The Minimum Wage and Crime

Andrew Beauchamp   Stacey Chan
Boston College   Boston College

August 23, 2013

Abstract

Does crime respond to changes in the minimum wage? A growing body of empirical evidence indicates that increases in the minimum wage have a displacement effect on low-skilled workers. Economic reasoning provides the possibility that dis-employment may cause youth to substitute from legal work to crime. However, there is also the countervailing effect of a higher wage raising the opportunity cost of crime for those who remain employed. We use the National Longitudinal Survey of Youth 1997 cohort to measure the effect of increases in the minimum wage on self-reported criminal activity and examine employment-crime substitution. Exploiting changes in state and federal minimum wage laws from 1997 to 2010, we find that workers who are affected by a change in the minimum wage are more likely to commit crime, become idle, and lose employment. Further, there is an increase of property theft among both unemployed and employed individuals, suggesting that reduced employment effects dominate any wage effects. These findings have implications for policy regarding both the low-wage labor market and efforts to deter criminal activity.

1 Introduction

Does raising the minimum wage have the unintended effect of increasing crime? Economic reasoning and the recent literature in the minimum wage lead us to believe that the answer may be yes. If increases in the minimum wage lead to unemployment and idleness, some youth may choose crime as an alternative source of income. Research in "the new economics of the minimum wage" shows that increases in the minimum wage displace lower-skill workers and cause higher levels of unemployment among youth and workers with weak labor attachment.[1] Moreover, increases in the minimum wage raise the probability that teenagers will be idle: they are more likely to leave school and, conditional on not being in school, more likely to be unemployed.[2] Numerous studies have shown that idle youth are more likely to engage in crime, whether because they are not in school or not working.[3]

The existing evidence for the causal relationship between the minimum wage and crime is somewhat limited. Hashimoto (1987) provides national time-series evidence that a positive relationship between the minimum wage and crime does exist in the United States. A limitation, however, of using nationally aggregated data to examine crime is that much of the variation in crime is lost. Additionally, national changes in the minimum wage may not be exogenous with respect to low-skill labor markets and crime-employment trends. We expand on the evidence by using micro-level panel data on the criminal activity of minimum wage workers.

We employ panel data from the National Longitudinal Survey of Youth 1997 (NLSY97) cohort to identify the effect of changes in the minimum wage on participation in crime. We exploit changes in state and federal minimum wage laws between 1997 and 2010. The NLSY97 data allows our study to make several contributions. First, due to the detailed nature of the employment and crime history in the data, we are able to test if movement in or out of crime is due to changes in employment status. Next, the fine level at which the NLSY is collected allows us to control

[1]Neumark and Wascher (2006) conduct a review of studies that examine the employment effect of changes in the minimum wage. See also Currie and Fallick (1996), Ahn et al. (2011), Burkhauser et al. (2000) and Sabia et al. (2012).

[2]Neumark and Wascher (1995) use matched CPS data to study the effect of minimum wages on employment and enrollment decisions of youth. They find that increases in the minimum wage raise the likelihood that lower-skilled teenagers will become unemployed, replaced by higher-skilled teenagers who leave school. They also find an increase in the probability that displaced workers will be not only unemployed but also not enrolled in school.

[3]Jacob and Lefgren (2003) and Luallen (2006) estimate that daily juvenile property crime decreases by 14% and 28.8% on days that students must be in school, respectively. Raphael and Winter-Ember (2001) and Gould et al. (2002a) find that declining labor opportunities cause an increase in crime. In particular, Raphael and Winter-Ember (2001) find that an increase in unemployment causes a rise in property crimes, which are crimes often associated with illicit income.

for individual characteristics and examine many types of crime. Our ability to examine such heterogeneity suggests that our work can be considered a micro-level complement to Hashimoto (1987). Lastly, the data allow us to directly identify individuals who were bound by changes in the minimum wage, rather than approximating the treatment group based on general demographics.[4]

We find compelling evidence that an increase in the minimum wage displaces youth from licit employment and increases criminal activity. Interestingly, both crimes related to monetary gain and violence increase. Our estimates show that workers who are affected by a change in the minimum wage are 1.5 percentage points more likely to be idle and 3.9 percentage points less likely to be employed. The probability of being employed and committing crime increases by 2.1 percentage points (relative to an average probability of 7.3%).

These findings have implications for policy regarding both the low-wage labor market and criminal activity. Our results 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 activity and raises the opportunity costs of future crime.[5] The findings also point toward the short and long-term dangers of policies which increase unemployment, even for short durations, 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 along this dimension.

2 Data

The National Longitudinal Survey of Youth is an ideal data set for studying the effects of the minimum wage on crime because it allows us to identify workers affected by changes in the minimum wage and control for individual-level heterogeneity. The annual survey collects detailed information about youth educational and labor market experiences, as well as family background, relationships, and personal behavior (including criminal behavior).

