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SKILL-BIASED TECHNOLOGICAL CHANGE, EARNINGS OF UNSKILLED WORKERS, AND CRIME

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ABSTRACT

This paper investigates the impact of unskilled workers' earnings on crime. Following the literature on wage inequality and skill-biased technological change, we employ CPS data to create state-year as well as state-year-and (broad) industry specific measures of skill-biased technological change, which are then used as instruments 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, but that wages have no impact on violent crime. The paper also estimates, for the first time in this literature, structural crime equations using micro panel data from NLSY97 and instrumenting real wages of young workers. Using state-year-industry specific technology shocks as instruments yields elasticities that are in the neighborhood of -2 for most types of crime, which is markedly larger than previous estimates. 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.

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1 Introduction

This paper analyzes the impact of unskilled workers' earnings on criminal propensity by bringing together two strands of literature: the research on wage inequality and skill-biased technological change, and literature on the impact of labor market conditions on crime. A number of influential papers have documented the rapid growth in wage inequality in the United States since the late 1970s (Autor et al., 2008; Katz and Autor, 1999; Bound and Johnson, 1992; Katz and Murphy, 1992). It has been argued that adoption of new technologies is positively correlated with the relative demand for skilled workers (Doms et al., 1997; Autor et al., 1998), and the common view in the literature is that technological change and the resultant increase in the demand for skill have been major determinants of the rise in wage inequality (Acemoglu and Autor, 2010).[1]

Another line of research is concerned with the impact of legal market earnings on crime. While the relationship is well-determined theoretically since the pioneering work of Becker (1968) and Ehrlich (1973), empirical studies have been plagued with the difficulty of credibly identifying the impact of wages on crime. Specifically, endogeneity of legal labor market earnings in crime regressions has created a major challenge in identifying the causal impact of legal labor market earnings on crime.

We investigate the extent to which variations in unskilled workers' earnings, induced by skill-biased technological change, cause crime. Following the literature on wage inequality, we create a theoretically well-defined construct of skill-biased technological change, and employ this measure as an instrument for unskilled workers' earnings in crime regressions. In addition to analyzing an annual state panel spanning 1983 to 2005, we also analyze, for the first time in this literature, a micro panel data set from NLSY97 covering the years 1997 to 2003 while employing an instrumental variable.

[1] The slowdown in the relative supply of skilled workers is another potentially contributing factor to the widening of the wage gap between skilled and unskilled workers (Card and Lemieux, 2001).

Results from state panels show that weekly earnings of unskilled workers have a significant impact on property crime with an elasticity of -1.0. Violent crime is not influenced by unskilled workers' earnings. We also find that the impact of earnings on crime is asymmetric. That is, a decline in real weekly earnings of unskilled workers has a larger impact on crime than an equivalent increase in their earnings.

Using the NLSY97 panel, we find that wages impact the propensity to commit a variety of crimes ranging from theft to selling drugs, and that the elasticities are substantially higher. Specifically, the estimated elasticities are in the neighborhood of -2, indicating that movements in unskilled workers' earnings are more significantly related to criminal activity than recognized before. The asymmetric impact of wages on crime is also detected in micro data. While men's wages cause their criminal activity, women's wages have no significant impact on their criminal propensity.

The next section of the paper briefly describes the previous research on wages and crime, and puts the contribution of this paper in perspective. Section 3 presents a simple theoretical framework. Section 4 presents the aggregate crime equation and the asymmetry hypothesis. Section 5 explains the instrument –skill biased technological change– that is employed in the paper. Section 6 describes the data used in the aggregate (state panels) analysis and Section 7 displays the results obtained from aggregate data. Section 8 describes the econometric setup of the analysis of micro data, section 9 explains the data sets used in this analysis. Section 10 presents the results obtained from micro data and Section 11 is the conclusion.

2 Previous Research and the Contribution of this Paper

Although economic models of crime predict that legal market opportunities are negatively related to criminal activity, identification of the impact of labor market conditions on crime has been a challenge because of empirical difficulties. This is especially true for the impact of wages on crime due to endogeneity of wages. In micro data an individual's market wage and his/her unobserved proclivity for criminal activity are likely to be correlated. Criminal activity will also impact the relevant wages of the individual because participation in the criminal sector deteriorates legal human capital (Mocan et al., 2005). These endogeneity and reverse causality issues produce biased estimates if such confounding is not carefully addressed. Grogger (1998) tackles these issues by estimating a reduced form model using cross-sectional data from one year (1980) of NLSY79 to explain the impact of wages on income from property crime. The estimated coefficients of the model are used in GMM to obtain the structural parameters, which generate a wage elasticity of crime participation of -1.0.

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. For example, Machin and Meghir (2004) use average area wages to explain area-level crime rates in England and Wales. Gould et al. (2002) employ residuals of a state-level wage regression for males to explain county-level crime rates. OLS regressions provide wage elasticity estimates for property crime, which are about -0.9 in the former paper, and about -0.5 in the latter.

However, exogeneity of wages is questionable even in aggregate data. For example, unobserved attributes of a state may impact legal 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.[2] Thus, it is desirable to

[2]There is arguably no reverse causality from the crime rates to the minimum wages because the adjustments to minimum wages are determined largely by political, rather than economic factors, at least in the U.S. Hashimoto (1987) employed aggregate U.S. time series data and used arrests as a proxy for crime in analyzing the impact of minimum wages on crime. Corman and Mocan (2005) use monthly

find an instrument that is correlated with wages at the local level, but not related to crime.

It has been a major challenge to find a convincing and uncomplicated instrument, even in aggregate data. For example, in addition to their OLS specifications, Gould et al. (2002) also run instrumental variables regressions of county-level crime rates on state-level wages, where the instrument for state wages consists of the product of three elements: 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. The wage elasticity obtained from this instrument is about -1.1 for property crimes.

There are only a handful of crime studies that employed panel data on individuals, but these studies investigate the impact of the local unemployment rate, rather than individual wages.[3] Furthermore, there is no crime study that has employed an instrumental variables strategy using individual-level data.

The contribution of this paper is three-fold. First, following closely the literature on wage inequality, it creates a straightforward and theoretically well-defined instrument for the earnings of unskilled workers and employs it to identify the effect of wages on crime. Second, this is the first paper to employ an individual-level panel data and an

time series data from New York City to investigate the impact of economic conditions, including the minimum wage and deterrence measures on crime. However, unobserved local characteristics may be correlated both with the level of minimum wages and the crime propensity. Hansen and Machin (2002) analyze the impact of a national minimum wage increase in the U.K. in 1999 by exploiting regional difference in crime rates and in the proportion of low-paid workers.

[3]Williams and Sickles (2002) use 426 men ages 19 to 24 over the period of 1977-82 that are part of the 1958 Philadelphia Birth Cohort Study. Mocan and Bali (2010) employ more than 27,000 individuals in the same data, and focus on the impact of the unemployment rate. A number of studies investigated the impact of unemployment on crime using instruments for the unemployment rate in *aggregate* panel data (e.g. panel of states– Lin, 2008, Raphael and Winter-Ebmer, 2001; or panel of municipalities– Öster and Agell, 2007). The typical instrument in these papers consists of an interaction of two or more variables, such as the interaction of the initial sectoral composition of employment in each aggregate unit with the national composition trends in employment (Öster and Agell, 2007), the interaction of the share of manufacturing employment in the aggregate unit and the change in the relative price of crude oil, or the interaction of the change in real exchange rates with the share of the state manufacturing employment, or the state union membership in the aggregate unit (Lin, 2008).

instrumental variables strategy to investigate the impact of unskilled workers' wages on crime. Specifically, it employs NLSY97 to analyze the behavior of young, unskilled workers, in addition to using more standard state-level panel data. The wage elasticities obtained using our instrument on micro panel data are substantially larger than previous estimates reported in the literature.[4] Third, it investigates, in both data sets, whether a decrease in earnings of unskilled workers has a larger impact on criminal propensity than an equivalent increase in earnings.

