)	(0.021)	(0.013)
Arrest	-0.002**	-0.003**	-0.008**	-0.000	-0.000	0.002	-0.007***	-0.003
	(0.001)	(0.001)	(0.003)	(0.000)	(0.002)	(0.001)	(0.002)	(0.003)
High School +	-0.002	-0.005	0.005*	0.001	-0.008	-0.003	0.002	-0.001
	(0.007)	(0.007)	(0.002)	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)
Household Income	0.000	-0.000	0.000	0.000	-0.000	0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household Size	-0.000	0.002	-0.001	0.001	-0.000	-0.000	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Age	-0.016***	-0.013***	-0.001	-0.003	-0.002	-0.001	-0.003**	-0.001*
	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Gun	0.098***	0.086***	0.042***	0.087***	0.094***	0.063***	0.053***	0.036***
	(0.009)	(0.010)	(0.005)	(0.007)	(0.009)	(0.007)	(0.006)	(0.005)
Heavy Drinking	0.003***	0.002***	0.001***	0.002***	0.005***	0.003***	0.002***	0.001**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Marijuana Use	0.003***	0.003***	0.000	0.002***	0.011***	0.003***	0.001**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
State Per	-0.004	-0.003	-0.001	-0.001	0.000	-0.001	-0.002*	0.000
Capita Income	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
Observations	54,411	47,479	47,479	54,398	54,386	54,382	47,479	54,658

Robust standard errors, clustered at the individual level, are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. Urban, marital status, number of children, share of population aged 15-24, share of black population, state and year dummies are included in all regressions.

Table 7B: NLSY Data. Instrumental Variables Regressions, Wage Increase & Wage Decrease

	Larceny/ Car Theft/ Robbery (1)	Larceny (2)	Car Theft (3)	Stolen Property etc. (4)	Selling Drugs (5)	Selling Hard Drug (6)	Burglary (7)	Robbery (8)
Log Wage (+)	-0.284***	-0.155	-0.052	-0.114*	-0.056	-0.146***	-0.003	0.022
	(0.108)	(0.095)	(0.033)	(0.068)	(0.083)	(0.052)	(0.039)	(0.028)
Log Wage (--)	-0.301***	-0.165	-0.053	-0.122*	-0.058	-0.156***	-0.003	0.022
	(0.116)	(0.101)	(0.035)	(0.072)	(0.088)	(0.056)	(0.041)	(0.029)
Arrest	-0.004*	-0.004	-0.004	-0.000	-0.001	-0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.004)	(0.000)	(0.002)	(0.001)	(0.001)	(0.005)
High School +	-0.009	-0.012**	0.003	-0.003	-0.010**	-0.005	0.001	-0.001
	(0.006)	(0.006)	(0.002)	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)
Household Income	0.000	0.000	0.000*	0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household Size	-0.002	-0.000	-0.001	0.000	0.001	-0.001	0.000	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.020***	-0.019***	-0.001	-0.005**	-0.005	0.000	-0.005***	-0.001
	(0.005)	(0.004)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Gun	0.095***	0.077***	0.031***	0.081***	0.097***	0.060***	0.043***	0.035***
	(0.011)	(0.011)	(0.005)	(0.009)	(0.010)	(0.008)	(0.007)	(0.005)
Heavy Drinking	0.003***	0.002***	0.001**	0.002***	0.004***	0.003***	0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Marijuana Use	0.003***	0.003***	0.000	0.001***	0.010***	0.002***	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
State Per	-0.008**	-0.007*	-0.001	-0.001	0.002	0.002	-0.001	-0.000
Capita Income	(0.004)	(0.004)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
Observations	43,043	36,565	36,566	43,041	43,028	43,025	36,566	43,234

Standard errors, clustered at the individual level, are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. Urban, marital status, number of children, share of population aged 15-24, share of black population, state and year dummies are included in all regressions.

Table 8A: NLSY Data. Instrumental Variables Regressions – Men.