[4] A similar panel analysis could be performed on state- or county-level crime data, but such an analysis would be unable to capture individual levels of heterogeneity and the ability to identify minimum wage workers.

[5] Raphael and Winter-Ember (2001), Gould et al. (2002b), and Machin and Meghir (2004) demonstrate that criminal activity responds to both employment and wages.

The NLSY97 follows a cohort of nearly 9,000 respondents who were between the ages of 12 to 16 years old as of 1997. The data spans from 1997-2010, during which time there were four increases in the Federal minimum wage and several changes at the state level. We use NLSY97 data linked to confidential state geocoded information to match respondents to the binding minimum wage during each survey wave as in Currie and Fallick (1996). The binding minimum wage in a given state-year is determined by the maximum of the state and federal minimum wage at that time.

We are able to identify individuals affected by changes in the binding minimum wage by observing employment histories and wages. Bound workers are identified by three criteria. First, they must have lived in a state that experienced a change in the minimum wage during the years directly before and after the change. Second, in the year preceding a minimum wage increase, the individual must have been employed in a job where his/her nominal wage was less than the upcoming nominal minimum wage but not less than the current minimum wage. Lastly, the minimum wage job must be in an industry covered by the minimum wage. In our data, we consider jobs reported as agricultural, military, self-employed, or public administration to be uncovered.[6]

In each wave, survey respondents were asked about their participation in criminal activity, including selling illegal drugs and stealing. We are confident in the use of self-reported criminal activity: self reports have been found to be accurate representations of official crime reports (Hindelang, 1981). Further, we do not use arrest data because of the possible endogeneity of policy changes and policing.[7] We denote criminal activity by an indicator that respondents reported having engaged in selling drugs, stealing, vandalism, other property crimes, or violence since the date of their last interview. For respondents who ever report criminal activity, missing values are replaced by zeros under the assumption that any lack of response is due to inactivity.[8]

We also separate crimes by monetary and non-monetary motivation, with money-related crimes being theft, drug sale, and "other property" crimes.[9] Non-monetary crimes are defined as property damage and violent crimes (fighting or attacking with the intent to hurt).

[6]Respondents to the NLSY97 report up to 11 wages in a given survey year. A respondent is considered to be bound by a minimum wage change if at least one of the reported jobs fits the aforementioned criteria. Jobs with reported wages of zero dollars are considered invalid and excluded from the data.

[7]We are unable to make use of national incident-based data, such as National Incident-Based Reporting System data, due to changes in jurisdictional reporting during the time period that we study.

[8]Alternative treatments of missing values did not impact our analysis.

[9]The NLSY questionnaire suggests "other property" crimes as "fencing, receiving, possessing or selling stolen property, or cheat[ing] someone by selling them something that was worthless or worth much less than what [the respondent] said it was."

Table 1 provides summary statistics of employment, wage, and individual characteristics for the full data sample as well as by age. Approximately 60 percent of the individual-year observations have wage information that can be used to assign minimum wage worker status. Of those, approximately 4% are records for individuals in a state and year where they were bound by a minimum wage change. Minimum wage employment is most common at ages 14-19, as is generally known to be the case (Bureau of Labor Statistics, 2011). The crime statistics reflect the usual age-crime profile, with highest criminal activity occurring during teenage years.[10] Wage and hour information based on the job at which respondents work the most hours per week show increasing wages and hours with age.

3 Empirical Strategy

We are interested in whether a change in the minimum wage causes bound workers to turn to crime, possibly from losing their jobs and becoming idle, thus we examine criminal activity and employment outcomes. Our estimating equation in the crime regressions is

$$\mathbb{1}\{Crime_{ait} = 1\} = \alpha_0^a + \beta^a \mathbb{1}\{MWBound_{ait}\} + \gamma^a X_{ait} + e_{ait} \tag{1}$$

where the dependent variable is an indicator that respondent i committed a crime (e.g. drug sale, property theft/illegal sale, violence, etc.) at age a in year t, the year of the minimum wage increase. Age is defined as four age groups: 14-16, 17-19, 20-24, and 25-30 years old. Estimations are run separately by age group.[11] The treatment indicator, $\mathbb{1}\{MWBound_{ait}\}$, for being bound by the minimum wage change is defined above. X_{ait} includes gender, race, individual background controls (defined below) and vectors of year fixed effects and single-year age effects to control for national trends in crime and the crime-age profile. The coefficients of interest are the vector of β^{α}'s.

One concern with the baseline estimates may be that they miss a low-wage worker effect on crime or an endogeneity problem with increases in the minimum wage. The low-wage worker effect would be present if workers who receive low remuneration from licit labor are more likely to commit

[10] It is difficult to make a direct comparison between these numbers and national crime statistics. Here we present crime participation rates, whereas national crime statistics are measures of crime incidence.