3 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) who follows Gronau (1977), 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.[5] 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

[4] Gould et al. (2002) and Grogger (1998) used NLSY79, but they could only use data from one year (1980); so they ran cross-sectional regressions.

[5] Recent dynamic economic models propose a richer interplay between investment in human capital and crime (Mocan et al., 2005; Lochner, 2004), but the main insight regarding the impact of returns to human capital is the same.

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 will work in the labor market if $W > W_0$. Similarly, he will commit crime if $R'(T_c) = \partial R/\partial T_c > W_0$. An individual who allocates time to both crime and the labor market finds the optimal crime hours where marginal return to an extra hour of crime is equal to the market wage; i.e. where $R'(T_c) = W$ is satisfied.[6] 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 a crime participation equation using micro data, the details of which are presented in Sections 8-10. It also provides guidance for an aggregate (state-level) crime equation, which is discussed in the next section.

4 Analysis of Aggregate Data

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

$$CR = F(W, X, D), \tag{1}$$

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

Within this framework and following the literature that employs aggregate crime data (Corman and Mocan, 2000; Raphael and Winter-Ebmer, 2001; Gould et al., 2002),

[6] The expected costs of crime, such as those associated with the certainty and severity of punishment, can be thought of as having been incorporated into the shape of the returns-to-crime schedule $R(T_c)$.

we estimate the following model

$$CR_{st}^{c} = \alpha_c + \beta_c W_{st} + X_{st}^{'}\Omega_c + D_{st}^{c}\Psi_c + \mu_s^c + \lambda_t^c + \varepsilon_{st}^{c}, \tag{2}$$

where CR_{st}^{c} is the crime rate of type–c crime (c=robbery, burglary, motor vehicle theft, etc.) in state s and year t. W_{st} stands for the real weekly earnings of unskilled workers in state s and year t. X_{st} represents time-varying state attributes such as per capita income, and D^c stands for the arrest rate for the corresponding crime (for example, if the dependent variable is the robbery rate, D stands for the robbery arrest rate; if the dependent variable is the burglary rate, D stands for the burglary arrest rate, and so on). μ_s^c stands for unobservable state attributes that influence crime type c in that state, λ_t^c represents the time trend and year fixed effects, and ε_{st}^{c} is a random error term. The details of the variables and the data sources are provided in the data section below.

As shown by Mocan et al. (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 earnings 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

$$CR_{st}^{c} = \alpha_s + \beta_c^{+} W_{st}^{+} + \beta_c^{-} W_{st}^{-} + X_{st}^{\prime}\Omega_c + D_{st}^{c}\Psi_c + \mu_s^c + \lambda_t^c + \varepsilon_{st}^{c}, \tag{3}$$

where

$$W_{st}^{+} = \begin{cases} W_{st} & \text{if } W_{st} \geqslant W_{st-1} \\ 0 & \text{otherwise} \end{cases}, \qquad W_{st}^{-} = \begin{cases} W_{st} & \text{if } W_{st} < W_{st-1} \\ 0 & \text{otherwise} \end{cases}.$$

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 $\beta_c^+ = \beta_c^-$ 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. Similar empirical difficulties exist in aggregate data. For example, unobserved attributes of a state may impact labor market wages as well as criminal activity. 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 et al. (1998) and Autor et al. (2008), we calculate an index of relative demand shifts favoring skilled workers, as detailed in the next section.

5 The Instrument

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

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

where H and L stand for efficiency-adjusted skilled and unskilled labor inputs (employment), respectively. A_H and A_L represent factor-augmenting technology terms. 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 et al., 2008).[7] The parameter σ is the elasticity of substitution between skilled and unskilled labor and is assumed to be greater than unity. Thus, skill-neutral

[7] Our results remain unchanged if we consider the following extended version of the above CES function:

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

where K denotes capital stock, A_K stands for capital-augmenting technology, and $\alpha \in (0,1)$ and $\eta \geqslant 0$ are time invariant parameters. Assuming that markets are competitive, the first-order conditions still yield equation (5).

technological improvement raises A_H and A_L by the same proportion, while skill-biased technological change increases A_H/A_L.

Under the assumption of competitive factor markets, the first order conditions yield the following relationship between the relative wages, W_H/W_L, and relative supply of skills, H/L :

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

where W_H and W_L stand for efficiency-adjusted wages of skilled and unskilled labor, respectively.[8] With data on wages and labor supply of both skilled and unskilled labor, A_{Hst}/A_{Lst} can be backed out for each state and year from equation (5), given that σ is known.

There is a large body of research that estimates the elasticity of substitution between skilled and unskilled labor and the estimates are between 1.4 and 2.[9] In our analysis, we set $\sigma = 1.6$ which is consistent with more recent estimates (e.g., 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.

We employ $\ln(A_H/A_L)$ as an index for skill-biased technological change (Autor et al.,

[8] The creation of efficiency-adjusted H, L, W_H and W_L is described in the Appendix.

[9] Using the CPS data over 1963-87, Katz and Murphy (1992) estimate that σ is about 1.4. Autor et al. (2008) extend the period to 2005, and find that it is around 1.6. Krusell et al. (2000), on the other hand, find that the elasticity is about 1.7. Using a state-level panel data, Ciccone and Peri (2005) find this elasticity to be around 1.5. Based on extensive econometric estimates, Autor et al. (1998) conclude that this elasticity is unlikely to be greater than 2.

1998; Autor et al., 2008; Goldin and Katz, 2007).[10] 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.[11] When we estimate models which include W^+ and W^- as regressors (see Equation 3), we construct the corresponding instruments using $\ln(A_H/A_L)$, the same way W^+ and W^- are generated.

Although a change in $\ln(A_H/A_L)$ can arise for a variety of reasons, ranging from variations in the relative prices of non-labor inputs to international trade and to the evolution of labor market institutions, the consensus in the literature is that the primary driver of $\ln(A_H/A_L)$ is skill-biased technological change (Autor et al., 2008; Goldin and Katz, 2007).[12] A related point is whether skill-biased technological change and the resultant change in the relative demand for skilled workers would induce a policy reaction, which would render our instrument invalid. For example, if state governments increase minimum wages in reaction to a change in technology favoring skilled workers, the instrument would be invalid to the extent that the minimum wage has a direct impact on crime. However, the scenario that states increase the level of minimum wages in response to technology shocks does not seem realistic because minimum wages are not adjusted frequently. Between 1980 and 2005 there were six increases in the minimum

[10]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 skilled-biased technical change. Second, calculation of $\ln(A_H)$ and $\ln(A_L)$ requires the exact specification of the production function (Caselli and Coleman, 2006; Unel, 2010) along with data on capital stocks and rental prices, which are not available. Furthermore, a production function such as the one depicted in footnote 7 involves unknown parameters α and η. Calculation of A_H and A_L is even more difficult at the individual-level panel analysis, because it requires data on the price of output in each industry in each state, which are not available either.

