Crime and the Minimum Wage

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July 2, 2012

Abstract

A wave of recent research has demonstrated that changing minimum wages disproportionately influences the labor market prospects of youth and minorities. Models incorporating a search framework have proven useful in interpreting evidence on minimum wage effects. We examine whether standard insights from a two-sector labor market model are born out when the sectors considered are licit and illicit work. We show, using rich data on crime patterns among youth in the United States, that recent increases in the minimum wage had the unintended consequence of increasing a variety of crime rates. Results from the state level are concentrated among male teenagers and young adults. We find a one-percent increase in the minimum wage increases juvenile drug crime by 1.4-2.8%, property crime by 1.8-2.3%, and violent crime by 2.1-2.4%. Violent crime increases were concentrated among crimes with a clear monetary reward.

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1 Introduction

Could raising the minimum wage have the unintended effect of increasing crime? Competitive labor models predict that increases in the minimum wage, as a price floor for wage labor, will cause an increase in unemployment. Recent empirical evidence has shown that this net employment effect may be small or insignificant (see Neumark and Wascher (2006)), however there are disparate effects along the distribution of unskilled and skilled workers (see Ahn, Arcidiacono and Wessels (2011) and Burkhauser, Couch and Wittenburg (2000)). The question then arises: who is displaced from the labor market when the minimum wage rises, and what alternatives to wage labor do they face? Criminologists have long pointed toward a lack of employment opportunity as a key determinant of crime.[1]

The minimum wage is largely viewed by policy makers as an instrument for helping the working poor of society. Arguments for increasing the minimum wage as aid to low-income workers are bolstered by the recent debate in the "new economics of the minimum wage" that questions whether raising the minimum wage causes unemployment. If, however, the small net employment effects of changes in the minimum wage mask larger movements in and out of employment by workers of different skill levels, then the unintended consequences of the minimum wage may be worst for the most vulnerable subgroups of the population - those with low levels of education and skills. If increases in the minimum wage result in more crime then the unintended effects are even larger for society than for those initially displaced from work.

This paper brings together three lines of literature in examining whether minimum wage changes increased crime. The first concerns the net employment effects of minimum wage changes. This begins the intuition for the link that we hypothesize between wages, unemployment, and crime.[2] Second, we are informed by research on the distributional effects of

[1]Bushway (2011) conducts a complete literature review of research related to youth employment markets and crime.

[2]The literature of the "new economics of the minimum wage" debates the neoclassical result that minimum wage increases will cause a rise in unemployment. Neumark and Wascher (2006) provide a comprehensive review of this literature.

minimum wages as to whether certain subgroups of the labor market (e.g. unskilled youth) are disproportionately affected by minimum wage changes.[3] This motivates our interest in whether the minimum wage causes unemployment of workers who may be more likely to participate in crime as an alternative to the wage market. Lastly, recent literature exposing a positive relationship between unemployment and crime brings us to the bridge between the markets for wage and criminal labor.[4] Taken together, these areas of research provide a compelling motivation to examine the link between minimum wages and youth arrest rates.[5]

In this paper we use detailed crime data from the National Incident Based Reporting System (NIBRS) from 1994-2008 to look at the effect of plausibly exogenous minimum wage changes on criminal incidents (as opposed to arrests). The data contain detailed records of the crime committed and offender characteristics. Using state-level variation in the minimum wage we estimate the impact of changes in the minimum wage on age-specific crime rates for blacks and whites in the United States. Further disaggregating the data, we argue violent crime may provide a placebo test, and show that indeed the effects estimated appear concentrated among crimes which generate income.

Our estimates provide substantial evidence that recent minimum wage increases had the unintended effect of increasing crime rates among young men. The age profile of the results and the heterogeneous patterns across types of crime point toward a causal effect on employment through the displacement of youth. We anticipate increase in income producing crimes, as well as vandalism and crimes that may be the result of youth idleness.[6] The

[3]Burkhauser, Couch and Wittenburg (2000) show that minimum wages both reduce overall teen and young adult employment and have the strongest effect on teenagers, black young adults and teens, and young adults with low levels of education. Ahn, Arcidiacono and Wessels (2011) find that despite small changes in overall employment, teenagers from more well-educated families saw their employment probabilities increase with the minimum wage while their less-privileged counterparts saw a decline.

[4]Raphael and Winter-Ember (2001) estimate a significant and positive impact of state unemployment rates on property crime rates from 1971 to 1997. Gould, Weinberg and Mustard (2002) find that young, unskilled men are responsive to changes in employment conditions, with wages playing a stronger role than unemployment in crime trends.

[5]Both Hashimoto (1987) and Chressanthis and Grimes (1990) used national time-series variation in minimum wages and found higher minimum wages were correlated with higher crime. Hansen and Machin (2002) find the opposite conclusion using time-series variation in the UK.

[6]Neumark and Wascher (1995) show minimum wage increases lead to an increase in youth “idleness” those both unemployed and un-enrolled using CPS data.

estimated effects are sizable: the effect of a 1% increase in the minimum wage is between a 1.7% and 2.4% increase in the cohort-specific property crime rate; drug crime saw similar percent changes, between 1.4 and 2.5%. Although these magnitudes are large, they are plausible given that Lin (2008) finds an property crime elasticity of 4% with respect to the unemployment rate. We generally find larger elasticities of black crime with respect to the minimum wage as well.