[11] Age groups are admittedly adhoc, though the division does capture major features of the crime-age profile. Results combining all teenagers were largely similar.

crime or lose their job, regardless of whether they are affected by a change in the minimum wage. The policy endogeneity problem may occur if states that raise the minimum wage are also the states with the largest crime, employment, or enrollment problems.[12] In both cases, our minimum wage worker indicator alone cannot differentiate these effects from our focus: the effect of a minimum wage increase on workers bound by the change.

To address this problem, we also specify models that include an indicator for low-wage workers ($LowWage$) and for living in a state where the minimum wage increased ($ChangeMW$). In the event that some changing states have higher crime rates than non-changing states, we also include state fixed effects in some specifications. If any of these effects is the driving factor behind what we observe in our baseline results, the coefficient on $MWBound$ should lose significance with the appropriate indicators absorbing the effect. Low wage workers are defined as individuals who had a wage within \$0.36 of the binding minimum wage, even if there is no change in the minimum wage. We use \$0.36 because on average, workers bound by the minimum wage have wages \$0.36 below the new binding minimum wage. We also add controls for observable individual-level characteristics, such as academic achievement measured by math PIAT score in 1997, mother's education, and household income in 1997.

We pool the age groups to estimate effects on employment, using an indicator for employment as the dependent variable.[13] The controls remain the same, so we estimate

$$\mathbb{1}\{Employ_{it} = 1\} = \alpha_0 + \sum_{a=1}^{4} \beta_a \mathbb{1}\{MWBound_{it}\} \times \mathbb{1}\{agegrp_{it} = a\} + \gamma X_{it} + e_{it}, \tag{2}$$

with a common γ vector to improve precision.

The estimation procedure is limited to individuals who were working in the year before the change in the minimum wage. Individuals who were not working cannot be included because it is impossible to assign minimum wage worker status to someone who has no reported wages. Moreover, we are interested in movement from licit to illicit labor, so the correct starting group is individuals involved in licit labor.

[12] Lemos (2005) shows that minimum wage changes do not appear to be endogenous to employment conditions in Brazil.

[13] Missing data for each variable are replaced as zeros for respondents who reported this information in any other year of the survey.

4 Estimates

4.1 Crime

We estimate linear probability and logit models on self-reported crime. We look at overall criminal activity, crimes grouped by motive, and finally crimes by offense. We find that crimes increase among minimum wage-bound workers and most strongly among teenagers, and that these increases occur among both monetary and non-monetary crimes.

Overall crime increases with the minimum wage for all of our age groups. Table 2 provides OLS results in the top panel and logit results in the bottom panel. Youth's crime-related decisions appear to be the most sensitive to changes in the minimum wage. OLS estimates show that affected 14-16 year-olds are 8.4 percentage points more likely to commit crimes, and 17-19 year-olds increase crime by 3.4 to 4.1 percentage points.[14] Older ages experience smaller effects. The additional controls in Column (2) help to uncover the minimum wage effect for 14-16 year-olds. For older age groups, however, Column (2) contains smaller estimates. For those workers, some of the estimated effect from Column (1) may be due to a low wage worker propensity towards crime.

Disaggregated Crime Table 3 presents the results for monetary and non-monetary crimes, as well as crimes by different offenses. Here we use the specification that controls for low-wage worker effects and additional individual controls, so that identification comes from within state changes in minimum wage laws.

Monetary crimes, defined as stealing, drug sale, and "other property" crimes such as dealing in stolen property, increase among young teens but decline among young adults, which may be due to substitution among different-aged workers in low-skill labor markets. In particular, among 14-16 year-olds crime increases by 8.3 percentage points but declines by 2 percentage points for 20-24 year-olds.[15] A disaggregated look at monetary crimes also shows a sizable an increase in theft by 25-30 year-olds, consistent with increases in idleness.

Non-monetary crimes, defined as vandalism and violence, also increase for older age groups. Violent acts performed by 17-19 year-olds increase by 2.3 percentage points and by 1.6 percentage points for 25-30 year-olds, consistent with increases in idleness. For 17-19 year-olds, relative to an

[14] Marginal effects from the logit specification are similar.

[15] Marginal effects from the logit and OLS specifications are comparable.

unconditional average crime rate of 8.26, this is a 28% increase in violence. Jacob and Lefgren (2003) also find that youth violence increases by approximately 28%, usind different data and when identification is driven by school cancellations. Logit results account for the non-linearity of the dependent variable and confirm the same patterns as the LPM.[16]

4.2 Employment and School Enrollment Effects

We look at employment and school enrollment for increases in unemployment and idleness. Given the evidence on increases in crime, we examine whether there are corresponding changes in the labor market and schooling.