[11] 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 et al., (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.

[12]Minimum wage is an example of an institutional factor tat may have impacted the wage gap between skilled and unskilled labor. Although Lee (1999) argues that minimum wage can account for the rise in the inequality in the lower tail of the wage distribution, Autor et al. (2010) find that the impact of minimum wage on overall wage inequality is modest, and it is almost negligible for males.

wage mandated by the federal government, but the average number of state-induced increases was 3.5 during the same period. Running a regression of the logarithm of state minimum wages (the greater of the federal or the state) on state-level $\ln(A_H/A_L)$ by controlling for state and time fixed-effects produced a coefficient of 0.001 with a p-value of 0.87.[13] This indicates that minimum wage is not impacted by variations in skill-biased technology shocks.

It is possible that states react to technology shocks that create a labor market disadvantage for unskilled workers in ways that are more subtle than minimum wage increases. We consider two state welfare expenditures and investigate whether states alter these expenditures in reaction to changes in the skill-biased technology index. The first expenditure item, *welfare cash spending,* measures cash assistance to individuals. It includes all state expenditures on cash programs as well as AFDC/TANF and assistance programs not under federal categorical programs (e.g., general assistance, refugee assistance, home relief, and emergency relief). The second variable, *non-cash welfare*, includes medical vendor payment benefits to individuals through Medicaid, state childrens health insurance program (SCHIP), administration of medical and cash assistance, general relief, vendor, nursing homes and welfare institutions owned and operated by a government.[14] Thus the welfare expenditure measures include the amount contributed by the state and federal matches. Running a regression of the logarithm of real welfare cash spending on $\ln(A_H/A_L)$ produces a coefficient of -0.09 with a p-value of 0.29, and the estimated coefficient is 0.02 (p=0.45) when the logarithm of real non-cash welfare spending is the dependent variable.[15]

[13] Minimum wage is the greater of the federal and state minimum wage in a year. It is obtained from documents found at state departments of labor websites, the Monthly Labor Review publication of the Bureau of Labor Statistics, or from other official government documents. The time period of the regression, 1983-2005, is the same as the period covered by the state panel analyzed in section analyzed in the next two sections. Variations in this specification in various ways did not change neither the point estimate nor the statistical significance of the estimated coefficient of $\ln(A_H/A_L)$.

[14] These data are obtained from U.S. Census Bureau, *Annual Survey of State Government Finances and Census Government*.

[15] As in the case with the minimum wage regression, these models contain state and time fixed effects.

These results indicate that states do not react in systematic ways to increase the minimum wage or welfare spending in order to counteract the potentially adverse effects on unskilled workers produced by shocks in skill-biased technology. This could be because state governors and state legislature cannot easily recognize these shocks, or alternatively, they may not worry about the impact of these shocks on unskilled workers.[16]

When we analyze micro data from the NLSY97, we follow the same procedure to create the instrument, with one difference. We generate state-year-and-industry specific measures of relative demand shifts ($A_{Hjst}/A_{Ljst},$) in each state s, year t, and for three broad industry categories (service, manufacturing, and other industries) j. 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 8 and the details of the creation of skill-biased technological change measure are displayed in the Appendix.

6 Data Used in State Panel

We follow the literature on wage inequality to construct measures of earnings and employment for both skilled and unskilled labor (e.g. Autor et al. 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

Neither the estimated coefficient, nor statistical significance changed appreciably when the specification was altered by, for example, by adding state-specific trends, or by adding lagged values of the index of skill-biased technology.

[16]This result is not surprising because even if skill-biased technology shocks were immediately observable, state's reaction to such shocks to protect unskilled workers would require political support, which is not likely to be strong as unskilled low-income workers have little influence in state politics (Rose-Ackerman, 2003).

salaries) in the previous year by the number of weeks worked.[17] Following Gould et al. (2002), we construct average weekly earnings by considering all employed people between 16 and 64 years of age (excluding self-employed workers) and who work on a full-time basis (defined as working 35-plus hours per week). They are deflated by state-specific price deflators from Berry et al. (2000). 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. 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. To avoid ratio bias, arrest rates are calculated by deflating arrests by population, rather than by offenses. In this calculation we used 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 (which is 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.

Figures 1A-6A display the efficiency-adjusted real weekly earnings of unskilled work-

[17]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 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. May/ORG data, which is another potential source, have undergone a serious re-design in mid-1990s which created substantial problems. Acemoglu and Autor (2010) indicate that the non-response rate to earnings in the May/ORG increased from 15% in 1993 to 23% in 1994 and reached 31% in 2001.

ers as well as the crime rates in a sample of states from different regions of the country. There is significant heterogeneity in the behavior of the crime rates. For example, 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 mid-1980s and early 1990s in Massachusetts before it subsequently started declining, and the crime in West Virginia went up, rather than decline, between early1980s and 2005.

Figures 1B-6B present the efficiency-adjusted real weekly earnings of unskilled workers in the same states. 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, real weekly earnings of unskilled workers were going up between 1980 and 2005 when crime was declining. The opposite was happening in West Virginia Crime during the same period. 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.[18] Note that Figures 1B-6B display efficiency-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 both follow the same time-series

[18] 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.

pattern in a state.

7 Estimation Results of the 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 71. Regressions also control for state and time fixed-effects and a time-trend; the standard errors are clustered at the state level. Following Levitt (1998), Corman and Mocan (2000), and Katz et al. (2003), arrest rates are lagged once to minimize the impact of simultaneity between crime and deterrence.

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 (Autor et al., 1998; Autor et al., 2008; Acemoglu and Autor, 2010). 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 et al., 2008). Thus, models presented in Tables 2A and 2B include state unemployment rates, but dropping them has no effect on the magnitude or statistical significance of other coefficients.

Column (1) of Table 2A shows that the IV-estimate of the coefficient of unskilled (non-college) workers' weekly earnings is -9.2 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 184 (or about 9,670 fewer property crimes in a state in a year), which corresponds to a 4.4% decline. This suggests an elasticity of property crime with respect to real weekly earnings of -0.9. 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 56, or 6%, which translates into 3,160 fewer burglaries. The same increase in earnings brings about a decline in the larceny rate by 150 (5.4%). This suggests that the elasticity of burglary and larceny with respect to 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.

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.[19] 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 regressions of this specification use $\ln(A_H/A_L)^{+}$ and $\ln(A_H/A_L)^{-}$ as instruments, which are constructed the same way as Weekly Earnings^{+} and Weekly Earnings^{-}. The F-value for the instruments are between 45 and 50.[20] 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 five percent level. Specifically, if real

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

[20]The first stage regressions are not identical between specifications because each crime type regression (burglary, larceny, etc.) has its own specific arrest rate as part of the explanatory variables.

weekly earnings of unskilled workers go down by \$10, the property crime rate goes up by about 184, which corresponds to an increase in the number of property crimes by about 9,700.[21] On the other hand, if weekly earnings increase by \$10, the property crime rate goes down by only 173, which translates into a decline in the number of property crimes by 9,120. 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. The difference in the effects is statistically different from zero at the 8-percent level for burglary, and at the 2-percent level for larceny.

