Regulation and the Labor Supply of Criminals: A Study Using Local City Arrest Data

Darwyyn Deyo[1]

December 2017

Abstract:

Unemployment generated by a regulatory shock to labor markets may lead to spillover effects in illegal labor markets. In particular, high-risk or low-skill individuals who face strict budget constraints may seek alternative forms of illegal employment in addition to or as a substitute for savings or public assistance. I employ city crime data and state level changes in the minimum wage for Chicago and New York City to test the effect of state minimum wage increases on the number and percent of crimes which may generate income. I focus on the minimum wage as a regulatory shock which may generate spillover effects to illegal labor markets. I find a positive relationship between increases in state minimum wages and increases in crime, as well as increases in the different types of crimes. I include several specification tests to which the results are robust. My preliminary results suggest that regulatory shocks to legal labor markets have a significant effect on crimes which can generate income.

JEL Codes: J08, J24, J46

Keywords: minimum wage, economics of crime, labor markets

Acknowledgements: The author gratefully acknowledges comments from Thomas Stratmann and seminar participants at the 2017 American Law and Economics Association Meeting and the 2016 Southern Economics Association Annual Meeting.

[1] Assistant Professor of Economics, San Jose State University (darwyyn.deyo@sjsu.edu)

1. Introduction

There are many regulatory shocks to labor markets which have the potential to increase the criminal labor force. These shocks can theoretically shift a labor surplus from the legal labor market into illegal labor markets, especially if members of that labor surplus have limited savings or other income insurance. As legal labor markets become more regulated, parts of the labor supply may be priced out of the legal labor market and face a trade-off between observing the law and covering the costs of their household. This may be particularly true for groups employed in low skill industries, or for groups which face non-price based discrimination in labor markets. Examining the impact of these labor market shocks can illuminate broader effects of regulatory policies.

One such shock which often receives popular support is increasing the federal minimum wage. In recent years, there has been a movement toward significantly increasing minimum wages at the state level. At the federal level, then President Obama issued an executive order in 2014 to increase the minimum wage for federal employees. Although the literature demonstrates unemployment effects for low-skilled workers, relatively less is known about the secondary effects of increasing the minimum wage (Card, Krueger, Card, & Krueger, 1994; Sabia, Burkhauser, & Hansen, 2012; Zavodny, 2000). Individuals who cannot find legal employment may seek employment in alternative labor markets. The literature examining these secondary effects has primarily focused on how increases in the minimum wage change the labor-leisure tradeoff and whether the income or substitution effect dominates between minimum wage increases and the opportunity cost of committing crime. However, literature on the employment effects from increasing the minimum wage highlights the fact that low-skilled and high-risk individuals are more vulnerable to changes in the labor market, and young women, single mothers, and minorities may be even more vulnerable (Ahn, Arcidiacono, & Wessels, 2011a; Currie & Fallick, 1996a; Kolker, 2013). Therefore, there are significant implications for what happens to these groups if they are priced out of the legal labor market.

One potential outcome from increasing the minimum wage is that low-skilled and high-risk individuals may seek employment in the illegal labor market. Research on the impact of wage mandates, such as the minimum wage or living wages, has been focused on how increasing the minimum wage impacts urban and youth crime (Beauchamp & Chan, 2014; Fernandez, Holman, & Pepper, 2014a; Hashimoto, 1987; Thompson, 2009). These studies have produced conflicting results over whether wage mandates increase crime. Crime is often divided into the two categories of property crime and violent crime (Fernandez, Holman, & Pepper, 2014b; Jacob & Lefgren, 2003; Raphael & Winter-Ebmer, 2001). These studies also use the Federal Bureau of Investigation's Uniform Crime Reports (UCR) methodology for crime, which divides most crimes into property or violent crime. For example, burglary is listed under property crime while robbery is listed under violent crime, even though the functional difference between the two categories is that the criminal uses a gun in the latter. However, some violent crimes such as robbery may generate illegal income. Stealing someone's wallet or television may provide temporary funds for an individual without other labor prospects, although repeated thefts also bring increased contact with the police authorities (Becker, 1974). Using the UCR crime categories may therefore not be the best way to capture the substitution effects from the minimum wage increase for individuals treating illegal activity as an alternative labor market.