Disemployment Table 4 shows the increase in the minimum wage has a negative effect on the employment of minimum wage workers. The first panel of Table 4 presents OLS estimates, while the second panel presents logit estimates. In each panel, Columns (1) and (3) present the estimates of Equation 2 for OLS and logit specifications, respectively. Column (2) and (4) add state fixed effects, controls for changing the minimum wage, low-wage status, and individual controls.

Here employment is defined as working any type of job at any time during the year, whether self-employed or as an employee. Teenagers experience a decline in employment of 4 percentage points, while even older adults become see reduced employment, by about 3 percentage points. These results align with the competitive model of the labor market. There is no significant disemployment effect, however for 20-24 year-olds.[17] The logit results remain significant for older adults, but become insignificant for teens. Imprecision in the estimates may be due to the limited number of young teenagers working in our sample.

The results for youth are directly comparable in magnitude to what Currie and Fallick (1996) find using NLSY79 data. Zavodny (2000) also finds a negative effect on the likelihood of employment, though not as large. Although few studies have observed disemployment effects of the minimum wage among adults in their 20s, that may be due to the fact that those studies depend upon data at a higher aggregation level and cannot identify which workers in those age groups were bound by changes in the minimum wage. Because a small group of adults work at the minimum

[16]Standard errors are not clustered at the state level because we include state fixed effects.

[17]Thompson (2009) finds that workers of a similar age range, 19-22 years-old, do not experience disemployment effects due to the minimum wage.

wage, it stands to reason that aggregate data may miss the effect that we find here.

Weeks employed To take a closer look at the disemployment effects, we examine how the time spent employed, measured in weeks, is affected by increases in the minimum wage. This measurement allows us to observe disemployment effects at a finer level of detail than the binary employment measure. For example, if it is the case that some individuals become unemployed but find employment within the same year, the effect would be captured in the weeks-worked measurement but overlooked by the binary measurement. This may also explain why, although most of the point estimates in the binary regressions are negative, not all are statistically significant.

Columns (5) through (7) of Table 4 show the results of regressing weeks employed at time t on an increase in the minimum wage. Columns (5) and (6) show tobit regressions of weeks worked conditional on being employed previous to a change in the minimum wage. Column (5) uses the controls of Equation 1. Column (6) adds state fixed effects, controls for changing the minimum wage, low-wage status, and individual controls. Column (7) shows a linear regression of weeks worked conditional on being employed both before and after the minimum wage change. Column (7) contains the full set of controls described earlier.

Column (5) shows that, with the inclusion of individuals who become unemployed, an increase in the minimum wage decreases the time spent employed by nearly 2 weeks for 17-19 year-olds, 4 weeks for 20-24 year-olds, and over 11 weeks for 25-30 year-olds. With the inclusion of additional controls in Column (6), these effects persist. Part of the effects observed in Column (5) may be attributable to a low-wage worker effect: low-wage workers work nearly 2 weeks less than higher wage workers. However, the change in the minimum wage still has a negative effect on bound workers with the magnitude of the effect increasing monotonically with age.

Column (7) focuses on the employment hours of workers who remain employed after a change in the minimum wage. Predictably, these estimates are smaller in magnitude than those in Columns (5) and (6). In Column (7), it appears that young adults who are bound by a change in the minimum wage and remain employed still experience some disemployment effects.

These results, when combined with the binary employment results, suggest that an increase in the minimum wage raises the likelihood that individuals will become unemployed and experience longer spells of unemployment.

School Enrollment Students who reach the legal dropout age are more likely to dropout of school when the minimum wage increases. We restrict the data to 14-19 year-olds to estimate the effect on school enrollment. Columns (1) and (2) of Table 5 show that 17-19 year-olds of dropout age have lower enrollment rates by 3 to 4.7 percentage points.[18]

Overall, these results indicate that youth spend more time unemployed and out of school when the minimum wage increases, and adults also experience greater unemployment. This pattern of results is consistent with the increases in crime rates that we observed earlier. Namely, substitution from work to crime fits with two age groups who experience an increase in crime: 14-16 and 25-30 year-olds also displayed disemployment effects.[19] Meanwhile, among adults aged 20-24 results are consistent with a rising opportunity cost, as they do not display strong disemployment effects and therefore should decrease crime as the minimum wage raises the opportunity cost of crime. Finally, age 17-19-year-olds see an increase in the probability of dropping out of school alongside a noticeable increase in violence.

5 Multinomial Choice

Our estimates show that an increase in the binding minimum wage has an effect on employment and criminal activity related to monetary gain among minimum wage workers. To understand to what degree the increase in crime is due to substitution with licit work, we estimate a multinomial choice model where individuals decide over four choices: being unemployed and not in crime (E0C0), being an unemployed criminal (E0C1), being employed and not in crime (E1C0), and being an employed criminal (E1C1).