An increase in the unemployment rate increases robberies, which is a violent crime that has a monetary motive. The estimated coefficients in tables 2A and 2B imply that a one-percentage point increase in the state unemployment rate increases property crime rate by 72-108, which translates into an increase in property crimes by about 2 percent. This magnitude is remarkably similar to the ones reported by previous research (Freeman and Rodgers, 2000; Gould et al., 2002; Corman and Mocan, 2005). The same one-percentage point increase in the unemployment rate generates a 3.8 perecnt increase in robberies.

Very similar results to those reported in Tables 2A-2B are obtained when composition-adjusted (instead of efficiency-adjusted) wages and the corresponding skill-biased technology measure are used in regressions.[22] 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 earnings of non-college workers would increase crime, and it underlines the importance of addressing endogeneity.

[21] The coefficients of Weekly Earnings^{+} and Weekly Earnings^{-} are larger in comparison to the coefficients 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).

[22] See the Appendix for the details of composition-adjusted wages.

8 Analysis of Micro Data

Based on the theoretical framework summarized in Section 3 above, and following Grogger (1998), in this section we estimate a structural crime participation equation using data from NLSY97. Specifically, consider the following equations:

$$\ln W = X^{'}\Omega + \varepsilon, \tag{6a}$$

$$R'(T_c) = X^{'}\Phi + D^{'}\Psi + \lambda T_c + \mu, \tag{6b}$$

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

As described in Section 3, if the person is engaged in crime, it should be the case that $R'(T_c = 0) > \ln W$. 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

$$\Pr(CR = 1) = Pr(\mu > \ln W - X^{'}\Phi - D'\Psi). \tag{7}$$

Equation (7) 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 (7) using only those who work could produce sample selection bias. Second, ε and μ in equations (6a) and (6b) 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 5. 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, 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

$$CR^c_{ist} = \beta_c W_{ist} + X^{'}_{ist}\Omega_c + D_{ist}\Psi_c + \zeta^c_i + \varphi^c_s + \lambda^c_t + \nu^c_{ist}, \tag{8}$$

where CR_{ist} stands for an indicator of various types of criminal activity (i.e., the subscript c stands for theft, stealing cars, drug sales, etc.) for person i who resides in state s 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 age-specific arrest rates for various crimes. W_{ist} is the logarithm of the market wages of worker i, in state s, and time t, instrumented with skill-biased technological change, ζ_i represents unobserved time-invariant individual heterogeneity, φ_s stands for state fixed-effects, λ_t represents the time fixed effects, and ν stands for the error term. As in the case of state panels, we also investigate the asymmetric impact of wages on crime.

9 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. The individuals in the sample were aged 12 to 16 as of December 31^{st} 1996, indicating that the sample consists of young and unskilled (low educated) people, with average age of about 18 (see Table 3). The respondents have been followed annually since the survey was initiated. We limit the sample to the 1997–2003 waves because everyone who took the survey between these years was asked of questions 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 (which is titled Larceny); and whether the person received, possessed or sold stolen property, committed embezzlement and fraud. This last category is called *Stolen Property* We also employ a variable to indicate if the person committed Larceny, Car Theft or Robbery.[23]

In each wave, individuals are asked about the jobs they have taken since the last

[23] These outcome variables are constructed based on a series of questions in the following form "Have you done X since the last interview?" where X 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 X?" followed by "How many times have you committed X in the last 12 months?" or "How old were you when you last did X?" Thus, we used these variables to construct the outcome variables for the first wave.

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 the relevant wage. To eliminate outliers, observations above the 95^{th} 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 equation and a market wage equation. 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.[24] 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 include whether the person 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

[24]The Census Bureau has reclassified some of the jobs in 2002. We utilized this new classification.

in the last month the individual has consumed more than 5 alcoholic beverages and used marijuana.[25] In addition, we use state level control variables. They consist of 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.

County-level arrest data are obtained from 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 any 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. 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.

Table 3 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 reported in column (1) of Table 6A.[26]

[25] 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.

[26] 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. Second, when calculating the arrest rates, we deflated the total number of

10 Estimation Results Using Micro Data

Table 4 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. Non-labor 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 Hispanics have lower propensities to participate.[27]

Table 5A presents the crime regressions that employ the NLSY97 data. Potential market wages of non-workers are imputed using the selection-corrected wage equation displayed in Table 4 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. The instrument is powerful with the F-statistics in the range of 127-155.

Real wages have no significant impact on robbery or burglary,[28] but they impact

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, in calculating the juvenile (adult) arrest rate for, say, larceny, we divide the number of juvenile (adult) larceny arrests by 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. Third, and most important, 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 3. 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 U.S. Therefore, it is natural to have smaller means for the arrest rates in the individual level analysis.

[27]The correlation between the errors of the selection and wage equation is negative as it is sometimes found in other studies (Wright and Ermisch, 1991; Steinberg, (1989)). This is possible in variety of circumstances. For example a negative correlation emerges if the variance of market wages is smaller than the covariance between market wages and reservation wages (Ermisch and Wright, (1994)).

[28]Robbery is a violent crime, where the perpetrator takes or attempts to take something valuable

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 18 percentage points. The same increase in wages generates a decline in the propensity to steal a car by 4 percentage points. Similarly, an increase in 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 burglary, car theft, larceny, 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 5B 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 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 explain selling hard drugs with a p-value of 0.02 (column 6), and where larceny/car theft/robbery is the dependent variable (column 1) with a p-value of 0.07.

The results obtained from estimating the models for men are presented in Tables 6A and 6B. Wages have a negative and statistically significant impact on all crimes with the exception of robbery and burglary. Table 6B 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/car theft/robbery (column 1) and selling hard drugs (column 6).

When we ran the models for females, the estimated wage coefficients were small and

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.

statistically not different from zero in any crime category. For example, the wage coefficient was -0.097 (std=0.084) in the larceny equation indicating that females' market wages have no significant impact on their propensity to steal a purse or a wallet, or to steal something from a store.[29] It should be noted this result could be because of low variation in the dependent variable (less criminal activity for females). Suggestive evidence for this is that the estimated coefficients are closer to being significant in case of larceny and larceny/car theft/robbery– crime categories with higher participation rates. An increase in the minimum wage has a negative impact for females in case of property crimes other than car theft: larceny, and the joint category of larceny/car theft/robbery.

11 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 was little evidence to support the hypothesis that economic conditions impact crime and that there was a disconnect between theory and empirical evidence. In the analysis of the impact of market wages on crime truly exogenous variation in wages is difficult to find, and it has been a tough challenge to come up with convincing and functional instruments for wages that can be used in aggregate crime regressions. No study so far has employed an instrumental variables strategy in crime-wage regressions using micro data.