Previous studies have found that with minimum wage increases, firms will lay off the least productive workers, where the value of the individual's marginal product (VMPL)is greater than the minimum wage (Gould, Weinberg, & Mustard, 2002). However, although income and substitution effects will influence whether individuals seek income through illegal activity, it is unclear which effect dominates (Ahn, Arcidiacono, & Wessels, 2011b). Individuals with jobs and higher incomes will substitute away from commercial street crime, while individuals without jobs may substitute toward commercial street crime. Even if labor in these two markets are not considered perfect substitutes, the net effect of a higher minimum wage on crime is still unclear when considering an individual's tradeoffs and opportunity cost of entering the illegal labor market.

In this study, I identify a set of crimes that provide a repeated stream of payments to the individual and are directly linked to an employment category. These include lifestyle crimes, such as prostitution, the sale or shipment of prohibited drugs, theft, and a general list of other income-generating crimes such as pandering or fraud. Theft of higher-value items with a defined market, such as cars or car parts, would also offer reliable repeated payments to the criminal. I term these "commercial street crimes" and include any crimes that provide income, such as prostitution, drug sales, pandering, counterfeit sales, burglary, or robbery, as compared with non-income-producing crimes, such as murder or arson. Commercial street crime is a useful analysis group because it captures crimes across many categories. I also contribute to the literature by focusing on the types of crimes most likely to be committed by low-skilled workers who are priced out of the legal market for labor (Ahn et al., 2011b; Currie & Fallick, 1996b; Gardecki & Neumark, 1998; Neumark & Wascher, 2006).

I also add to the literature by considering what happens to the labor surplus after an increase in the minimum wage and by using an alternative data source that may better represent changes in the illegal labor market. I find that arrests for commercial street crime go up 14 percent after an increase in the state minimum wage. Arrests for drug sales go up 18 percent, arrests for theft go up 12 percent, and arrests for other commercial street crimes go up 24 percent. There were 351,813 arrests for commercial street crimes in Chicago and New York City in the base year of the study, suggesting that an increase in the minimum wage would result in an additional 49,254 arrests for commercial street crimes, compared with no increase in the minimum wage and conditional on other labor market factors.

2. Empirical Model

I start with a two-period model where Period 1 takes place before an increase in the state minimum wage and Period 2 takes place after the increase in the state minimum wage. In Period 2, firms and labor will maximize their respective incomes. In this model, I have three agents: firms, labor, and police. In Period 1, firms freely contract for labor within a competitive labor market at the equilibrium wage rate. In this study I consider the competitive labor market wage rate to be the competitive legal labor market wage rate (WLEG). In Period 2, the state minimum wage increases and firms reallocate their labor selection based on labor productivity. Firms will change their aggregate labor selection based on who is hired on the margin due to the value of their marginal product (VMPL) and based on the overall mix of labor and capital in production. Labor is not treated as homogenous as differences in human capital determine whether individuals retain or gain employment in Period 2. Individuals with the lowest VMP of labor will not be employed in Period 2. The least skilled, least educated individuals will then be unemployed. Individuals not employed in the legal labor market will face a choice of whether to enter the illegal labor market for the competitive illegal labor market wage rate WILL (Figure 1).

In general, if the wage WILL an individual is offered in the illegal labor market exceeds their E[WLEG] in the legal market, the offer of the illegal labor will dominate, conditional on the individual's human capital and risk preference. The individual's human capital will determine their opportunity cost of committing commercial street crimes and how much the illegal labor market will substitute for the legal labor market. Individuals also choose the share of their labor that is supplied to the illegal labor market and the legal labor market, where α is the labor surplus in the legal market and %α is the share of labor supplied to the illegal labor market, where α is bounded between 0 and 1. Over time, the individual's opportunity cost of participating in the illegal labor market may change due to changes in the labor force and other macroeconomic factors. The elasticity of the individual's labor supply may also change over time as other labor opportunities arise. Police will increase the probability of getting caught in the illegal labor market and will change the expected value of income from commercial street crime.

I employ a linear regression model with neighborhood and month fixed effects to estimate the effect of increasing the minimum wage on commercial street crime. I estimate this model using two different specifications.

(1) $LNCRIME_{ost} = \alpha + \beta_1 \text{CRIME}_t + \beta_2 \text{MINWAGE}_{st} + \beta_3 \text{INTERACTION}_{ost} + \beta_4 \text{MONTHS}_t + \beta_5 \text{POLICE}_{st} + \beta_6 \text{LABOR}_{st} + \varepsilon_i$,

where *LNCRIME* is the logged number of crimes by crime type, city neighborhood, and unique month; CRIME is a binary indicator = 1 if the individual committed a commercial street crime, with separate regressions for each crime type; MINWAGE is a binary indicator = 1 if the state increased the minimum wage in that year, and = 0 otherwise; INTERACTION = 1 if CRIME = 1 and MINWAGE = 1 for each observation; MONTHS is the number of months since an increase in the state minimum wage, where MONTHS = 0 in the month where a state increases the minimum wage; POLICE is the number of police officers in the city where crimes take place; and LABOR is the percent change in the labor force participation rate by month and city.