	Larceny/ Car Theft/ Robbery (1)	Larceny (2)	Car Theft (3)	Stolen Property etc. (4)	Selling Drugs (5)	Selling Hard Drug (6)	Burglary (7)	Robbery (8)
Log Wage	-0.197***	-0.162**	-0.048**	-0.092*	-0.141**	-0.088**	-0.014	0.013
	(0.070)	(0.065)	(0.023)	(0.049)	(0.061)	(0.036)	(0.033)	(0.020)
Arrest	-0.002	-0.003	-0.014**	-0.000	-0.002	0.004	-0.012***	-0.003
	(0.002)	(0.002)	(0.006)	(0.000)	(0.003)	(0.002)	(0.004)	(0.006)
High School +	0.002	-0.003	0.005	-0.009	-0.009	-0.002	0.004	-0.002
	(0.010)	(0.010)	(0.004)	(0.007)	(0.009)	(0.006)	(0.005)	(0.003)
Household Income	0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household Size	0.001	0.004*	-0.001	0.003**	0.001	-0.002*	0.002	0.001
	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Age	-0.026***	-0.022***	-0.001	-0.007**	-0.001	-0.002	-0.005**	-0.001
	(0.005)	(0.005)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Gun	0.091***	0.078***	0.038***	0.080***	0.087***	0.059***	0.048***	0.037***
	(0.010)	(0.010)	(0.006)	(0.008)	(0.009)	(0.007)	(0.007)	(0.005)
Heavy Drinking	0.003***	0.002**	0.001***	0.002***	0.004***	0.003***	0.002***	0.001***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Marijuana Use	0.003***	0.002***	0.000	0.002***	0.011***	0.002***	0.000	0.000*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
State Per	-0.001	0.003	-0.000	-0.000	0.001	-0.001	-0.003	0.001
Capita Income	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Observations	27,428	23,987	23,987	27,415	27,410	27,407	23,987	27,567

Standard errors, clustered at the individual level, are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. Urban, marital status, number of children, share of population aged 15-24, share of black population, state and year dummies are included in all regressions.

Table 8B: NLSY Data. Instrumental Variables Regressions—Men. Wage Increase & Wage Decrease

	Larceny/ Car Theft/ Robbery	Larceny	Car Theft	Stolen Property etc.	Selling Drugs	Selling Hard Drug	Burglary	Robbery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Wage (+)	-0.335**	-0.246*	-0.066	-0.095	-0.042	-0.172**	-0.003	0.016
	(0.147)	(0.127)	(0.047)	(0.098)	(0.115)	(0.073)	(0.055)	(0.038)
Log Wage (--)	-0.355**	-0.266*	-0.067	-0.101	-0.041	-0.181**	-0.002	0.017
	(0.157)	(0.136)	(0.050)	(0.105)	(0.123)	(0.078)	(0.058)	(0.040)
Arrest	-0.003	-0.004	-0.008	-0.000	-0.002	0.001	-0.003	-0.003
	(0.003)	(0.003)	(0.008)	(0.000)	(0.005)	(0.003)	(0.002)	(0.008)
High School +	-0.004	-0.011	0.005	-0.008	-0.015*	-0.006	0.003	-0.002
	(0.010)	(0.009)	(0.004)	(0.007)	(0.008)	(0.006)	(0.005)	(0.003)
Household Income	0.000	-0.000	0.000	-0.000	-0.000*	0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household Size	-0.003	0.000	-0.001	0.003	0.004*	-0.002	0.001	0.001
	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Age	-0.031***	-0.023***	-0.003	-0.011***	-0.007	0.000	-0.007***	-0.001
	(0.007)	(0.006)	(0.002)	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)
Gun	0.092***	0.072***	0.028***	0.074***	0.089***	0.057***	0.039***	0.036***
	(0.012)	(0.012)	(0.006)	(0.009)	(0.011)	(0.008)	(0.007)	(0.006)
Heavy Drinking	0.003***	0.002**	0.001**	0.002***	0.004***	0.003***	0.002***	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Marijuana Use	0.003***	0.003***	0.000	0.002***	0.010***	0.002***	0.000	0.000*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
State Per	-0.008	-0.004	0.000	0.001	0.005	0.005*	-0.002	0.000
Capita Income	(0.006)	(0.006)	(0.002)	(0.004)	(0.005)	(0.003)	(0.003)	(0.001)
Observations	21,462	18,280	18,280	21,454	21,447	21,444	18,280	21,565

Standard errors, clustered at the individual level, are in parentheses. * signifies statistical significance at the 10% level; ** at 5% level, and *** at the 1% level or less. Urban, marital status, number of children, share of population aged 15-24, share of black population, state and year dummies are included in all regressions.

APPENDIX

A.1. Construction of Quality-adjusted Wages at the State Level

We use the March Current Population Survey (CPS) files from 1978 to 2010 (covering earnings from 1977 to 2009) for full-time workers ages 16 to 64. In constructing the key variables, we closely follow the previous literature on wage inequality (Katz and Murphy, 1992; Krusell et al., 2000; Card and DiNardo, 2002; and in particular, Autor et al., 2008). Full-time workers are those who work 35 hours or more in a week, and they are identified using the Census Bureau's full-time worker flag. Using the individual earnings allocation flags, we dropped those people with allocated earnings. Similarly, self-employed people are dropped.