The utility for each choice j made by individual i in period t is

$$U_{ijt} = \alpha_j + \beta_j \mathbb{1}\{MWBound_{it}\} + \delta_j X_{it} + e_{ijt} \tag{3}$$

Our covariates include an indicator for being bound by a minimum wage change, which combines wage and disemployment effects, such as losing one's job or experiencing a change in work hours.

[18] Chaplin et al. (2003) also find that dropout-eligible teens leave school when the minimum wage rises.

[19] Although the disemployment effects for 14-16 year-olds lack precision, teens who commit crime also experience the strongest disemployment effects. OLS estimates on employment become more negative and precise when limited to individuals who ever commit crime.

We also include controls for living in a state that changed the minimum wage, low-wage status, gender, race, age group, and year. Assuming that the error terms have a joint normal distribution, we can estimate this model using a multinomial probit.

Rewriting the equation in general form as

$$U_{ijt} = Z_{it}\theta_j$$

The probability of each choice j is $\phi(Z_i t\theta_j)$. We are interested in the marginal effect of being bound by a minimum wage change on each choice probability, so we evaluate the derivate of each choice probability with respect to a change in the minimum wage.

Given the competitive model of labor markets, we expect to see positive effects on choices without employment (E0). The substitution between work and crime suggests that as youth are forced out of employment, either through losing a job or a reduction in hours, they will move into illicit labor. This gives us a second expected result on choices that involve crime (C1).

5.1 Results

Tables 6 through 7 present the average marginal effect on the probability of each employment-crime choice for raising the minimum wage or being a worker bound by a change relative to others in a state that has changed the minimum wage, respectively. Each table row represents separate estimates on each type of crime: overall crime, monetary vs. non-monetary motivation, and the disaggregated crimes. Standard errors for the marginal effects are calculated by the delta method. We also report the results of a significance test for the relevant variable across the three equations of the model, given as a Wald test statistic and the corresponding p-value.

Table 6 shows the marginal effects associated with a change in the minimum wage, overall. These can be interpreted as the change in choice probabilities for workers in states where minimum wage increases (relative to workers where there was no increase). Workers who are not bound by changes in the minimum wage appear relatively unaffected by the policy change: there is a small and weakly significant increase in crime among those not employed. In particular, property theft increases by less than 0.2 percentage points. These weak results may indicate that minimum wage effects are concentrated among workers who are actually bound by the change.

The marginal effects of an increase in the minimum wage for bound workers are given in Table 7. These results represent the change in choice probabilities for bound workers relative to workers in an uncovered industry or who have wages above the wage floor. For each crime, the coefficients on the indicator for bound worker status are significant at least at the 95% significance level. We see an increased movement from employment to idleness, with the probability of being an employed non-criminal falling by 3.8 percentage points and the probability of being idle increasing by 1.5 points (when considering overall crime). Those who formerly would have been employed and not committing crime now turn to crime – the probability of committing a crime while employed increases by 2 percentage points. This occurs among both money-motivated and non-money crimes.

The results suggest that among the population who are bound by the minimum wage, the probability of both working and committing crime increases within a year. Thus for these individuals it appears the crime complements employment, both through monetary and non-monetary channels. These may include supplementary income (theft) or through increased violence during spells of idleness. The lack of substitution toward non-work and crime may be due to the fact that minimum-wage-bound workers are a selected group, more likely to work and less likely to rely solely on crime for income.

6 Conclusion

Did raising the minimum wage increase crime in the United States over the past 15 years? The evidence we present suggests the answer is yes. Further, our results indicate that this increase in crime occurs across the board, with increases in theft, drug sale, and violent crime. Among the employed these increases may occur due to a decrease in labor income from reduced work.

Our results highlight the importance of providing employment opportunities for young, unskilled-youth given the evidence for a relationship between licit and illicit work. They also point to the dangers both to the individual and to society from policies that restrict the already limited employment options of this group. Our results indicate that crime will increase by 1.9 percentage points among 14-30 year-olds as the minimum wage increases, with effects being even larger among teenagers. With an average overall crime rate at 12.1%, this is a substantial increase. 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.

Bureau of Labor Statistics, "Characteristics of Minimum Wage Workers," Technical Report 2011.

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.

Chaplin, Duncan D., Mark D. Turner, and Andreas D. Pape, "Minimum wages and school enrollment of teenagers: a look at the 1990's," *Economics of Education Review*, February 2003, *22* (1), 11–21.

Currie, Janet and Bruce C. Fallick, "The Minimum Wage and the Employment of Youth Evidence from the NLSY," *Journal of Human Resources*, 1996, *31* (2), 404–428.