(2) $PERCENT_{ost} = \alpha + \beta_1 \mathrm{CRIME}_o + \beta_2 \mathrm{MINWAGE}_{st} + \beta_3 \mathrm{INTERACTION}_{ost} + \beta_4 \mathrm{MONTHS}_t + \beta_5 \mathrm{POLICE}_{st} + \beta_6 \mathrm{LABOR}_{st} + \varepsilon_i$,

where *PERCENT* is the percent of crimes by crime type, city neighborhood, and unique month.

I group the commercial street crimes into separate samples where the treatment group includes commercial street crimes and the control group includes traffic crimes. Regressions are run separately for each sample with fixed effects by neighborhood and unique month in the sample. I also include two-way clustering by both city neighborhood and unique month.

I employ individual arrest data for Chicago and New York City (City of Chicago, 2015; New York City Police Department, 2015). As all individuals in the data were arrested, a control group for income-producing crime was necessary. Traffic crimes, such as speeding, running a red light, or driving while under the influence, are also included in the datasets. Traffic crimes are an ideal control group because they are non-commercial street crimes, they are relatively unresponsive to changes in the minimum wage, they are not usually considered criminal activity, and they contain a broad range of arrestee demographics. It is also useful to compare commercial street crimes with traffic crimes as individuals arrested for these crimes should have more similar non-violent risk preferences. Comparing commercial street crimes with homicide, for example, may pool individuals with very different risk preferences. The arrest data include the type of crime the individual was arrested for, demographic information for the arrestee, the location of the crime and the arrest, and several other identifying variables. I do not consider city-level prevailing wage laws in this study, which apply more commonly to government contract positions and not the low-skilled labor I consider in this study. The federal minimum wage exceeds the state minimum wages in the study except for the last five months in 2009, which I control for with unique month fixed effects. Individual-city-level crimes are then compared with state-level changes in the minimum wage.

Given the study design, t-tests were run between the treatment and control group. Future work includes an alternative sample with a traditional parallel trends test.

3. Data

I employ individual-level arrest data from the Chicago Police Department and stop-and-frisk and arrest data from the New York Police Department, which includes information on the crime associated with each arrest, the location of the arrest, and the date of their arrest. I pool these samples as I am interested in the observation of crime rather than arrests for crime. Crime data is aggregated to the level of neighborhoods by unique month in the study. I consider both the number of crimes by neighborhood and unique month as well as the percent of commercial street crimes by neighborhood and unique month. Table 1 lists the summary statistics for the variables in this study.

I use crime observations from Chicago and New York City to conduct a within-city, across-time analysis. The Chicago data come from publicly available Chicago Police Department arrest data for 2006-2009, and the New York City data come from the New York City Stop and Frisk database for 2006-2009. State minimum wage data come from the U.S. Department of Labor. Definitions for each variable in are included in Table 2. Importantly, the cities in this study do not increase their minimum wages during the study period. I conduct a balanced panel using 25 local neighborhood identifiers for Chicago using the city districts identified in the original data, 77 local neighborhood identifiers for New York City using the police precincts identified in the original data, 48 unique months, two crime groups in each analysis, and the comparison of the two cities. There are 9,792 observations in each panel using the number of crimes, and 9,404 observations in each panel using the percent of commercial street crime. There are fewer observations in the panel using the percent of commercial street crimes due to some observations being dropped with a base of zero.

The data from Chicago and New York City provide a clean natural experiment. Table 3 illustrates that in 2006 and 2007, Illinois did not increase its minimum wage but New York did increase its minimum wage. Then, in 2008 and 2009, Illinois increased its minimum wage but New York did not. This provides an opportunity for a city-to-city difference-in-differences analysis for changes in the minimum wage using four years of arrest data. I create a binary indicator for each crime in the study, where the commercial street crime = 1 as the treatment group and the traffic crime = 0 as the control group. I include an indicator variable for a minimum wage increase = 1 for a given year when a state increases the minimum wage. If a state increases the minimum wage in Year 2 and Year 4 but not in Year 3, the minimum wage variable = 1 for Year 2 and Year 4, and = 0 for Year 3. Historical state minimum wage data comes from the U.S. Department of Labor. I then create an interaction variable between the crime indicator variable and the minimum wage variable, where the interaction = 1 when the crime indicator = 1 and the minimum wage indicator variable = 1.