In this paper we investigate the impact of unskilled (non-college educated) workers'

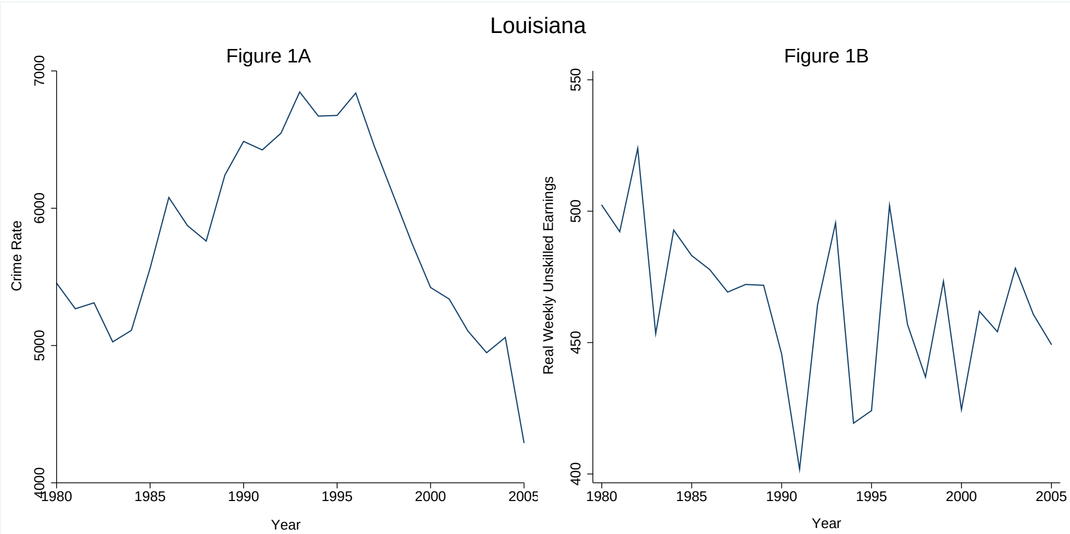
[29]The estimated wage coefficients for females (and the standard errors) were as follows in other crime categories. Car theft: -0.014 (0.020), stolen property: -0.011 (0.026), larceny/car thft/robbery: -0.094 (0.077), selling drugs: -0.016 (0.046), selling hard drugs: 0.001 (0.027), burglary: 0.010 (0.021), robbery: 0.013 (0.013).

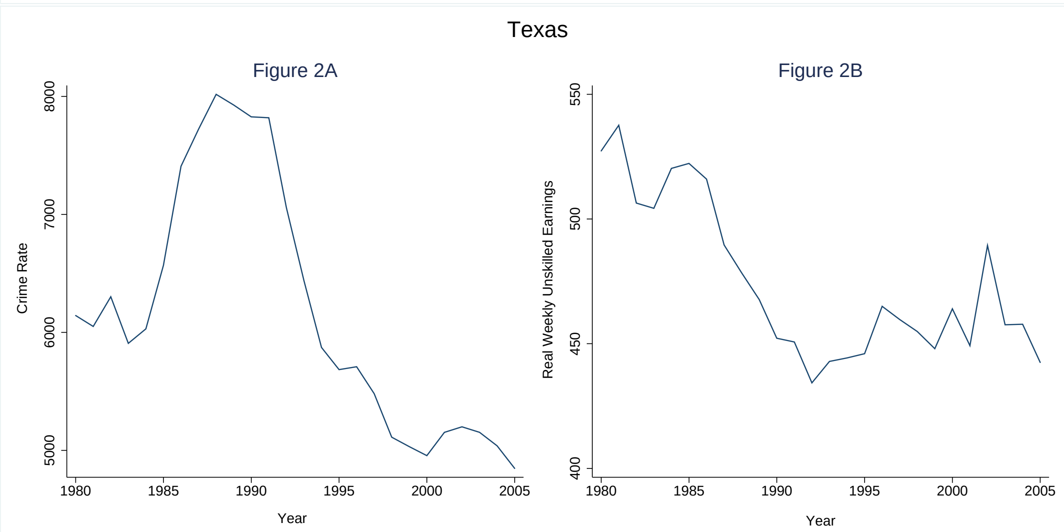
earnings on crime using both aggregate (state level) and micro (NLSY97) panel data sets. Using the framework employed in the literature on wage inequality, and using CPS data, we create a state-and-year specific measure of skill-biased technological change and use it as an instrument for unskilled workers' earnings.

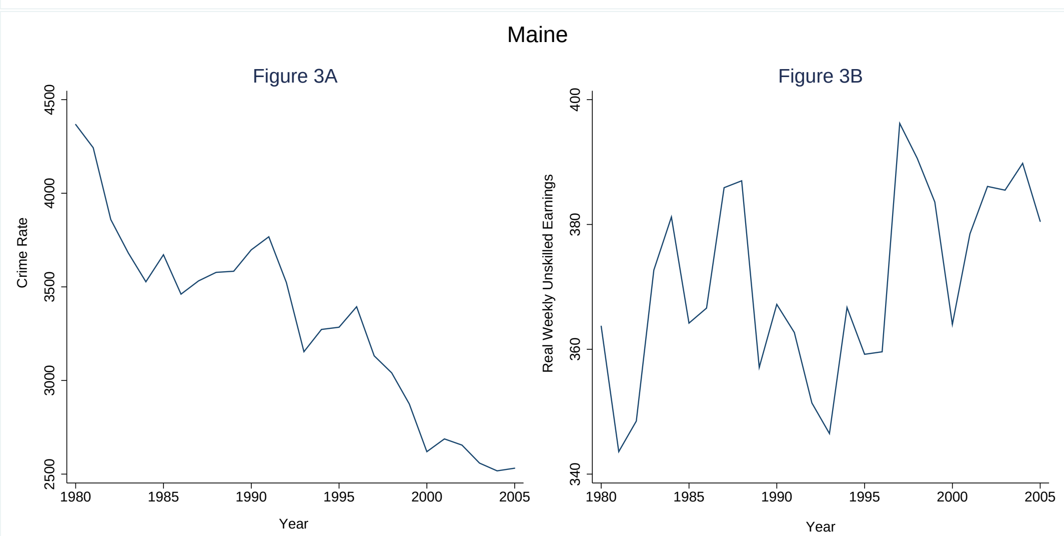
Estimation of crime regressions using state panels demonstrates that a decrease in unskilled workers' real weekly earnings, induced by skilled-biased technological change, has a positive impact on state property crime with an elasticity of -1.0. Individual components of property crime, such as burglary and larceny, are also impacted by unskilled wages. Violent crime is not influenced by weekly earnings of unskilled workers. We 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 also employ micro data from the geo-coded confidential version of the NLSY97 to estimate models of criminal participation. The data set consists of young and mostly unskilled workers, spanning the years 1997-2003. The NLSY97 contains detailed measures of individuals' criminal activity as well as personal and household attributes and wages, along with information on participation in a variety of crimes, ranging from theft to selling drugs. Geo-codes allow us to identify the location of the individual and to merge them with age-specific (juvenile v. adult) arrest rates in their county of residence. 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. We instrument market wages with state-year-industry specific technology shocks and find wage elasticities in the neighborhood of -2, which is markedly larger than previous estimates. The asymmetric impact of wages on crime is also detected in micro data. Market wages have no significant impact on criminal activity of females.

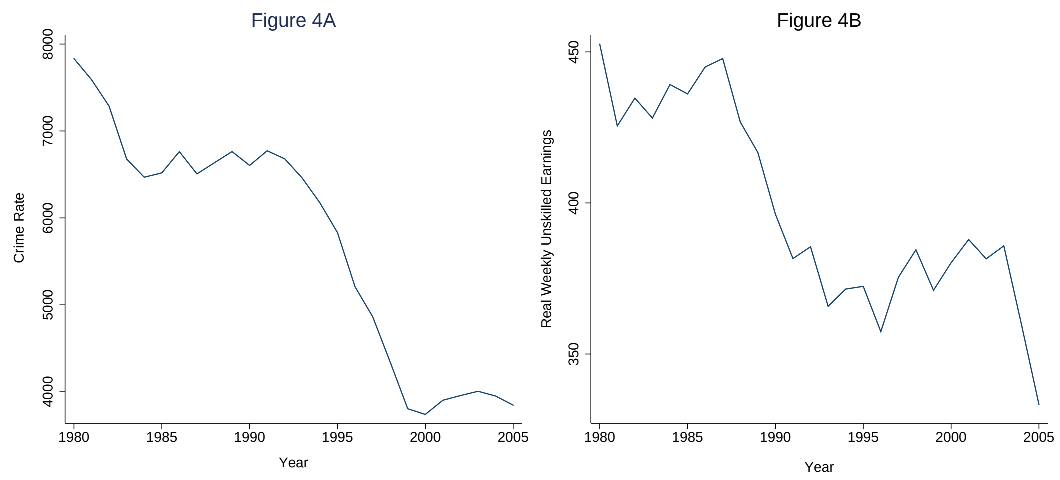
These results indicate that individual crime decisions respond to labor market incentives as predicted by theory, and that variations in unskilled workers's earnings have a significantly larger impact on criminal activity than recognized before.