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.

Gould, Eric D, Bruce A Weinberg, and David B Mustard, "Crime rates and local labor market opportunities in the United States: 1979-1997," *Review of Economics and Statistics*, 2002, *84* (1), 45–61.

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

Hindelang, Michael J, "Variations in sex-race-age-specific incidence rates of offending," *American Sociological Review*, 1981, pp. 461–474.

Jacob, Brian A. and Lars Lefgren, "Are Idle Hands the Devil's Workshop? Incapacitation, Concentration, and Juvenile Crime," *American Economic Review*, December 2003, *93* (5), 1560–1577.

Lemos, Sara, "Political Variables as Instruments for the Minimum Wage," *The B.E. Journal of Economic Analysis & Policy*, December 2005, *4* (1), 1–33.

Luallen, Jeremy, "School's out... forever: A study of juvenile crime, at-risk youths and teacher strikes," *Journal of Urban Economics*, 2006, *59* (1), 75 – 103.

Machin, Stephen and Costas Meghir, "Crime and economic incentives," *Journal of Human Resources*, 2004, *39* (4), 958–979.

Neumark, David 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, Richard V. Burkhauser, and Benjamin Hansen, "Are the Effects of Minimum Wage Increases Always Small? New Evidence from a Case Study of New York State," *Industrial and Labor Relations Review*, 2012, *65* (2).

Thompson, Jeffrey P., "Using Local Labor Market Data to Re-Examine the Employment Effects of the Minimum Wage," *Industrial and Labor Relations Review*, April 2009, *62* (3), 343–366.

Zavodny, Madeline, "The effect of the minimum wage on employment and hours," *Labour Economics*, November 2000, *7* (6), 729–750.

Table 1: Summary Statistics

	All	Ages 14-16	Ages 17-19	Ages 20-24	Ages 25-30
% Assignable wage info	61.98	10.41	60.43	77.45	78.81
% MW bound	3.91	7.81	7.47	2.39	3.1
Hourly wages	14.28	7.13	7.66	15.09	18.9
Hours per week	32.4	17.0	27.1	33.5	36.4
% Any crime	12.11	31.30	21.68	9.12	4.25
% Monetary crime	8.79	20.70	15.03	6.55	3.27
% Non-Monetary crime	7.33	21.15	12.51	5.24	2.45
% Sold drugs	5.61	8.08	7.40	4.78	3.56
% Stole value $<$ \$50	4.65	13.87	8.52	2.94	1.19
% Stole value $\geq$ \$50	2.03	5.25	3.11	1.39	0.65
% Property destruction	3.66	12.58	6.30	2.32	0.94
% Other property crime	1.95	5.12	2.96	1.30	0.74
% Violent crime	5.48	12.15	8.26	4.26	2.40
% Male	50.3	58.08	51.46	49.55	49.84
% Female	49.7	41.92	48.54	50.45	50.16
% Black	24.8	21.94	22.87	24.9	26.53
% Hisp	20.75	17.7	18.83	21.28	21.77
% Mixed, non-Hisp	0.9	0.86	0.9	0.92	0.86
% Not black, non-Hisp	53.55	59.5	57.39	52.9	50.84
Observations	62,878	1,627	14,733	29,174	17,344

Table 2: Probability of Committing a Crime

Linear Probability Model

	(1)	(2)
14-16	0.0526	0.0838*
	(0.046)	(0.048)
17-19	0.0416***	0.0345**
	(0.014)	(0.015)
20-24	-0.0051	-0.0160
	(0.012)	(0.013)
25-30	0.0201**	0.0215**
	(0.010)	(0.010)

Logit

	(1)	(2)
14-16	0.239	0.398*
	(0.210)	(0.228)
17-19	0.226***	0.185**
	(0.079)	(0.087)
20-24	-0.08	-0.222
	(0.158)	(0.169)
25-30	0.428**	0.448**
	(0.213)	(0.219)

Binary crime outcome regressed on (1) an indicator for being bound by a change in the minimum wage interacted with age group indicators along with year, age, race, and gender fixed effects; (2) controls of (1) with indicators for state change in minimum wage and low-wage worker status, mother's education, math PIAT score, household income in 1997, and state fixed effects conditional on being employed. Crimes are defined as property destruction, stealing, other property crime (such as dealing in stolen property), violence, and drug sale. Regression is run separately for each age group. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Table 3: Crime by Offense