Each individual's average weekly earnings are created by dividing his/her annual income (from wages and salaries) by the number of weeks he/she worked during the previous year. Earnings are deflated using the state-specific level price deflators from Berry et al. (2000).[19] We make two adjustments for topcoded earnings. First, following Autor et al. (2008) income of workers with top-coded earnings are imputed by multiplying the annual topcode amount by 1.5. Second, starting in 1996, top-coded earnings values are assigned the mean of all top-coded earners. In these cases, we simply reassign the topcoded values to all such observations and again multiply by 1.5. Workers whose weekly earnings are below $70 in 2005 dollars are dropped, as are non-full-year workers (i.e., those who work fewer than 40

[19] Berry et al. have recently extended their original data set to 2007; and we used the updated series. The last two years (2008 and 2009) are imputed from the gross state product deflators. As an alternative deflator, we also used the US PCE index (2005=1) from the BLS as in Autor et al. (2008). However, results remain qualitatively similar to those reported in the paper.

weeks) whose weekly earnings exceed 1/40th the top-coded value of weekly earnings (Gould et al, 2001; Autor et al., 2008).

We construct labor input and wages for high-skill and low-skill as follows. The data in each year in each state are divided into 24 distinct groups characterized by 2 genders, 4 educational categories ($E \le 11, E = 12, 13 \le E \le 15, E \ge 16$),[20] and three potential experience categories (0--9, 10--19, 20+ years).[21] Following Autor et al. (2008), potential experience is calculated as Min{age-years of schooling-6, age-16}. In calculating each group's average weekly earnings, earnings are weighted by the product of the corresponding CPS sampling weight and weeks worked.

We assume that high-skill labor consists of workers who have at least some college education, and low-skill labor consists of those who have no college education (those with a high school degree or less). Groups within high-skill and low-skill categories are assumed to be perfect substitutes and we use group relative weekly earnings of full-time workers as weights for the aggregation of labor inputs into skilled and unskilled classes. As is standard in this literature, the assumption here is that relative wages reflect relative labor qualities. More specifically, following Autor et al. (2008), we designate the group that contains male workers with fewer than 12 years of education and with less than 10 years of potential experience as the base group. A relative wage measure is then constructed by dividing each group's average weekly earnings by the average weekly earnings of this base group. The relative quality index measure for each group, q_g, is computed as the arithmetic mean of the

---

[20] Commencing in 1992, the Bureau of the Census changed the emphasis of its educational attainment question from years of education to degree receipt. To obtain a comparable educational-attainment data across years, the classification proposed by Jaeger (1997) is followed.

[21] This taxonomy is the same as in Autor et al. (2008) and many others. However, due to limitations in the availability of state-level data, we consider a higher level of divisions. Since there are 50 states, the above taxonomy divides the annual data into 1200 groups.

relative wage measures in that group over 1977 to 2009. Then the total quality-adjusted labor input in each class is given by

$$H_t = \sum_{g \in G_H} q_g N_{gt}, \qquad L_t = \sum_{g \in G_L} q_g N_{gt},$$

where N_{gt} represents the total labor weeks in group *g* in year *t*.

Following Krusell et al. (2000), we calculate quality-adjusted earnings for skilled and unskilled labor

$$W_{Ht} = \sum_{g \in G_H} \frac{W_{gt} N_{gt}}{H_t}, \qquad W_{Lt} = \sum_{g \in G_L} \frac{W_{gt} N_{gt}}{L_t},$$

where W_{gt} represents the average weekly earnings of group *g* in year *t*.

As an alternative measure of earnings, we adjust for the composition of labor input so that the average weekly earnings of high-skill and low-skill workers are not mechanically affected by shifts in the experience, gender composition, or average level of completed schooling (Autor et al. 2008). To this end, we first normalize the labor input in each group by the total labor input in its class (i.e., $n_{gt} = N_{gt} \Big/ \sum_{g \in G_j} N_{gt}$,*j*=*H, L*). The composition index for each group, n_g, is computed as the arithmetic mean of n_{gt} over 1977 to 2009. Then the composition-adjusted weekly wages are

$$W_{Ht} = \sum_{g \in G_H} n_g W_{gt}, \qquad W_{Lt} = \sum_{g \in G_L} n_g W_{gt}.$$

Calculation of adjusted earnings and labor as described above allows us to construct the measures of relative efficiency as portrayed in Equation (5).

A.2. Industry-State Level Construction

Construction of the key variables at the industry level follows the same steps. In each state, industries are classifies into three categories: service, manufacturing, and other (agriculture + mining + construction). Annual data *in each* industry *in each* state are divided into 8 distinct groups characterized by 2 gender and 4 education categories as in the state-level analysis.[22] In calculating each group's average weekly earnings, earnings are weighted by the product of the corresponding CPS sampling weight and weeks worked. High-skill and low-skill labor classes are the same as above; and while aggregating labor inputs into skilled and unskilled classes, we choose the group that contains male workers with less than 12 years of education as the base group.