I also include a linear time variable for the number of months since an increase in the state minimum wage. When New York increased its minimum wage in 2006, for example, the number of months since a minimum wage increase = 0, and the month afterward = 1, and so forth. This accounts for the passage of time associated with changes in the minimum wage, over which time the labor supply for illegal markets may become more elastic. A positive sign suggests that labor substitutes into illegal labor markets as demand in legal labor markets becomes more inelastic, while a negative sign suggests that labor substitutes out of illegal labor markets as demand in legal labor markets becomes more elastic. I also include the total number of police officers in Chicago and New York City by year, which comes from the UCR. Although the direction of the effect between more police and crime is difficult to identify, I only attempt to control for the effect of more police. Finally, I also include the monthly percent change in the labor force participation rate for each city, which comes from the Bureau of Labor Statistics Local Area Unemployment Statistics. A positive sign here suggests that as the legal labor force participation grows, the illegal labor force participation should fall. Although the minimum wage influences the legal labor force participation rate, including changes in the labor force participation rate controls for other macroeconomic factors which may influence labor markets separate from the minimum wage.

As previously discussed, I also include fixed effects by each city's local neighborhood and unique month in the study. As crime is local, I can expect that crime occurs near the criminal's home based on the sociological distance decay function (Brantingham & Brantingham, 1995; O'Leary, 2011). This allows me to use local neighborhood fixed effects for the arrest location to control for local neighborhood differences within cities. Finally, I include the share of Democratic state legislatures by state and year in an instrumental variable robustness test. Data on state legislator parties comes from Ballotpedia.

4. Results

4.1. The Number of Crimes

I report the results for the number of commercial street crimes in Table 4. Increasing the minimum wage increases arrests for commercial street crime by 14 percent. This suggests that over time, individuals shift their labor into illegal labor markets as legal labor market opportunities or other opportunities become less available. I report the results for the number of individual crime types in Table 5. I find a significant effect from the minimum wage for all crimes except prostitution. I find that increasing the minimum wage increases arrests for drug sales by 18 percent, arrests for theft by 12 percent and arrests for other commercial street crimes by 24 percent.

4.2. The Percent of Crimes

I report the results for the percent of commercial street crimes in Table 6. In this case, increasing the minimum wage would increase the percent of arrests for commercial street crime by 0.01 percentage points. I report the results for the percent of individual crime types in Table 7. I find a significant effect from the minimum wage for all crimes. I find that increasing the minimum wage increases the percent of arrests for prostitution by 0.01 percentage points, the percent of arrests for drug sales by 0.02 percentage points, and the percent of arrests for other commercial street crime by 0.01 percentage points. I also find that increasing the minimum wage decreases the percent of arrests for theft by 0.01 percentage points.

4.3. Robustness Tests

I also address the possibility that unobservable variables may be driving the results using the selection on unobservable variables test (Altonji, Elder, & Taber, 2005; Bellows & Miguel, 2009; Nunn & Wantchekon, 2011). I use a restricted model that does not include the police

(Table 8). I do not find evidence that unobservable variables are driving the results, especially for the variables of interest. In fact, the estimates for the interaction term are the same for both the full and restricted models. Further, in several cases the test produces a null value as the estimates for the variables of interest are the same in both the full and restricted models. This suggests the results are not being driven by omitted variable bias. I also conduct a linear trends test to determine whether the results are simply the result of changes over time and do not find support for this hypothesis.

Although minimum wage changes occur at the state level and crimes are measured at the city neighborhood level, it is possible that state governments increase the state minimum wage in response to city crime, particularly when crime occurs in major metropolitan cities. I therefore include an instrumental variable test using the total share of Democratic state legislators in the Illinois and New York state legislatures by city and year. Although Democratic state legislators are more likely to support minimum wage increases and could increase the state minimum wage in response to crime rates, it is unlikely that the share of state Democrats would affect an individual's choice to commit a crime (Bolton, 2013; Campbell, 2017; "Democrat-led Legislature likely to increase minimum wage," 2016, "Iowa Democrats Hoping to Increase State's Minimum Wage," 2015).

I first conduct a Durbin-Wu-Hausman test for endogeneity and find support for including the instrumental variable test. The results for these regressions are reported in Table 9. This model omits the number of police as it is collinear with the share of state Democrats. The instrumental variable test supports the initial results, as the signs and magnitudes of the variables of significance are consistent with the primary OLS analysis.