Our results have implications for policy regarding both the low-wage labor market and criminal activity. The findings raise the hope of using policies that encourage employment to reduce crime in the short and long term, given that current market work both decreases current criminal work and raises the opportunity costs of future crime. They also point toward the short and long-term dangers of policies which increase unemployment among those on the margin of licit and illicit work. Regardless of overall net-employment effects, it appears minimum wage increases also increase crime. Given the contemporaneous costs of crime and especially the long-term consequences (generating "criminal" human capital, future arrests and recidivism), minimum wages as a policy for fighting poverty appear unattractive.

The paper proceeds to outline a simple model of a labor market with two sectors in Section 2 and the data in Section 3. Sections 4 and 5 present our identification strategy and our results, respectively. Section 6 offers some final thoughts.

2 Theoretical Background

Two important literatures on the labor market intersect when trying to understand how criminal activity may be influenced by minimum wage laws: search theory and human capital theory. Given the focus in the minimum wage literature on the displacement of younger workers from employment, analysis of how the minimum wage influences human capital and ultimately crime decisions is complicated by formal schooling choices. Lochner (2004) provides a life-cycle model of crime and human capital accumulation whose predictions are borne out by the life-cycle crime data. He shows that as human capital accumulates (via age and education), the direct opportunity costs of time discourages crime, and indirectly the prospect of prison and a lack of returns to the human capital stock also discourage crime.[7] Neumark and Wascher (1995) points out that minimum wage increases induce youth in school to seek employment, and those employed to become "idle"(not working or receiving formal training); Ahn, Arcidiacono and Wessels (2011) make a similar point within a two sided matching model. If minimum wages change the skill mix of the employed, it will reduce human capital levels for those left unemployed, generating an increased incentive for crime.

We focus on a simple search setting where all human capital is determined prior to entering the labor market: the choice of whether to search for licit or illicit employment is governed by wages and offers. Consider an agent exclusively deciding between searching for criminal (c) or non-criminal (nc) minimum-wage employment. In an expected utility frame work the agent looks for criminal work if:[8]

$$P_c \times W_c > P_{nc} \times W_{nc} + (1 - P_{nc}) \times b, \tag{1}$$

where P_c, P_{nc} are the offer probabilities, W_c, W_{nc} are the net wages received in each sector, b are potential unemployment benefits and we have normalized returns to not working in the crime-sector to zero. Wages and offers are functions of the minimum wage and human capital. A change in the minimum wage increases the marginal individuals' incentives for crime if:

$$\underbrace{\frac{\partial P_c}{\partial \underline{w}}}_{(\leq 0)} W_c + \underbrace{\frac{\partial W_c}{\partial \underline{w}}}_{(\leq 0)} P_c > \underbrace{\frac{\partial P_{nc}}{\partial \underline{w}}}_{(\leq 0)} (W_{nc} - b) + \underbrace{\frac{\partial W_{nc}}{\partial \underline{w}}}_{(>0)} P_{nc}, \tag{2}$$

where $\underline{w}$ is the minimum wage.[9] In this setup, the left-hand side derivatives represent equilibrium effects in the crime market from an influx of criminal labor. Both $\partial P_c / \partial \underline{w}$ and

[7] As Lochner (2004) addresses, this result need not hold for white collar crime.

[8] A more complete search model, including human capital investment choices, is developed by Huang, Laing and Wang (2004).

[9] We assume $b < W_{nc}$.

$\partial W_c/\partial \underline{w}$ are negative if labor supply moves to the criminal sector but firms' labor demand does not completely offset the labor supply shift; the derivative is zero if there is no effect, or a criminal labor demand effect which offsets the labor supply response of workers. For crime to increase we need (1) the minimum wage increase ($\partial W_{nc}/\partial \underline{w}$) to be small enough that individuals do not queue for jobs in the non-criminal sector (see Harris and Todaro (1970)), and (2) for the minimum wage increases' negative employment effects ($\partial P_{nc}/\partial \underline{w}$) to dominate any possible crime-market equilibrium effects.

We expect differential effects for blacks and whites for at least three reasons. Firstly, young black men have lower human capital levels than their white counterparts: on average they obtain less formal schooling and have worse labor market experiences (longer and more frequent unemployment spells and consequently less experience).[10] This means on average the opportunity costs of crime are lower for blacks; in the model above the human-capital gap means the right-hand of (1) is likely to be lower for blacks. Secondly, blacks on average work more frequently at the minimum wage and the negative employment effect ($\partial P_{nc}/\partial \underline{w}$) should therefore be larger. Finally, if blacks experience discrimination in the non-criminal labor market then P_{nc} and W_{nc} may be lower for blacks, further decreasing the opportunity costs of crime.

3 Data

We bring data together from a number of sources, most notably the National Incident Based Reporting System (NIBRS), which catalogs crimes committed, as opposed to arrests or incarcerations, and importantly provides demographic information on the assailants. We also combine data on labor market and population demographics at the state and county

[10]The Current Population Survey found that in 2011 blacks had longer unemployment spells than whites and Hispanics, with a median duration of unemployment of 27.0 weeks (compared to 19.7 for Whites and 18.5 for Hispanics). In 2010, 16 percent of blacks 25 years or older were un-credentialed school dropouts, compared to 7.9 percent of White non-Hispanics. Blacks were more likely to hold a high school diploma or GED as their highest degree relative to Whites (35.2 percent vs. 31.7 percent), and held fewer college and advanced degrees.

levels from the Current Population Survey (CPS) and the U.S. Census.