Linear Probability Model

	Money	Non-Money	Drug Sale	Steal < \$50	Steal ≥ \$50	Other Property	Vandalism	Violence
14-16	0.0826*	0.0401	0.0576**	0.0505	0.0513**	0.0533**	0.0302	0.0196
	(0.043)	(0.042)	(0.029)	(0.036)	(0.024)	(0.023)	(0.035)	(0.034)
17-19	0.0168	0.0287**	0.0014	0.0121	0.00359	0.00123	0.0134	0.0228**
	(0.013)	(0.012)	(0.010)	(0.011)	(0.007)	(0.006)	(0.009)	(0.010)
20-24	-0.0202*	-0.0012	-0.0082	-0.0105	-0.0095	-0.0032	-0.0018	0.00424
	(0.012)	(0.011)	(0.011)	(0.008)	(0.006)	(0.006)	(0.007)	(0.010)
25-30	0.0113	0.0135	-0.0050	0.0161***	0.00992*	0.00165	0.0037	0.0160*
	(0.010)	(0.008)	(0.012)	(0.006)	(0.005)	(0.006)	(0.006)	(0.009)

Logit

	Money	Non-Money	Drug Sale	Steal < \$50	Steal ≥ \$50	Other Property	Vandalism	Violence
14-16	0.463*	0.244	0.642*	0.396	1.039**	0.723*	0.285	0.144
	(0.244)	(0.264)	(0.344)	(0.285)	(0.450)	(0.390)	(0.310)	(0.334)
17-19	0.117	0.226**	0.0232	0.133	0.106	0.0343	0.169	0.270**
	(0.098)	(0.105)	(0.133)	(0.119)	(0.185)	(0.188)	(0.139)	(0.127)
20-24	-0.352*	-0.0555	-0.175	-0.379	-0.753	-0.223	-0.113	0.0746
	(0.209)	(0.212)	(0.251)	(0.307)	(0.533)	(0.452)	(0.338)	(0.234)
25-30	0.317	0.435	-0.175	0.933**	1.047*	0.155	0.344	0.512*
	(0.279)	(0.291)	(0.376)	(0.370)	(0.570)	(0.756)	(0.538)	(0.306)

Binary crime outcome regressed onan indicator for being bound by a change in the minimum wage interacted with age group indicators along with year, age, race, and gender fixed effects, indicators for state change in minimum wage and low-wage worker status, mother's education, math PIAT score, household income in 1997, and state fixed effects conditional on being employed. Monetary crimes are drug sale, stealing, and "other property" crimes. Non-monetary are vandalism and violence. Regressions are run separately for each offense and age group. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effects on Employment

	Employment				Weeks Employed		
	OLS		Logit				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
14-16	-0.0439*	-0.0399*	-0.254	-0.21	-1.61	-1.373	0.186
	(0.024)	(0.024)	(0.229)	(0.233)	(2.746)	(2.738)	(1.472)
17-19	-0.0135	-0.0104	-0.173	-0.136	-1.897**	-2.336**	-0.609
	0.009	0.009	0.117	0.122	(0.995)	(1.018)	(0.510)
20-24	-0.0105	-0.0083	-0.177	-0.137	-4.053***	-3.884***	-1.538***
	0.010	0.010	0.153	0.159	(1.153)	(1.181)	(0.562)
25-30	-0.0375***	-0.0331***	-0.551***	-0.483***	-11.43***	-10.79***	-3.888***
	0.011	0.011	0.153	0.154	(1.320)	(1.320)	(0.631)
$\mathbb{1}\{ChangeMW\}$		-0.0042		-0.0356		-0.23	-0.0533
		(0.003)		(0.054)		(0.392)	(0.179)
$\mathbb{1}\{LowWage\}$		0.0034		0.0573		-1.688***	-0.687***
		(0.003)		(0.053)		(0.395)	(0.193)
Observations	60,354	60,354	60,354	60,343	60,200	60,200	56,794
R-squared	0.018	0.024					0.1

Columns (1) through (4) regress a binary employment outcome on an indicator for being bound by a change in the minimum wage interacted with age group indicators along with year, age, race, and gender fixed effects. Columns (1) and (2) are a linear probability model, and (3) and (4) are logistic. Expanded controls in Columns (2) and (4) are indicators for state change in minimum wage and low-wage worker status, mother's education, math PIAT score, household income in 1997, and state fixed effects. Columns (5) through (7) show regressions of weeks worked. (5) and (6) are tobit regressions with basic and expanded controls, respectively. Column (7) results from an OLS model of hours conditional on employment with expanded controls. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effects on School Enrollment

Linear Probability Model

	(1)	(2)
14-16	-0.0044	-0.0008
	(0.053)	(0.053)
17-19	0.0226	0.0382
	(0.044)	(0.044)
$\mathbb{1}\{CanDropOut\}$	-0.0339	-0.0539**
	(0.025)	(0.025)
14-16 Can Dropout	0.0147	0.0303
	(0.062)	(0.062)
17-19 Can Dropout	-0.0471***	-0.0309*
	(0.017)	(0.017)
$\mathbb{1}\{ChangeMW\}$		-0.0099
		(0.011)
$\mathbb{1}\{LowWage\}$		-0.0137*
		(0.007)
Observations	25,157	25,157
R-squared	0.079	0.101