5. Conclusion

The preliminary results of this study suggest that an increase in the minimum wage substitutes labor into some illegal markets. This also suggests that labor is not homogenous to illegality. Unemployed individuals may work in the shadow economy, off the books, or depend on other social and welfare networks, including private savings. This study illustrates that some labor may also shift into illegal labor markets for commercial street crime. Further work on this subject is continuing, with additional tests for the state minimum wage and expanding the sample size to the broader United States.

It is possible that sample selection from false arrests is influencing the study results, such that more individuals are falsely arrested for crimes after an increase in the minimum wage. Although police officers may have an incentive to engage in false arrests, the incentives associated with police making false arrests should not be influenced by changes in the minimum wage as police officers are not paid at the minimum wage. Similarly, although conviction rates likely do not include the full sample of arrests, it is unlikely that conviction rates for a subset of crimes would change after an increase in the minimum wage. If conviction rates are significantly different from arrest totals, I would expect the conviction rates to be related to other new legislation that was enacted at the same time as the minimum wage increase and would therefore treat both commercial street crimes and traffic crimes in the same way.

The capital intensity of the market may also determine which illegal labor market individuals enter, so the demand for labor in complex illegal markets may be more inelastic than the demand for labor in illegal markets with low barriers to entry. There are also oligopolies and local monopsonies within cities in both legal and illegal labor markets. Although labor in monopsonistic markets may not shift into illegal markets, monopsony labor is not the representative low-skill, high-risk labor supply most susceptible to unemployment from the minimum wage. Other related factors, such as changes in demand, may also influence the magnitude of the effect from the minimum wage but the selection effect test suggests that omitted or unobservable variables are not driving the primary results. Future research will include a test for how commercial street crime demand changes in response to the minimum wage.

I find a positive and significant relationship between an increase in a state's minimum wage and local commercial street crimes, including separate analyses for different types of commercial street crimes. I also find that the amount of time since a minimum wage increase influences the number of commercial street crimes, illustrating an elastic labor supply response. Given the theoretical implications of a labor surplus following a minimum wage increase, these results are particularly illuminating for considering how some individuals in the labor surplus respond to unemployment from regulatory labor shocks, with significant policy implications.

References

Ahn, T., Arcidiacono, P., & Wessels, W. (2011a). The Distributional Impacts of Minimum Wage Increases When Both Labor Supply and Labor Demand Are Endogenous. *Journal of Business & Economic Statistics*, *29*(1), 12–23. https://doi.org/10.1198/jbes.2010.07076

Ahn, T., Arcidiacono, P., & Wessels, W. (2011b). The Distributional Impacts of Minimum Wage Increases When Both Labor Supply and Labor Demand Are Endogenous. *Journal of Business & Economic Statistics*, *29*(1), 12–23. https://doi.org/10.1198/jbes.2010.07076

Altonji, J. G., Elder, T. E., & Taber, C. R. (2005). Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy*, *113*(1), 151–184.

Beauchamp, A., & Chan, S. (2014). The Minimum Wage and Crime. *The B.E. Journal of Economic Analysis & Policy*, *14*(3), 1–23. Retrieved from https://ideas.repec.org/a/bpj/bejeap/v14y2014i3p23n20.html

Becker, G. S. (1974). Crime and Punishment: An Economic Approach, 1–54. Retrieved from http://econpapers.repec.org/bookchap/nbrnberch/3625.htm

Bellows, J., & Miguel, E. (2009). War and local collective action in Sierra Leone. *Journal of Public Economics*, *93*(11), 1144–1157. https://doi.org/10.1016/j.jpubeco.2009.07.012

Bolton, A. (2013, November 7). Democrats gird for minimum-wage battle. *The Hill*. Retrieved from http://thehill.com/homenews/senate/189524-democrats-gird-for-minimum-wage-battle

Brantingham, P., & Brantingham, P. (1995). Criminality of Place: Crime Generators and Crime Attractors. *European Journal on Criminal Policy and Research*, *3*(3), 1–26.

Campbell, C. (2017). NC Democrats file bill to raise minimum wage, require paid sick leave. *The News & Observer*. 2. Retrieved from http://www.newsobserver.com/news/politics-government/state-politics/article135983968.html

Card, D. E., Krueger, A. B., Card, D., & Krueger, A. (1994). Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania. *American Economic Review*, *84*(4), 772–93. Retrieved from http://econpapers.repec.org/article/aeaaecrev/v_3a84_3ay_3a1994_3ai_3a4_3ap_3a772-93.htm

City of Chicago. (2015). Crimes Database. Retrieved from https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2

Currie, J., & Fallick, B. (1996a). The Minimum Wage and the Employment of Youth Evidence from the NLSY. *Journal of Human Resources*, *31*(2), 404–428. Retrieved from http://econpapers.repec.org/article/uwpjhriss/v_3a31_3ay_3a1996_3ai_3a2_3ap_3a404-428.htm

Currie, J., & Fallick, B. (1996b). The Minimum Wage and the Employment of Youth Evidence from the NLSY. *Journal of Human Resources*, *31*(2), 404–428.