[22] Unlike the state-level analysis, this partition does not include experience due to the limited number of observations.

References

Acemoglu, Daron, “Directed Technical Change,” *Review of Economic Studies*, October 2002, *69*, 781-809.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney, “Trends in U.S. Wage Inequality: Revising the Revisionists,” *Review of Economics and Statistics*, May 2008, *90*, 300-323.

Autor, David H., Lawrence F., Katz, Alan B., Krueger, “Computing Inequality: Have Computers Changed the Labor Market?” *The Quarterly Journal of Economics*, Vol. 113, No. 4 (Nov., 1998), pp. 1169-1213

Berry, William D., Richard C. Fording, and Russell L. Hanson, “An Annual Cost of Living Index for the American States, 1960-95,” *Journal of Politics*, 2000, *62*, 550-67

Bound, John and George, Johnson, “Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations,” *The American Economic Review*, Vol. 82, No. 3 (Jun., 1992), pp. 371-392

Card, David and John E., DiNardo, “Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles,” *Journal of Labor Economics,* 2002, vol. 20, No. 4; pp. 733-83.

Card, David, and Thomas Lemieux, “Can Falling Supply Explain the Rising Return to College for Younger Men?” *Quarterly Journal of Economics* 116 (May 2001), pp. 705-46

Caselli, Francesco and Willbur John Coleman II, “The World Technology Frontier,” *American Economic Review*, 2006, *96*, pp. 499-522.

Ciccone, Antonio and Giovanni Peri, “Long-run Substitutability between More and Less Educa- ted Workers: Evidence from U.S. States 1950-90,” *Review of Economics and Statistics,* 2005, *87*, pp. 652-63

Corman, Hope, and H. Naci Mocan, “A Time-Series Analysis of Crime, Deterrence, and Drug Abuse in New York City,” *American Economic Review* 90 (2000): 584-604.

Doms, Mark, Timothy Dunne, and Kenneth R. Troske, “Workers, Wages and Technology,” *Quarterly Journal of Economics 122* (February 1997), 253-290

Ehrlich, Isaac, “Participation in Illegitimate Activities: A Theoretical and Empirical Investigation” *The Journal of Political Economy*, Vol. 81, No. 3 (May - Jun., 1973), pp. 521-565

Gould, Eric D., Bruce A. Weinberg, and David B. Mustard, “Crime Rates and Local Labor Market Opportunities in the United States: 1979-1997,” *Review of Economics and Statistics,* 2002, 84(1), 45-61.

Grogger, Jeff, “Market Wages and Youth Crime,” *Journal of Labor Economics,* Volume 16, Number 4, October 1998, pp.756-791

Juhn, Chinhui, Kevin M. Murphy, and Brooks Pierce, “Wage Inequality and the Rise in Returns to Skill,” *Journal of Political Economy* 101 (June 1993), 410-442.

Katz, Lawrence F. and David H., Autor, 1999, “Changes in the Wage Structure and Earnings Inequality,” in: O. Ashenfelter and D. Card (ed.), Handbook of Labor Economics, ed. 1,Volume 3, Chapter 26, p. 1463-1555 Elsevier

Katz, Lawrence F. and Kevin M. Murphy, “Changes in Relative Wages, 1963-87: Supply and Demand Factors,” *Quarterly Journal of Economics*, 1992, *107*, 35-78.

Katz, Lawrence F., Steven D. Levitt,and Ellen Shustorovich, “Prison Conditions, Capital Punishment and Deterrence,” *American Law and Economics Review* 5 (2003): 318-43.

Krusell, Per, Lee E. Ohanian, Jose-Victor Rios-Rull, and Giovanni L. Violante, “Capital Skill Complementarity and Inequality: A Macroeconomic Analysis,” *Econometrica*, 2000, *68*, 1029-53.

Lemieux, Thomas, “Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?” *The American Economic Review,* Vol. 96, No. 3 (Jun., 2006), pp. 461-498

Levitt, Stephen D., “Juvenile Crime and Punishment,” *Journal of Political Economy* 106 (1998):1156-85

Machin, Stephen and Costas Meghir, “Crime and Economic Incentives,” *Journal of Human Resources* (2004) 39:4, 958-79.

Mocan, H. Naci, Billups, Stephen C., and Overland, Jody, “A Dynamic Model of Differential Human Capital and Criminal Activity,” *Economica* (2005) 72, 655–681

Mocan, H. Naci, Turan G. Bali, “Asymmetric Crime Cycles” *The Review of Economics and Statistics,* Vol.XCII, November 2010, Number 4, 899-911