The National Incident Based Reporting System, part of the Uniform Crime Reporting (UCR) Program, provides national crime data as submitted by law enforcement agencies at the city, county, state, and Federal level. All incidents known to law enforcement are reported through the system, providing data on the nature and types of offenses involved in the incident, demographic information on the victim(s) and offender(s), types and values of property involved, and demographic data on individuals arrested in relation to the incident. This level of detail allows us to focus on property and drug offenses and male offenders of certain age and race characteristics. A key advantage of the NIBRS is also that the data includes all reported crimes, therefore our measure of crime is not dependent upon police or judicial action (as arrest or incarceration data would be), and non-violent crimes are not superseded by violent crimes.[11]

Although first approved at a national UCR conference in 1988, the NIBRS has gradually been adopted by agencies across the nation. As of 2007, 6,444 law enforcement agencies contributed to the NIBRS data, representing 25% of the national population and 25% of the crime statistics reported through the (national) UCR Program. Because participation in the NIBRS occurs at the law enforcement agency level, if a state or county does not have full participation from all agencies then the crime data may not be representative of the true crime rates for the area. For this reason, we include both weighted an unweighted analyses of crime rates below.[12] Here, we aggregate individual property and drug crime incidents to the state level.[13]

Comparing to UCR crime rates is difficult since the two series generally report different crimes. The UCR may also under-report crimes: only the most serious crime of multi-offense

[11] The older and more widely participated in UCR series of data under counts non-violent crime by reporting the most "serious"(e.g. violent) offense when multiple offenses occurred.

[12] Weights are the fraction of the overall state population covered by a geographic police reporting agency participating in NIBRS.

[13] Each incident reports up to three offenses. An incident is considered a property (drug) offense if any property (drug) offense is listed in the incident record. State aggregations are performed in a straightforward manner by summing property and drug crime counts by the state affiliation of reporting agencies.

incidents is reported. A Congressional Research Service Report (James and Council (2008)) was published in 2008 outlining the major reporting differences between UCR and NIBRS data. Murder results across the two sources are identical, but generally UCR under-reporting becomes more evident as less violent crimes are compared. To deal with the fact that certain state-years have crime rates clearly below those of the UCR, we trim our crime rates at the fifth percentile. For most data this generated series with plausible lower bounds for each age and race-specific crime rate.[14]

Table 1 presents a comparison of the NIBRS and UCR rates observed in state-years used in the analysis below, for both black and white juveniles. Splitting by type of offense we can see the drug crime rates are very similar after our trimming procedure is applied. It is also the case that the types of drug crimes reported in the two series are virtually identical (James and Council (2008)), while for both property and violent crimes we expect different means given the counting methods. NIBRS data record more crimes (the means are significantly larger), and because they are less violent these crimes are more likely to be influenced by changes in the minimum wage. We proceed with our analysis on NIBRS data mainly because it allows us to disaggregate by gender, race and age of the offender.

We also add other data to the analysis using bridged-race intercensal population estimates to account for state demographic makeup, as well as calculate NIBRS coverage rates.[15] We collect the demographic counts of state residents by age, race and gender. To control for the labor conditions at the state or county level, we compile data from the May CPS of each year in our study's time frame; we also include data from the Statistical Abstract of the U.S. on school enrollment, income, and poverty. Minimum wage data are compiled from the Council of State Governments and the U.S. Department of Labor's Office of State Standards Programs Wage and Hour Division and adjusted to 2010 dollars. We find the binding

[14]Trimming at higher and lower percentiles provide similar results.

[15]These estimates are calculated by the National Center for Health Statistics based on the 1990 and 2000 decennial census counts by "bridging" the Census 2000 race categories into the four standard race categories under 1977 standards (Asian/Pacific Islander, Black/African American, American Indian/Alaska Native, and White).

minimum wage in a given state year as the maximum of the state and federal minimum wage.[16] Finally we include relevant policy changes like marijuana decriminalization.

In Table 2 we regress an indicator for a minimum wage increase on 1-year lagged crime rates. Each entry comes from a separate regression. The major concern in this setting is that either crime itself enters into policy makers decisions to increase the minimum wage, or more likely, that minimum wage changes are correlated with other policies related to crime such as state-level policing or sentencing reforms.[17] At least at the one-year lag, including all of our controls and state and year fixed effects, we find no evidence for a correlation of this sort. We proceed to use the state-time variation commonly employed in efforts to identify the effect of minimum wage on employment in our setting.

4 Empirical Strategy

To address the question of whether increases in the minimum wage have increased crime rates we exploit state-time variation in the minimum wage laws as many other author's before us have done.[18] Given the data outlined above we estimate a basic linear specification of the form:

$$\log(CR^c_{st}) = \beta^c_0 + \beta^c_1 \log(MinWage_{st}) + X^{'}_{st}\beta^c_2 + \gamma^c_s + \alpha^c_t + \varepsilon^c_{st}, \tag{3}$$

where s denotes state, t year, c cohort and $X^{'}_{st}$ captures other controls included in the regression, including population, education, income, and policy changes like marijuana decriminalization. We include cohort-by-state specific unobservables γ^c_s and year effects α^c_t in each cohort regression, so as to identify minimum wage effects from changes within a given state over time. Standard errors for this specification are clustered at the state level and estimation is run separately.