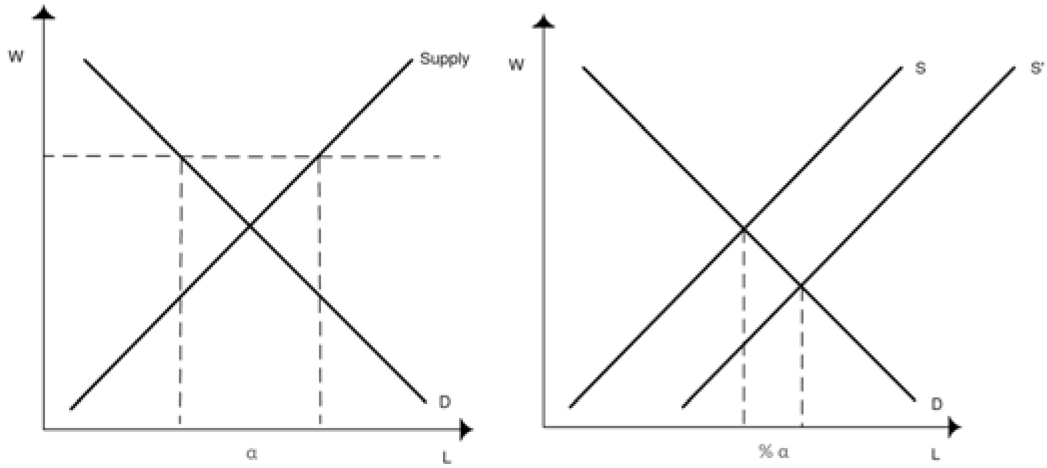
Democrat-led Legislature likely to increase minimum wage. (2016, December 28). *The Washington Times*. Retrieved from http://www.washingtontimes.com/news/2016/dec/28/democrat-led-legislature-likely-to-increase-minimu/

Fernandez, J., Holman, T., & Pepper, J. V. (2014a). The Impact of Living-Wage Ordinances on Urban Crime. *Industrial Relations: A Journal of Economy and Society*, *53*(3), 478–500. https://doi.org/10.1111/irel.12065

Fernandez, J., Holman, T., & Pepper, J. V. (2014b). The Impact of Living-Wage Ordinances on Urban Crime. *Industrial Relations: A Journal of Economy and Society*, *53*(3), 478–500.

https://doi.org/10.1111/irel.12065
Gardecki, R., & Neumark, D. (1998). Order from Chaos? The Effects of Early Labor Market Experiences on Adult Labor Market Outcomes. *ILR Review*, *51*(2), 299–322. https://doi.org/10.1177/001979399805100209
Gould, E. D., Weinberg, B. A., & Mustard, D. B. (2002). Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997. *Review of Economics and Statistics*, *84*(1), 45–61. https://doi.org/10.1162/003465302317331919
Hashimoto, M. (1987). The Minimum Wage Law and Youth Crimes: Time-Series Evidence. *The Journal of Law and Economics*, *30*(2), 443–464. https://doi.org/10.1086/467144
Iowa Democrats Hoping to Increase State's Minimum Wage. (2015, February 12). *NBC 13*. Retrieved from http://whotv.com/2015/02/12/iowa-democrats-hoping-to-increase-states-minimum-wage/
Jacob, B. A., & Lefgren, L. (2003). Are Idle Hands the Devil's Workshop? Incapacitation, Concentration, and Juvenile Crime. *American Economic Review*, *93*(5), 1560–1577. https://doi.org/10.1257/000282803322655446
Kolker, R. (2013, June 29). The New Prostitutes. *The New York Times*. Retrieved from http://opinionator.blogs.nytimes.com/2013/06/29/the-new-prostitutes/?_r=0
Neumark, D., & Wascher, W. L. (2006). Minimum Wages and Employment. *Foundations and Trends® in Microeconomics*, *3*(1–2), 1–182. https://doi.org/10.1561/0700000015
New York City Police Department. (2015). New York Police Department (NYPD) Stop, Question, and Frisk Database. ICPSR21660-v1. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2008-06-18.
Nunn, N., & Wantchekon, L. (2011). The Slave Trade and the Origins of Mistrust in Africa. *American Economic Review*, *101*(7), 3221–3252. https://doi.org/10.1257/aer.101.7.3221
O'Leary, M. (2011). Modeling Criminal Distance Decay. *Cityscape*, *13*(3), 161–198.
Raphael, S., & Winter-Ebmer, R. (2001). Identifying the Effect of Unemployment on Crime. *The Journal of Law and Economics*, *44*(1), 259–283. https://doi.org/10.1086/320275
Sabia, J., Burkhauser, R., & Hansen, B. (2012). Are the Effects of Minimum Wage Increases Always Small? New Evidence from a Case Study of New York State. *ILR Review*, *65*(2). Retrieved from http://digitalcommons.ilr.cornell.edu/ilrreview/vol65/iss2/7
Thompson, J. P. (2009). Using Local Labor Market Data to Re-Examine the Employment Effects of the Minimum Wage. *ILR Review*, *62*(3), 343–366. https://doi.org/10.1177/001979390906200305
Zavodny, M. (2000). The effect of the minimum wage on employment and hours. *Labour Economics*, *7*(6), 729–750. https://doi.org/10.1016/S0927-5371(00)00021-X