Logit

	(1)	(2)
14-16	-0.2660	-0.2470
	(0.631)	(0.634)
17-19	0.311	0.401
	(0.441)	(0.443)
$\mathbb{1}\{CanDropOut\}$	-0.672**	-0.778***
	(0.293)	(0.297)
14-16 Can Dropout	0.421	0.518
	(0.742)	(0.745)
17-19 Can Dropout	-0.229**	-0.146
	(0.089)	(0.094)
$\mathbb{1}\{ChangeMW\}$		-0.0561
		(0.057)
$\mathbb{1}\{LowWage\}$		-0.0791*
		(0.042)
Observations	25,156	25,156

Binary enrollment outcome on (1) an indicator for being bound by a change in the minimum wage interacted with age group indicators along with year, age, race, and gender fixed effects; (2) controls of (1) with indicators for state change in minimum wage and low-wage worker status, mother's education, math PIAT score, household income in 1997, and state fixed effects. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Marginal Effects of Changing the Minimum Wage

	Average marginal effects				Wald test	
	E=0, C=0	E=1, C=0	E=0, C=1	E=1, C=1	χ^2 statistic	P-value
Any crime	-0.0008	0.0008	0.0004	-0.0004	0.16	0.984
	(0.003)	(0.005)	(0.001)	(0.004)		
Monetary	-0.0021	-0.0021	0.0017	0.0025	2.79	0.425
	(0.003)	(0.005)	(0.001)	(0.004)		
Non-Monetary	-0.0009	0.0030	0.0006	-0.0027	0.89	0.829
	(0.003)	(0.005)	(0.001)	(0.004)		
Steal $<$ \$50	-0.0011	-0.0046	0.0013	0.0044	4.41	0.220
	(0.004)	(0.005)	(0.001)	(0.003)		
Steal $\geq$ \$50	-0.0016	-0.0016	0.0013*	0.0018	3.96	0.266
	(0.004)	(0.005)	(0.001)	(0.002)		
Steal any value	-0.0020	-0.0030	0.0018*	0.0033	4.52	0.211
	(0.004)	(0.005)	(0.001)	(0.003)		
Drug sale	-0.0020	-0.0007	0.0004	0.0022	0.81	0.848
	(0.004)	(0.005)	(0.001)	(0.003)		
Violence	0.0013	0.0028	0.0002	-0.0043	1.78	0.618
	(0.004)	(0.005)	(0.001)	(0.003)		

Multinomial probit controlling for an indicator for being bound by a change in the minimum wage interacted with age group indicators along with year, age, race, and gender fixed effects, and indicators for state change in minimum wage and low-wage worker status. Each crime regression is run separately conditional on being employed. Average marginal effects reported. Standard errors calculated by the delta method are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Marginal Effects of Raising the Minimum Wage on Bound Workers

	Average marginal effects				Wald test	
	E=0, C=0	E=1, C=0	E=0, C=1	E=1, C=1	χ^2 statistic	P-value
Any crime	0.0150**	-0.0387***	0.0029	0.0208***	18.76	0.0003
	(0.006)	(0.009)	(0.003)	(0.007)		
Monetary	0.0174***	-0.0306***	0.0005	0.0127*	12.91	0.005
	(0.007)	(0.009)	(0.002)	(0.007)		
Non-Monetary	0.0160**	-0.0350***	0.0028	0.0162***	17.86	0.001
	(0.007)	(0.009)	(0.002)	(0.006)		
Steal < \$50	0.0169**	-0.0255***	0.0008	0.0078	10.34	0.016
	(0.007)	(0.008)	(0.002)	(0.005)		
Steal $\geq$ \$50	0.0171**	-0.0235***	-0.0009	0.0073*	10.63	0.014
	(0.007)	(0.008)	(0.001)	(0.004)		
Steal any value	0.0179***	-0.0306***	0.0003	0.0125**	14.73	0.002
	(0.007)	(0.008)	(0.002)	(0.005)		
Drug sale	0.0173**	-0.0248***	0.0013	0.0062	8.53	0.036
	(0.007)	(0.009)	(0.002)	(0.006)		
Violence	0.0147**	-0.0315***	0.0031	0.0137**	15.44	0.002
	(0.007)	(0.009)	(0.002)	(0.006)		

Multinomial probit controlling for an indicator for being bound by a change in the minimum wage interacted with age group indicators along with year, age, race, and gender fixed effects, and indicators for state change in minimum wage and low-wage worker status. Each crime regression is run separately conditional on being employed. Average marginal effects reported. Standard errors calculated by the delta method are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$