[16] We use log wages in our estimation, following the recent minimum wage-employment literature.

[17] For most major urban areas policing decisions are not made at the state level and so the argument that unobserved policing moves with the minimum wage seems unlikely.

[18] See Neumark and Wascher (2008) for a thorough review of the literature on identifying minimum wage effects using policy variation.

5 Results

We first outline our basic estimates, then proceed through a series of robustness checks and falsification exercises, and examine heterogeneity in the effects of minimum wages on crime.

5.1 Baseline Results

Table 3 reports the coefficients of the log-minimum wage from a series of cohort-specific crime rate regressions. The regressions use state-years for which we have available NIBRS coverage, and include state fixed-effects to deal with both geographic variation in minimum wages and the slow adoption by some states to NIBRS reporting. The first two columns show that increases in the minimum wage increased both drug and property crimes, with the largest property crime-effects coming for juveniles and drug-crime effects for those offenders aged 20-24. The next two sets of columns in the upper panel break out the results by race of the offender. The minimum wage-crime elasticity is generally larger for blacks, except for drug crimes committed by white men in their late 20s, which is more sensitive to the minimum wage, although the difference here is not significant. We also find significant effects for youth aged 10 to 14: namely we find significant effects for black drug crime and white property crime in these age bands. Since these teens cannot usually work in the labor market, this appears to be evidence that crime-spillovers from the affected age groups are driving these effects. We return to spillovers below when disaggregating the crime data.

The lower panel of Table 3 deals with the less-than-complete adoption of the NIBRS data across the country. We weight state-years in these regressions by the fraction of the state population living in areas which participated in the NIBRS program. The results look largely similar to those in the upper-panel with uniformly larger effects for black property and drug crime rates. Under the weighted results we find small or insignificant results for teens aged 10-14, with the exception of black drug crime. A concern with the evidence is that our estimates may not be picking up a behavioral response by those on the margin between licit and illicit work, but rather a state specific trend driving both the minimum wage and crime. A time varying unobservable, like changes criminal sentencing, should covary with adolescent crimes as well. These results are suggestive that the channel for these increases in crime is the low-skill labor market.[19]

In addition to the population controls included thus far, we add a vector of time varying observables at the state level to test whether underlying trends in education, unemployment, income, or criminal statutes are co-varying with changes in the minimum wage laws. Table 4 presents the baseline un-weighted results from Table 3, along with estimates including the vector of controls, with the footnote listing the full vector of controls. For blacks at younger ages (teenagers), the wage-crime elasticities shrink slightly but maintain the same pattern of significance. For whites, the results also look very similar but we note the standard errors in these regressions are considerably bigger (e.g. generating a lack of statistical significance for white drug crime rates between 15 and 19). This suggests these controls do influence the state-time variation in crime rates, but do not have a meaningful effect on the coefficients of interest. In their own right, income per-capita and the male unemployment rate were correlated with crime rates.[20] The decriminalization of marijuana had large negative effects on the crime rates of both blacks and whites as well.

Next we test whether a similar pattern can be detected among women. The results are presented in Table 5. We find positive coefficients for all crime rates, but none are significant at the 5% level. Furthermore controlling for the vector of other state level observables dramatically reduces the point estimates for female crime rates. These results may not be surprising given the much lower crime rates for women relative to men, and the higher levels of completed schooling for women over the period our sample covers. The lack of a finding is suggestive that female search for or willingness to engage in criminal behavior is substantially

[19] Age groups not participating in the labor market may not be a good control group if spillovers in crime occur across the age groups.

[20] If we could accurately measure the age-by-race specific unemployment rate across states and time, we expect the minimum wage coefficient to decrease significantly. We see small decreases when including overall unemployment.

lower than that of males, since the monetary rewards for drug and property crime do not appear at face value to be different for men and women.

5.2 Violent and Disaggregated Crime Rates

We now disaggregate crime-rates to present a possible placebo test, exploiting the in-depth nature of reporting provided in the NIBRS data. Certain types of crime, particularly crime with no monetary gain, are much less likely to see increases if the minimum wage represent a binding constraint in the licit labor market. Also, if we were picking up an overall trend in either crime, policing policies or the justice system that were systematically related to the minimum wage, we would expect *a priori* that it should influence all crimes, not just those with a profit motive. First we test whether violent crime incidence increases in response to minimum wage changes. We then disaggregate the violent crime data further. In principle violent crime may itself offer monetary rewards but also may be an externality or spillover from gang or drug dealing-related interactions.

Violent crime results are presented for teenagers between the ages of 15 and 19 in Table 6. The first three rows present prior results and show that violent crime did increase following the increases in minimum wages. Violent crime rates for blacks are more sensitive to the inclusion of our vector of controls, but the increases for whites from minimum wage increases appear robust. The middle-panel of Table 6 splits violent crime into its constituent crime series. The sub-series most frequently related to minimum wages are those related to monetary crime, (e.g. auto-theft or armed robbery). Because crime incidents in NIBRS can have multiple crimes reported in the same incident, we further disaggregate the violent assaults in the lower panel of Table 6. Each crime rate is calculated by summing over the indicator of whether all reported crime incidents in a given year and state were categorized as belonging to that crime series. This means the series are not mutually exclusive. Conditioning on a violent assault occurring, we examine the crime rates separately if the violent assault was also reported with either a drug-, monetary-, or sex-related crime. Among violent assaults we again find significant evidence that crimes with a monetary reward increased following an increase in the minimum wage. The results indicate, for example, increases in both general vehicle thefts and those where the assailant attacked the driver/owner. For homicide we find no effects, and for drug related violent crime we also find smaller or insignificant effects. These results point toward the minimum wage driving these estimates, rather than concurrent sentencing or policy changes.