Figure 1 Two Period Model of Legal and Illegal Labor Markets



Legal Labor Market **Illegal Labor Market**

Table 1 Summary Statistics

Variable	Mean	S.D.	Min	Max
Number of Crimes				
Commercial	4.99	1.52	0.00	7.45
Traffic	1.26	1.69	0.00	5.41
Percent of Crimes				
Commercial	0.01	0.03	0.00	0.39
Traffic	0.04	0.06	0.00	1.00
Minimum Wage Indicator	0.50	0.50	0	1
Months Since Minimum Wage Change	14.50	10.53	0	35
Logged Police Officers	10.24	0.42	9.48	10.48
Labor Force Percent Change	0.001	0.004	-0.010	0.010
Share of Democrats	0.61	0.04	0.54	0.66

Note: Study includes individual indicators for each crime type with each sample including 50 percent traffic crimes by neighborhood and unique months and 50 percent commercial crimes by crime type. N = 9,792 for the number of crimes samples and N = 9,404 for the percent of crimes samples.

Table 2 Variable Descriptions

Variable	Definition
Number of Crimes	Number of commercial or traffic crimes for each unique month and city neighborhood, logged.
Percent of Crimes	Percent of commercial or traffic crimes relative to the total number of crimes, for each unique month and city neighborhood
Minimum Wage Indicator	A binary arrest indicator = 1 if the state increased its minimum wage that year, and = 0 otherwise.
Crime Indicator	A binary indicator = 1 for commercial crimes and = 0 for traffic crimes
Crime*Minimum Wage	A binary indicator = 1 if the crime indicator = 1 and the minimum wage indicator = 1, and = 0 otherwise
Months Since Minimum Wage Change	The number of months since a minimum wage increase
Logged Police Officers	The number of police officers by city and year, logged
Labor Force Percent Change	Percent change in the labor force by city and year
Share of Democrats	The percent of Democrats in the state legislature by state and year

Table 3 Timeline of Minimum Wage Changes by State

	Illinois		New York	
Year	Wage	Change Indicator	Wage	Change Indicator
2006	6.50	0	6.75	1
2007	6.50	0	7.15	1
2008	7.50	1	7.15	0
2009	7.75	1	7.15	0

Note: The Illinois minimum wage listed applies to employers of four or more.

Table 4 Results for the Effect of a Minimum Wage Change on the Number of Commercial Crimes

Number of Crimes	**Total**
Crime Indicator	3.65***
	(0.03)
Minimum Wage Indicator	-0.17***
	(0.04)
Crime * Minimum Wage	0.14***
	(0.05)
Months Since Minimum Wage Increase	-0.00
	(0.00)
Police Officers	-5.23
	(3.57)
Labor Force Percent Change	-13.61***
	(2.98)
Observations	9,792
Groups	3,748
R-Squared	0.866

Note: Robust standard errors in parentheses.
* *P* < .10; ** *P* < .05; *** *P* < .01.