Louisiana
Figure 1A
Figure 1B
Crime Rate
Real Weekly Unskilled Earnings
Year
4000
5000
6000
7000
400
450
500
550
1980
1985
1990
1995
2000
2005


Texas
Figure 2A
Figure 2B
Crime Rate
Real Weekly Unskilled Earnings
Year
5000
6000
7000
8000
400
450
500
550
1980
1985
1990
1995
2000
2005


Maine
Figure 3A
Figure 3B
Crime Rate
Real Weekly Unskilled Earnings
Year
2500
3000
3500
4000
4500
340
360
380
400
1980
1985
1990
1995
2000
2005

California



Massachusetts

West Virginia

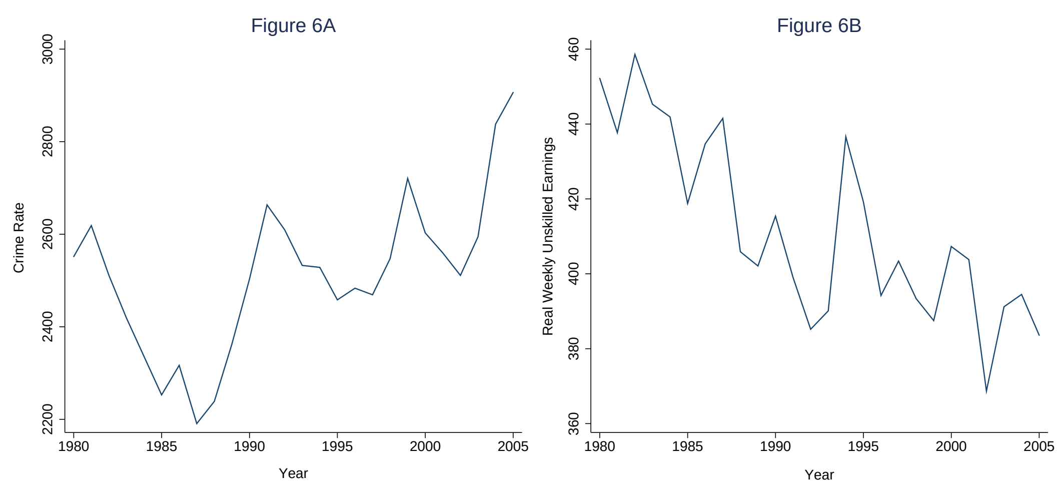


Table 1. Descriptive Statistics (State Panels, 1983–2005)

Variable	Mean	Standard Deviation	
		Overall	Within-State
Real Weekly Earnings-Unskilled Workers			
Reported Earnings (dollars)	680.7	64.4	34.6
Efficiency-Adjusted Earnings (dollars)	409.3	42.1	21.6
Crime Rates			
Property	4,149.5	1,102.2	605.3
Burglary	949.3	359.5	231.9
Larceny	2,796.3	699.6	364.0
Motor Vehicle Theft	404.0	210.6	110.5
Violent	470.3	238.0	93.9
Murder	6.0	3.4	1.5
Rape	36.0	13.8	6.5
Robbery	133.6	96.4	40.8
Assault	294.6	154.5	61.3
Arrest Rates			
Property	14.6	227.3	222.4
Burglary	2.3	30.3	29.7
Larceny	11.5	188.6	184.5
Motor Vehicle Theft	0.8	8.4	8.3
Violent	2.6	20.9	20.5
Murder	0.1	0.8	0.8
Rape	0.3	4.2	4.1
Robbery	0.6	5.4	5.3
Assault	1.7	10.5	10.3
Income Per Capita	22,085.1	7,161.5	6,410.7
Unemployment Rate	5.7	1.9	1.5
Percent 15-24 Year Old	14.9	1.5	1.3
Percent Black	10.0	9.4	0.5
Percent Urban Population	71.2	14.7	2.0
Alcohol Consumption	2,324.4	389.9	139.8

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. 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
Weekly Earnings	-9.231**	-2.835**	-7.659***	1.259	-0.170	-0.001	-0.049	-0.060	-0.070
	(3.729)	(1.368)	(2.481)	(1.030)	(0.479)	(0.009)	(0.058)	(0.246)	(0.317)
Arrest Rate (-1)	-0.086***	-0.181***	-0.069***	-0.023	-0.024	-0.002	0.016	0.023	-0.019
	(0.017)	(0.052)	(0.013)	(0.148)	(0.034)	(0.016)	(0.013)	(0.100)	(0.061)
Unemp. Rate	72.465***	23.995***	43.755**	4.726	4.204	-0.004	0.172	5.155***	-1.081
	(27.770)	(9.061)	(17.323)	(5.942)	(3.940)	(0.074)	(0.366)	(1.774)	(2.811)
State Inc/Cap	-0.044	-0.009	-0.001	-0.034***	-0.009	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)
% 15–24Yrs Old	-23.760	-4.489	-43.309*	24.070**	1.710	0.257***	1.225**	0.172	0.112
	(41.455)	(14.823)	(24.974)	(10.925)	(6.643)	(0.069)	(0.576)	(2.648)	(6.014)
% Black	93.899	16.887	56.405	20.632	12.246	0.467**	-1.389	1.993	11.319
	(77.931)	(29.395)	(45.828)	(19.606)	(16.337)	(0.203)	(1.309)	(7.433)	(10.075)
State Alcohol Cons.	1.746***	0.514***	1.126***	0.106	0.195***	0.002***	0.014***	0.091***	0.089***
	(0.319)	(0.103)	(0.202)	(0.084)	(0.049)	(0.001)	(0.004)	(0.026)	(0.034)
Observations	1,111	1,111	1,111	1,111	1,111	1,111	1,111	1,109	1,111

Notes: 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, state and time fixed-effects, and a common time-trend.