Next we disaggregate property crime rates in Table 7. The major dimensions we group the data into are: motor vehicle theft (denoted MV), stolen property offenses (e.g. shop-lifting), property destruction (e.g. arson, vandalism), building theft (e.g. burglary), and extortion.[21] The upper panel presents combined black and white results. Vandalism is concentrated among teenagers, consistent with other researchers finding that increasing minimum wages increased idleness;[22] splitting results for blacks and whites shows that increases in vandalism is further concentrated among white teenagers. Shop-lifting increases for all ages, and motor vehicle theft increases are concentrated among older individuals. Effects appear larger for blacks in both categories. Burglary also increases for both blacks and whites. Although extortion makes up a very small percent of property crime, it sees no influence from minimum wage changes.

Finally in Table 8 we disaggregate drug crimes. The NIBRS data allow us to split drug crimes into only two groups: drug/narcotic and drug-equipment violations. While drug/narcotic crimes may be both use and sale, drug equipment offenses involving "drug paraphernalia, equipment, chemicals, illegal labs, etc," these offenses are tied to the production of illegal drugs, like methamphetamines, which require a capital-stock to produce. In the combined black and white estimates, we see a large part of the minimum wage effect is concentrated among an increase in equipment violations. The equipment violation-elasticity

[21] We label to groups by the most common offense, but each group counts crimes under that heading. Shop-lifting includes: Pocket-picking, Purse-snatching, Theft From Coin-Operated Machine or Device and Stolen Property Offenses. Burglary also includes: Theft From Building and Breaking and Entering. Motor Vehicle theft also includes: Theft From Motor Vehicle, Theft of Motor Vehicle Parts/Accessories and All Other Larceny.

[22] Neumark and Wascher (1995)

with respect to the minimum also appears larger for older offenders. Retail and usage violations under Drug/Narcotic are concentrated among teenagers. Conditioning on black and white separately, we see the strength of the age pattern in equipment violations is even more severe for blacks, with a corresponding increase in retail and usage violations among black teenagers and those in their early 20s. These patterns are consistent with black males being constrained in their ability to begin or join a drug-production operation until older ages (perhaps because of the types drugs or geography of drug-markets), and they are therefore substituting toward retail sale of drugs at younger ages. White drug equipment violations meanwhile increase for younger ages. Although we cannot disaggregate by type of drug here, this pattern would be consistent with more whites entering methamphetamine production, which has lower fixed costs of production given the availability of ingredients (see Juozapavicius (2009)). Additionally we find consistently positive effects among those aged 10 to 14 for Drug/Narcotic incidents. These results were also present in Table 3, and suggest drug crime increases among this group could be the result of peer influence from increases in drug use among young teenagers.

6 Conclusion

Did the raising the minimum wage increase crime in the United States over the past 20 years? The evidence we present points toward a definite yes. Examining the available evidence with the NIBRS data provides a clear picture that both black and white male crime rates, across a host of different crimes, drug, property and violent, increased in states following increases in the minimum wage. These results dovetail with recent research on the minimum wage's effects on young males with low levels of skills which shows, despite a lack of net effects on employment, that these individuals disproportionately bear the costs of seeing decreased employment options. A natural question is whether this same group turns to criminal activity in the absence of opportunities in the labor market? While we find evidence that some of the crime rate increases are coming through idleness, most of the crime rates which increased had clear profit motives such as drug production, the joint occurrence of assault with burglary, and shop-lifting. Crimes without profit motives, like extortion and murder saw no corresponding increase. A back-of-the-envelope calculation of the effect of the minimum wage on crime through the unemployment channel corroborates our estimates. Multiplying the 4% unemployment rate elasticity of crime from Lin (2008) with the 0.27 to 0.43 minimum wage elasticity of teen employment estimated by Sabia (2006)[23], we anticipate crime rates to respond to a 1% increase in the minimum wage with a 1.08% to 1.72% increase. Our elasticity estimate for combined black and white property crime is 1.95%: statistically we cannot reject that this estimate falls within the predicted window.

These results highlight the importance of providing employment opportunities for young unskilled-youth given the evidence for a substitution between licit and illicit work. They also point to the dangers to the individual, and society, of encouraging policies which restrict the already limited employment options of this group. The social costs to raising the minimum wage may not appear in net employment or unemployment changes, but nonetheless appear non-trivial.

References

Ahn, Tom, Peter Arcidiacono, and Walter Wessels, "The Distributional Impacts of Minimum Wage Increases When Both Labor Supply and Labor Demand Are Endogenous," *Journal of Business & Economic Statistics*, 2011, *29* (1), 12–23.

Burkhauser, Richard V., Kenneth A. Couch, and David C. Wittenburg, "Who Minimum Wage Increases Bite: An Analysis Using Monthly Data from the SIPP and the CPS," *Southern Economic Journal*, July 2000, *67* (1), 16–40.