Table 5 Results for the Effect of a Minimum Wage Change on the Number of Crimes

Number of Crimes	**Prostitution**	**Drug Sales**	**Theft**	**Other**
Crime Indicator	-0.39***	0.91***	3.54***	-0.16***
	(0.03)	(0.03)	(0.03)	(0.02)
Minimum Wage Indicator	-0.21***	-0.30***	-0.16***	-0.07**
	(0.05)	(0.05)	(0.04)	(0.04)
Crime * Minimum Wage	-0.02	0.18***	0.12***	0.24***
	(0.04)	(0.05)	(0.05)	(0.03)
Months Since Minimum Wage Increase	0.01***	-0.00	-0.00	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Police Officers	-25.36***	-10.10**	-4.76	-7.36**
	(4.42)	(4.06)	(3.57)	(3.43)
Labor Force Percent Change	-11.26***	-11.65***	-14.25***	-9.73***
	(3.71)	(3.37)	(2.30)	(2.82)
Observations	9,792	9,792	9,792	9,792
Groups	3,748	3,748	3,748	3,748
R-Squared	0.755	0.621	0.860	0.791

Note: Robust standard errors in parentheses. * $P < .10$; ** $P < .05$; *** $P < .01$.

Table 6 Results for the Effect of a Minimum Wage Change on the Percent of Commercial Crime

Percent of Crimes	**Total**
Crime Indicator	0.95***
	(0.00)
Minimum Wage Indicator	-0.01***
	(0.00)
Crime * Minimum Wage	0.01***
	(0.00)
Months Since Minimum Wage Increase	0.01
	(0.17)
Police Officers	0.00***
	(0.00)
Labor Force Percent Change	-0.90***
	(0.20)
Observations	9,404
Groups	3,748
R-Squared	0.993

Note: Robust standard errors in parentheses.
* $P < .10$; ** $P < .05$; *** $P < .01$.

Table 7 Results for the Effect of a Minimum Wage Change on the Percent of Crimes

Percent of Crimes	**Prostitution**	**Drug Sales**	**Theft**	**Other**
Crime Indicator	-0.03***	0.04***	0.85***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
Minimum Wage Indicator	-0.02***	-0.02***	-0.00	-0.01***
	(0.00)	(0.00)	(0.01)	(0.00)
Crime * Minimum Wage	0.01***	0.02***	-0.01**	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Months Since Minimum Wage Increase	0.00***	0.00	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Police Officers	-1.67***	-1.15***	-0.68*	-0.77***
	(0.21)	(0.34)	(0.41)	(0.22)
Labor Force Percent Change	0.21	0.34	-0.54	0.38**
	(0.17)	(0.37)	(0.42)	(0.19)
Observations	9,404	9,404	9,404	9,404
Groups	3,748	3,748	3,748	3,748
R-Squared	0.480	0.340	0.966	0.397

Note: Robust standard errors in parentheses. * $P < .10$; ** $P < .05$; *** $P < .01$.

Table 8 Test for Omitted Variable Bias With Full and Restricted Models

Number of Crimes	β^F	β^R	Ratio
Crime Indicator	3.65***	3.65***	.
	(0.03)	(0.03)	
Minimum Wage Indicator	-0.17***	-0.15***	7
	(0.04)	(0.04)	
Crime * Minimum Wage	0.14***	0.14***	.
	(0.05)	(0.05)	
Months Since Minimum Wage Increase	-0.00	-0.01***	1
	(0.00)	(0.00)	
Police Officers	-5.23		2
	(3.57)		
Labor Force Percent Change	-13.61***	-13.88***	50
	(2.98)	(2.98)	
Observations	9,792	9,792	
Groups	3,748	3,748	
R-Squared	0.866	0.866	

Note: Test comes from Altonji, Elder, & Taber, 2005; Bellows & Miguel, 2009; Nunn & Wantchekon, 2011). A ratio of 7 suggests that unobservable variables would have to explain 7 times as much as observable variables to change the result for my variable of interest. Robust standard errors in parentheses. * $P < .10$; ** $P < .05$; *** $P < .01$.

Table 9 Instrumental Variable Test Using the Share of State Democrats

	First Stage - Minimum Wage	**IV – Number of Crimes**
Crime Indicator	-0.04***	3.65***
	(0.00)	(0.03)
Minimum Wage Indicator	.	-0.20***
		(0.05)
Crime * Minimum Wage	0.08***	0.15***
	(0.00)	(0.04)
Months Since Minimum Wage Increase	-0.05***	-0.01***
	(0.00)	(0.00)
Labor Force Percent Change	-2.80**	-13.87***
	(1.26)	(2.98)
Share of Democrats	21.43***	.
	(0.14)	
Observations	9,792	9,792
Groups	9,792	3,748

Note: Robust standard errors in parentheses. * $P < .10$; ** $P < .05$; *** $P < .01$.