Table 2B. Instrumental Variable State Panel Regressions
The Impact of Unskilled Labor Weekly Earnings (Increase and Decrease) on Crime

	Property				Violent				
	Total	Burglary	Larceny	MV Theft	**Total**	Murder	Rape	Robbery	Assault
Weekly Earnings^{+}	-17.353**	-5.357*	-15.090***	3.088	-0.070	-0.016	-0.060	0.184	-0.179
	(7.688)	(2.838)	(5.663)	(2.389)	(1.047)	(0.021)	(0.135)	(0.473)	(0.735)
Weekly Earnings^{-}	-18.360**	-5.670*	-16.011***	3.315	-0.057	-0.017	-0.061	0.215	-0.193
	(8.154)	(3.009)	(6.030)	(2.557)	(1.127)	(0.022)	(0.145)	(0.507)	(0.793)
Arrest rate (-1)	-0.081***	-0.170***	-0.063***	-0.049	-0.024	0.001	0.017	0.017	-0.018
	(0.019)	(0.055)	(0.015)	(0.142)	(0.032)	(0.016)	(0.011)	(0.098)	(0.059)
Unemp. Rate	107.507***	34.879***	75.816***	-3.167	3.771	0.058	0.218	4.102*	-0.609
	(38.278)	(13.022)	(25.654)	(10.689)	(5.437)	(0.096)	(0.600)	(2.275)	(3.770)
State Inc/Cap	-0.014	0.000	0.027	-0.041***	-0.009	0.000	0.000	-0.007**	-0.002
	(0.044)	(0.013)	(0.031)	(0.013)	(0.008)	(0.000)	(0.001)	(0.003)	(0.005)
% 15–24 Yrs Old	-36.235	-8.365	-54.722*	26.882**	1.864	0.234***	1.208**	0.541	-0.056
	(49.611)	(17.428)	(33.165)	(12.248)	(6.926)	(0.084)	(0.615)	(2.810)	(6.280)
% Black	120.648	25.196	80.879	14.608	11.916	0.515**	-1.353	1.182	11.679
	(90.144)	(33.418)	(61.604)	(23.871)	(15.708)	(0.230)	(1.494)	(7.098)	(9.992)
State Alcohol Cons.	1.980***	0.587***	1.341***	0.053	0.192***	0.002**	0.014**	0.084***	0.092**
	(0.417)	(0.137)	(0.284)	(0.109)	(0.056)	(0.001)	(0.006)	(0.027)	(0.041)
Observation	1,111	1,111	1,111	1,111	1,111	1,111	1,111	1,109	1,111

Notes: 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, state and time fixed-effects, and a common time-trend.

Table 3. Descriptive Statistics, NLSY97 Data

Variable	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 a car, = 0 otherwise	0.007	(0.086)
Stolen Property	= 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	949.8	(346.4)
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)

Table 3. Descriptive Statistics, NLSY97 Data (concluded)

Variable	Definition	Mean	Std
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)
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)
Car Theft	The number of arrests of relevant age group (juveniles or adults) for stealing a car per 1,000 people in the respondent's county	0.270	(0.280)
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)
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)
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)
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)
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 4. NLSY Data; Selection into Labor Force, and Market Wages

Variable	Selection Equation	Wage Equation
Non Labor Income	-0.0001**	
	(0.00005)	
Household Size	-0.001	-0.007***
	(0.005)	(0.002)
High School +	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 Inc/Capita	-0.026	0.016**
	(0.017)	(0.007)
Unemployment	-0.040**	0.009
	(0.019)	(0.007)
% 15-24 Yr. Old	-0.081**	0.034**
	(0.035)	(0.013)
% Black population	-0.059*	0.030*
	(0.035)	(0.015)
Observations	55,037	55,037
ρ	-0.811	

Notes: 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 5A: NLSY DATA, INSTRUMENTAL VARIABLES REGRESSIONS

	Larceny/ Car Theft/ Robbery	Larceny	Car Theft	Stolen Property	Selling Drugs	Selling Hard Drugs	Burglary	Robbery
Log Wage	-0.179***	-0.160***	-0.041**	-0.086**	-0.101**	-0.058**	-0.019	0.011
	(0.057)	(0.056)	(0.018)	(0.035)	(0.046)	(0.026)	(0.024)	(0.013)
Arrest Rate	-0.002*	-0.003**	-0.008***	-0.000	-0.000	0.002	-0.007***	-0.003
	(0.001)	(0.002)	(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
	(0.008)	(0.008)	(0.003)	(0.005)	(0.006)	(0.004)	(0.003)	(0.002)
Hshld Inc	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)
Age	-0.016***	-0.013***	-0.001	-0.003	-0.002	-0.001	-0.003**	-0.001*
	(0.004)	(0.004)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
Gun	0.098***	0.086***	0.042***	0.087***	0.094***	0.063***	0.053***	0.036***
	(0.010)	(0.010)	(0.006)	(0.008)	(0.009)	(0.007)	(0.007)	(0.004)
Heavy Drinking	0.003***	0.002***	0.001***	0.002***	0.005***	0.003***	0.002***	0.001**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Marijuana Use	0.003***	0.003***	0.000	0.002***	0.011***	0.003***	0.001**	0.000**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
State Inc/Cap	-0.004	-0.003	-0.001	-0.001	0.000	-0.001	-0.002	0.000
	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
% Black	0.009	0.015*	-0.003	0.003	0.000	0.002	-0.001	0.001
	(0.008)	(0.009)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.001)
Observations	54,411	47,479	47,479	54,398	54,386	54,382	47,479	54,658

Notes: 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, state and year dummies and individual fixed-effects are included in all regressions.

Table 5b: Nlsy Data, Instrumental Variables Regressions, Wage Increase and Decrease

	Larceny/ Car Theft/ Robbery	Larceny	Car Theft	Stolen Property	Selling Drugs	Selling Hard Drugs	Burglary	Robbery
Log Wage^{+}	-0.284**	-0.155	-0.052	-0.114	-0.056	-0.146**	-0.003	0.022
	(0.130)	(0.117)	(0.039)	(0.077)	(0.097)	(0.060)	(0.042)	(0.031)
Log Wage^{-}	-0.301**	-0.165	-0.053	-0.122	-0.058	-0.156**	-0.003	0.022
	(0.139)	(0.124)	(0.041)	(0.082)	(0.103)	(0.064)	(0.044)	(0.033)
Arrest Rate	-0.004	-0.004	-0.004	-0.000*	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.003)	(0.004)	(0.000)	(0.002)	(0.002)	(0.003)	(0.004)
High School +	-0.009	-0.012*	0.003	-0.003	-0.010*	-0.005	0.001	-0.001
	(0.007)	(0.007)	(0.002)	(0.004)	(0.005)	(0.004)	(0.003)	(0.002)
Hshld Inc	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)
Age	-0.020***	-0.019***	-0.001	-0.005*	-0.005	0.000	-0.005**	-0.001
	(0.005)	(0.005)	(0.001)	(0.003)	(0.004)	(0.002)	(0.002)	(0.001)
Gun	0.095***	0.077***	0.031***	0.081***	0.097***	0.060***	0.043***	0.035***
	(0.012)	(0.012)	(0.006)	(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)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Marijuana Use	0.003***	0.003***	0.000	0.001***	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 Inc/Cap	-0.008*	-0.007	-0.001	-0.001	0.002	0.002	-0.001	-0.000
	(0.004)	(0.004)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
% Black	0.008	0.013	-0.002	-0.000	-0.005	0.003	0.001	0.000
	(0.011)	(0.011)	(0.003)	(0.006)	(0.008)	(0.005)	(0.004)	(0.002)
Observations	43,043	36,565	36,566	43,041	43,028	43,025	36,566	43,234

Notes: 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, state and year dummies and individual fixed-effects are included in all regressions.