[23] Sabia (2006) estimates the employment elasticity of teenagers in the retail industry using a state panel of years from 1979-2004. These estimates are most relevant to the time window that we study in this paper.

Bushway, Shawn D., "Labor Markets and Crime," in Joan Petersilia and James Q. Wilson, eds., *Crime and Public Policy*, New York, NY: Oxford University Press, 2011, chapter 7, pp. 183–209.

Chressanthis, George A. and Paul W. Grimes, "Criminal Behavior and Youth in the Labour Market: The Case of the Pernicious Minimum Wage," *Applied Economics*, 1990, *22* (11), 1495–1508.

Gould, Eric D., Bruce A. Weinberg, and David B. Mustard, "Crime Rates And Local Labor Market Opportunities In The United States: 1979-1997," *The Review of Economics and Statistics*, February 2002, *84* (1), 45–61.

Hansen, Kirstine and Stephen J. Machin, "Spatial Crime Patterns and the Introduction of the UK Minimum Wage," *Oxford Bulletin of Economics and Statistics*, August 2002, *64*, 677–697.

Harris, John R. and Michael P. Todaro, "Migration, Unemployment and Development: A Two-Sector Analysis," *The American Economic Review*, 1970, *60* (1), pp. 126–142.

Hashimoto, Masanori, "The Minimum Wage and Youth Crimes: Time-Series Evidence," *Journal of Law Economics*, 1987, *30* (2), 443–64.

Huang, Chien-Chieh, Derek Laing, and Ping Wang, "Crime and Poverty: A Search-Theoretic Approach," *International Economic Review*, 2004, *45* (3), pp. 909–938.

James, Nathan and Logan Rishard Council, "How Crime in the United States Is Measured," Report for Congress RL34309, Congressional Research Service January 2008.

Juozapavicius, Justin, "New Do-It-Yourself Meth Formula Flys Under The Radar Of Anti-Drug Laws," *Huffington Post*, August 2009.

Lin, Ming-Jen, "Does Unemployment Increase Crime?: Evidence from U.S. Data 19742000," *Journal of Human Resources*, 2008, *43* (2), 413–436.

Lochner, Lance, “Education, Work, And Crime: A Human Capital Approach,” *International Economic Review*, 08 2004, *45* (3), 811–843.

Neumark, David and William L. Wascher, *Minimum Wages*, MIT Press, 2008.

_ **and William Wascher**, “The Effects of Minimum Wages on Teenage Employment and Enrollment: Evidence from Matched CPS Surveys,” NBER Working Papers 5092, National Bureau of Economic Research, Inc April 1995.

_ **and** _ , “Minimum Wages and Employment: A Review of Evidence from the New Minimum Wage Research,” Working Paper 12663, National Bureau of Economic Research November 2006.

Raphael, Steven and Rudolf Winter-Ember, “Identifying the Effect of Unemployment on Crime,” *Journal of Law and Economics*, April 2001, *44* (1), 259–83.

Sabia, Joseph J., “The Effect of Minimum Wage Increases on Retail and Small Businesses,” Technical Report, Employment Policies Institute 2006.

Tables and Figures

Table 1: Crime Rates Comparison[a]

Blacks Age < 18	NIBRS	UCR	Difference
Drug	0.0066	0.0070	-0.0003
N=303	(0.0009)	(0.0006)	
Property	0.0426	0.0328	0.0099***
N=312	(0.0066)	(0.0042)	
Violent	0.0269	0.0189	0.0080***
N=325	0.0041	0.0020	
Whites Age < 18			
Drug	0.0037	0.0039	-0.0003
N=303	(0.0001)	(0.0004)	
Property	0.0184	0.0146	0.0038*
N=312	(0.0008)	(0.0017)	
Violent	0.0084	0.0060	0.0024***
N=325	(0.0004)	(0.0006)	

[a]Each entry is a mean estimate for the set of state-years used in the analysis below.

Table 2: Predicting Minimum Wage Changes with Crime[a]

	Age Group		
Crime Rate	15-19	20-24	25-29
Black Property	-0.023	-0.020	-0.038
	(0.024)	(0.030)	(0.031)
Black Drug	-0.039	-0.032	-0.011
	(0.032)	(0.033)	(0.030)
White Property	-0.017	-0.021	-0.014
	(0.024)	(0.031)	(0.029)
White Drug	-0.037	-0.031	-0.048
	(0.032)	(0.032)	(0.033)

[a]Each entry is a coefficient from an LPM of a policy change on the crime rate one year earlier.

Table 3: Response of Crime Rates to Minimum Wages[a]

	Crime Rates					
	Black and White		Black		White	
Log Crime Rate:	Property	Drug	Property	Drug	Property	Drug
Age 10-14	1.112	1.146*	1.832	1.733*	1.387*	1.081
	(0.563)	(0.486)	(0.924)	(0.654)	(0.619)	(0.548)
Age 15-19	1.947*	1.459*	2.347*	2.763**	1.783*	1.384*
	(0.818)	(0.546)	(0.923)	(0.947)	(0.840)	0.619
Age 20-24	1.147*	1.938*	2.676*	2.992**	1.004	2.000
	(0.569)	(0.965)	(1.037)	(1.049)	(0.605)	(1.064)
Age 25-29	1.381*	1.333*	2.912*	1.651	1.974**	2.140**
	(0.661)	(0.552)	(1.129)	(0.998)	(0.692)	(0.720)
	Weighted by Reporting Coverage					
	Black and White		Black		White	
Log Crime Rate:	Property	Drug	Property	Drug	Property	Drug
Age 10-14	0.565	0.963	1.164	1.154 *	0.726	0.705
	(0.511)	0.492	(0.612)	(0.515)	(0.513)	(0.548)
Age 15-19	0.616	0.767	2.070**	3.046***	0.682	0.646
	(0.473)	(0.506)	(0.586)	(0.631)	(0.457)	0.548
Age 20-24	1.025	2.555*	2.795 *	3.306**	0.943	2.811*
	(0.729)	(1.047)	(1.063)	(1.028)	(0.721)	(1.157)
Age 25-29	1.502*	1.232*	3.184 *	2.094**	1.575*	1.504*
	(0.725)	(0.530)	(1.193)	(0.597)	(0.695)	0.567
Controls						
Population	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

[a]Each entry is a separate regression coefficient on the log-deflated minimum wage. Observations are state-years, standard errors are in parenthesis and clustered at the state level. Population controls are third order polynomials of total, black, white, Hispanic and non-black teen population, and linear cohort-specific population. NIBRS coverage is the fraction of the county population covered by NIBRS reporting.

Table 4: Including Other Controls[a]

	Black Crime Rates			
	Baseline		With Controls	
Log Crime Rate:	Property	Drug	Property	Drug
Age 10-14	1.832	1.733*	1.905	1.845*
	(0.924)	(0.654)	(0.948)	(0.678)
Age 15-19	2.347*	2.763**	2.216*	2.465*
	(0.923)	(0.947)	(0.915)	(1.079)
Age 20-24	2.676*	2.992**	2.281*	2.998**
	(1.037)	(1.049)	(1.110)	(1.097)
Age 25-29	2.912*	1.651	2.846*	1.628
	(1.129)	(0.998)	(1.030)	(1.136)
	White Crime Rates			
	Baseline		With Controls	
Log Crime Rate:	Property	Drug	Property	Drug
Age 10-14	1.387*	1.081	1.451	1.497
	(0.619)	(0.548)	(0.782)	(0.801)
Age 15-19	1.783*	1.384*	1.862*	1.403
	(0.840)	0.619	(0.865)	(0.775)
Age 20-24	1.004	2.000	1.152	2.201
	(0.605)	(1.064)	(0.723)	(1.147)
Age 25-29	1.974**	2.140**	1.898*	2.150*
	(0.692)	(0.720)	(0.774)	(0.846)
Controls				
Population	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Decriminalized	no	no	yes	yes
Unemployment	no	no	yes	yes
Education	no	no	yes	yes

[a]Each entry is a separate regression coefficient on the log-deflated minimum wage. Observations are state-years, standard errors are in parenthesis and clustered at the state level. Population controls are third order polynomials of total, black, white, Hispanic and non-black teen population, and linear cohort-specific population. Regressions "with controls" include fraction of the population living in metro areas, state enrollment, male and female unemployment, fraction below the poverty line, income per capita and decriminalized or medical marijuana indicators.

Table 5: Female Crime Rates[a]

	Black Crime Rates			
	Baseline		With Controls	
Log Crime Rate:	Property	Drug	Property	Drug
Age 10-14	-0.067	0.075	-0.004	0.156
	0.679	(0.911)	(0.604)	(0.742)
Age 15-19	0.806	0.717	0.331	0.600
	(0.675)	(0.663)	(0.824)	(0.650)
Age 20-24	1.049	1.249	0.961	0.985
	(0.695)	(0.880)	(0.738)	(0.768)
Age 25-29	1.593	0.583	1.412	0.26
	(0.889)	(0.706)	(0.858)	(0.604)
	White Crime Rates			
	Baseline		With Controls	
Log Crime Rate:	Property	Drug	Property	Drug
Age 10-14	1.276	-0.254	1.013	0.105
	(0.639)	(0.485)	(0.635)	(0.632)
Age 15-19	0.822	0.794	0.497	0.316
	(0.657)	(0.780)	(0.771)	(0.797)
Age 20-24	1.139	1.011	0.604	0.631
	(0.745)	(0.754)	(0.817)	(0.928)
Age 25-29	1.445	1.255	1.069	0.712
	(0.771)	(0.714)	(0.873)	(0.742)
Controls				
Population	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Decriminalized	no	no	yes	yes
Unemployment	no	no	yes	yes
Education	no	no	yes	yes

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Table 6: Including Violent Crime Rates[a]