Table 6a: Nlsy Data, Instrumental Variables Regressions –Men

	Larceny/ Car Theft/ Robbery	Larceny	Car Theft	Stolen Property	Selling Drugs	Selling Hard Drugs	Burglary	Robbery
Log Wage	-0.197**	-0.162**	-0.048*	-0.092*	-0.141**	-0.088**	-0.014	0.013
	(0.080)	(0.074)	(0.027)	(0.055)	(0.069)	(0.039)	(0.036)	(0.020)
Arrest Rate	-0.002	-0.003	-0.014***	-0.000	-0.002	0.004	-0.012***	-0.003
	(0.002)	(0.003)	(0.005)	(0.000)	(0.003)	(0.003)	(0.005)	(0.005)
High School +	0.002	-0.003	0.005	-0.009	-0.009	-0.002	0.004	-0.002
	(0.011)	(0.012)	(0.004)	(0.008)	(0.010)	(0.006)	(0.006)	(0.003)
Hshld Inc	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)
Age	-0.026***	-0.022***	-0.001	-0.007**	-0.001	-0.002	-0.005**	-0.001
	(0.005)	(0.006)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.001)
Gun	0.091***	0.078***	0.038***	0.080***	0.087***	0.059***	0.048***	0.037***
	(0.011)	(0.011)	(0.006)	(0.009)	(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 Inc/Cap	-0.001	0.003	-0.000	-0.000	0.001	-0.001	-0.003	0.001
	(0.005)	(0.005)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.001)
% Black	0.013	0.022*	-0.005	0.002	-0.000	0.002	-0.001	0.003
	(0.012)	(0.012)	(0.005)	(0.008)	(0.009)	(0.005)	(0.006)	(0.002)
Observations	27,428	23,987	23,987	27,415	27,410	27,407	23,987	27,567

Notes: 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, state and year dummies and individual fixed-effects are included in all regressions.

Table 6b: Nlsy Data, Instrumental Variables Regressions –Men, Wage Increase and Decrease

	Larceny/ Car Theft/ Robbery	Larceny	Car Theft	Stolen Property	Selling Drugs	Selling Hard Drugs	Burglary	Robbery
Log Wage$^+$	-0.335**	-0.246*	-0.066	-0.095	-0.042	-0.172**	-0.003	0.016
	(0.169)	(0.148)	(0.054)	(0.112)	(0.133)	(0.081)	(0.057)	(0.041)
Log Wage$^-$	-0.355**	-0.266*	-0.067	-0.101	-0.041	-0.181**	-0.002	0.017
	(0.180)	(0.158)	(0.058)	(0.119)	(0.142)	(0.087)	(0.060)	(0.044)
Arrest Rate	-0.003	-0.004	-0.008	-0.000	-0.002	0.001	-0.000	-0.003
	(0.003)	(0.004)	(0.007)	(0.000)	(0.004)	(0.004)	(0.005)	(0.006)
High School +	-0.004	-0.011	0.005	-0.008	-0.015*	-0.006	0.003	-0.002
	(0.011)	(0.011)	(0.004)	(0.007)	(0.008)	(0.006)	(0.005)	(0.003)
Hshld Inc	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)
Age	-0.031***	-0.023***	-0.003	-0.011**	-0.007	0.000	-0.007***	-0.001
	(0.007)	(0.007)	(0.002)	(0.004)	(0.005)	(0.004)	(0.003)	(0.002)
Gun	0.092***	0.072***	0.028***	0.074***	0.089***	0.057***	0.039***	0.036***
	(0.013)	(0.013)	(0.006)	(0.010)	(0.011)	(0.008)	(0.008)	(0.006)
Heavy Drinking	0.003***	0.002**	0.001**	0.002***	0.004***	0.003***	0.002***	0.001
	(0.001)	(0.001)	(0.001)	(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 Inc/Cap	-0.008	-0.004	0.000	0.001	0.005	0.005*	-0.002	0.000
	(0.007)	(0.007)	(0.002)	(0.004)	(0.005)	(0.003)	(0.003)	(0.001)
% Black	0.022	0.027*	-0.002	0.004	-0.006	0.005	0.003	0.001
	(0.016)	(0.015)	(0.005)	(0.010)	(0.012)	(0.007)	(0.006)	(0.003)
Observations	21,462	18,280	18,280	21,454	21,447	21,444	18,280	21,565

Notes: 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, state and year dummies and individual fixed-effects are included in all regressions.

A The CPS Data

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

A.1 Construction of Efficiency-adjusted Labor Inputs

Each individual's average weekly earning is formed by dividing his annual income (from wages and salaries) by the number of weeks that he worked during the previous year. Earnings are deflated using the state-specific level price deflators from Berry et al. (2000).[30] We make two adjustments for topcoded earnings. First, following Autor et al. (2008) income of workers with top coded earnings is imputed by multiplying the annual topcode amount by 1.5. Second, starting in 1996, topcoded earnings values are assigned the mean of all topcoded earners. In these cases, we simply reassign the topcoded values to all such observations and again multiply by 1.5. Workers whose weekly earnings below \$70 in 2005 dollars are dropped, as are those non-full-year workers (i.e., those who work less than 40 weeks) whose weekly earnings exceed $1/40^{th}$ the top-coded value of weekly earnings.

We construct the series for high-skill and low-skill labor input and wages as follows. The data in each year in each state are divided into 24 distinct groups characterized by 2 sexes, 4 education categories ($E \leqslant 11$, $E = 12$, $13 \leqslant E \leqslant 15$, and $E \geqslant 16$),[31] and

[30] Berry et al. (2000) have recently extended their original data set to 2007; and we used the updated series. 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.

[31] 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

three potential experience categories (0-9, 10-19, 20+ years).[32] Potential experience are calculated as Min{age–years of schooling–6, age–16} following Autor et al. (2008). 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 the high-skill labor class consists of college or college-plus workers and the workers with some college; and the low-skill labor class consists of those who have no college education. Groups within a class 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. Standard in this literature is the assumption that relative wages equal relative efficiencies of labor. More specifically, following Autor et al. (2008), we choose the group that contains male workers with less 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 earning of the base group. The relative efficiency index measure for each group, q_g, is computed as the arithmetic mean of the relative wage measures in that group over 1977 to 2009. Then the total efficiency-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 used in production by group g in year t.

Since H and L are efficiency-adjusted labor inputs, the corresponding earnings W_H and W_L in equation (5) are also efficiency-adjusted. Following Krusell et al. (2000), they are calculated as

$$\mathrm{w}_{Ht} = \sum_{g \in G_H} w_{gt} N_{gt} / H_t, \qquad \mathrm{w}_{Lt} = \sum_{g \in G_L} w_{gt} N_{gt} / L_t,$$

data across years, the classification proposed by Jaeger (1997) is followed.

[32]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.

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, for each state, the total weeks for each group are normalized by the sum of total weeks worked over all groups so that weeks for each group in each year are expressed as a fraction of total annual weeks (i.e., $n_{gt} = N_{gt}/\sum_g N_{gt}$). 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 given by

$$\mathrm{w}_{Ht} = \sum_{g \in G_H} n_g w_{gt} / \sum_{g \in G_H} n_g, \qquad \mathrm{w}_{Lt} = \sum_{g \in G_L} n_g w_{gt} / \sum_{g \in G_L} n_g.$$

A.2 Industry-State Level Analysis

Construction of the key variables at industrial level follows the same steps. In each state, we divide industries in three groups: manufacturing, service, and other (agriculture + mining + construction). Annual data in each industry in each state are divided into 8 distinct groups characterized by 2 sexes and 4 education categories ($E \leqslant 11$, $E = 12$, $13 \leqslant E \leqslant 15$, and $E \geqslant 16$). 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 less-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 and with less than 10 years of potential experience as the base group.

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