	Baseline		With Controls	
Log Crime Rate:	Black	White	Black	White
Property	2.347*	1.783*	2.465*	1.862*
	(0.923)	(0.840)	(1.079)	(0.865)
Drug	2.763**	1.384 *	2.216*	1.403
	(0.947)	(0.619)	(0.915)	(0.775)
Violent-Overall	2.410*	2.155*	2.062	2.131*
	(1.142)	(0.878)	(1.175)	(0.904)
Violent Disaggregated				
Violent-Drug Related	0.573	0.390	0.938	0.696*
	(1.200)	(0.323)	(1.084)	(0.281)
Violent-Monetary	1.570	1.121*	1.770*	1.172*
	(0.814)	(0.373)	(0.725)	(0.474)
Violent-Killing	0.410	0.331	0.370	0.246
	(1.292)	(0.812)	(1.368)	(0.782)
Violent-Sex Related	1.328	0.797	1.755	1.078
	(0.923)	(0.514)	(0.874)	(0.534)
Violent-Assault	2.376*	2.058*	2.003	2.053*
	(1.117)	(0.852)	(1.159)	(0.903)
Assaults Disaggregated				
Assault-Drug Related	0.074	0.736	0.420	0.988
	(1.146)	(0.408)	(1.031)	(0.560)
Assault-Money Related	1.634*	1.866*	1.890*	1.574
	(0.799)	(0.768)	(0.738)	(0.873)
Assault-Sex Related	-0.280	1.839	0.821	1.842
	(1.950)	(1.147)	(2.261)	(1.177)
Controls				
Population	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Decriminalized	no	no	yes	yes
Unemployment	no	no	yes	yes
Education	no	no	yes	yes

[a]Each entry is a separate regression coefficient on the log-deflated minimum wage. Observations are state-years, standard errors are in parenthesis and clustered at the state level. Population controls are third order polynomials of total, black, white, Hispanic and non-black teen population, and linear cohort-specific population. Regressions "with controls" include fraction of the population living in metro areas, state enrollment, male and female unemployment, fraction below the poverty line, income per capita and decriminalized or medical marijuana indicators.

Table 7: Disaggregated Property Crimes[a]

	Black and White				
Log Crime Rate:	MV	Shop-Lift	Vandalism	Burglary	Extort
Age 15-19	0.689	1.473	1.261	1.249	-1.804
	(0.891)	(0.805)	(0.763)	(0.756)	(1.136)
Age 15-19	1.633	1.743*	2.011*	2.134*	-0.709
	(0.878)	(0.858)	(0.927)	(0.869)	(1.220)
Age 20-24	1.177	1.750*	1.019	1.577	-1.489
	(0.735)	(0.776)	(0.838)	(1.009)	(1.252)
Age 25-29	1.749*	1.863*	1.587	2.072*	0.826
	(0.799)	(0.985)	(0.854)	(0.744)	(1.133)
	Black				
Log Crime Rate:	MV	Shop-Lift	Vandalism	Burglary	Extort
Age 10-14	1.930*	0.506	1.131	0.853	-2.132
	(0.836)	(0.764)	(1.029)	(0.807)	(2.014)
Age 15-19	1.409	1.650	1.104	1.340	-2.132
	(0.912)	(0.887)	(0.810)	(0.877)	(2.014)
Age 20-24	2.434*	1.404	0.773	2.055	-0.003
	(0.877)	(0.714)	(0.872)	(1.149)	(2.046)
Age 25-29	2.501*	1.936	1.564	2.235*	6.385
	(0.940)	(1.050)	(0.902)	(1.036)	(4.143)
	White				
Log Crime Rate:	MV	Shop-Lift	Vandalism	Burglary	Extort
Age 10-14	0.856	1.527	1.204	1.210	-1.879
	(0.644)	(0.832)	(0.724)	(0.810)	(1.600)
Age 15-19	1.593	1.321	2.050*	2.059*	-1.855
	(0.864)	(0.825)	(0.930)	(0.824)	(1.022)
Age 20-24	1.057	1.238	0.864	1.153	-0.591
	(0.737)	(0.686)	(0.825)	(0.936)	(1.090)
Age 25-29	1.777*	1.365*	1.572	2.114*	0.429
	(0.776)	(0.683)	(0.827)	(0.713)	(1.644)
Fraction of Avg Property Crime Rate	0.313	0.184	0.313	0.210	0.000

[a]Each entry is a separate regression coefficient on the log-deflated minimum wage. Observations are state-years, standard errors are in parenthesis and clustered at the state level. Population controls are third order polynomials of total, black, white, Hispanic and non-black teen population, and linear cohort-specific population. All regressions include fraction of the population living in metro areas, state enrollment, male and female unemployment, fraction below the poverty line, income per capita and decriminalized or medical marijuana indicators.

Table 8: Disaggregated Drug Crimes[a]

	Black and White	
Log Crime Rate:	Drug/Narcotic	Drug Equipment
Age 15-19	1.675*	1.245
	(0.811)	(0.937)
Age 15-19	1.646*	1.938*
	(0.754)	(0.942)
Age 20-24	1.429	2.468*
	(0.729)	(0.997)
Age 25-29	1.603	2.277*
	(0.857)	(1.018)
	Black	
Log Crime Rate:	Drug/Narcotic	Drug Equipment
Age 10-14	1.698*	0.490
	(0.816)	(1.205)
Age 15-19	2.260*	-0.035
	(0.948)	(0.957)
Age 20-24	2.729*	1.851
	(1.068)	(1.031)
Age 25-29	1.550	2.542*
	(1.121)	(1.030)
	White	
Log Crime Rate:	Drug/Narcotic	Drug Equipment
Age 10-14	1.594*	0.729
	(0.765)	(0.982)
Age 15-19	1.507	1.830*
	(0.771)	(0.864)
Age 20-24	1.233	2.111*
	(0.828)	(1.042)
Age 25-29	1.850*	2.334*
	(0.805)	(0.903)
Fraction of Avg Drug Crime Rate	0.698	0.302

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