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The Effect of the Minimum Wage on Crime

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Abstract

Evidence shows that education, labor market conditions for ex-offenders, and wages influence crime rates. The relationship between wages and crime specifically, has interesting potential policy implications, especially in arguments for increasing the minimum wage. Economists speculate that increasing the minimum wage may help reduce crime by increasing wages and thus increasing the opportunity cost of committing crime, making it riskier and less necessary for people to supplement their incomes through illegal avenues. Using crime data from the FBI's Uniform Crime Reports and minimum wage data from Vaghul Zipperer (2016), I employ a two-way fixed effects framework to analyze the effects of changes in the minimum-to-median wage ratio on various crime outcomes, including total crime rates and 16-24 year old crime rates. I find no effect on Core-Based Statistical Area (CBSA) crime rates with changes in the minimum-to-median wage ratio.

[1] I would like to thank my advisor Sarah West for her time and patience throughout this project. Additionally, I would like to thank my readers Felix Friedt and Victor Addona, as well as my fellow students with whom I engaged in helpful conversations and from whom I received useful feedback.

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1 Introduction

Evidence suggests that incarceration and crime reducing policies can be effective but expensive anti-crime initiatives [14]. Research has shown that crime is affected by many factors, such as unemployment rates, number of job options for ex-offenders, wages, and education [5]. Thus, many speculate that increasing the minimum wage may deter crime. Many minimum wage workers fall between the ages of 16-24 years old – specifically, about 50% of workers making the federal minimum wage or less are under the age of 25 [7]. Evidence from the Federal Bureau of Investigation (FBI) shows that this age range commits proportionally more crimes than older age groups, with 16 to 24 year-olds committing around 40% of all property crimes [28]. This leads to a naturally interesting research question about how changes in minimum wage policy affect crime rates.

Many states still maintain the $7.25 federal minimum wage established in 2009, which if it had been indexed to the consumer price index would be $10.36 as of March 2023 [9]. This is equivalent to $26.56 as of 2023 if it had also been adjusted for worker productivity [3]. To put the magnitude of the federal minimum wage into context, the 2022 poverty threshold is around $13,000 for individuals [18]. For workers working 40 hour weeks at the $7.25 federal minimum wage, this puts them just barely over the poverty line, bringing in $15,080 before taxes. For families, the minimum wage is actually below the poverty line.[1]

Using arrest data from the 2009 - 2016 Uniform Crime Reports, minimum wage data from Vaghul and Zipperer (2016), and median wage data from the 2009 - 2016 Merged Outgoing Rotation Groups of the Current Population survey, I fit a two-way least squares specification to analyze the effect of a change in the minimum-to-median wage ratio on various crime outcomes. I find minimal evidence of an effect of changes in the minimum-to-median wage ratio on crime outcomes. There is weakly significant evidence of an increase of 0.039 crimes

[1]The poverty line for a family of 2-3 is around $18,000 and $23,000 respectively. Thus, if a person has any dependents and only makes the minimum wage, they will be under the poverty line.

in the 16-24 year old crime rate of a CBSA for a 10% increase in the minimum-to-median wage ratio when controlling for the level of unemployment. More broadly, I interpret this as finding next to no effect in crime rates with increases in the minimum-to-median wage ratio. Similarly, I find a significant inelastic response of 0.017 in the 16-24 year old crime rate. This means that for a 1% increase in the minimum-to-median wage ratio, there is a subsequent 0.017% increase in the 16-24 year old crime rate. This suggests that crime rates do not respond very strongly to changes in the wage ratio. This result is in line with much of the existing literature on the subject which is fairly divided on what direction the effect truly is. My contribution to the literature will take a more granular approach than other studies by investigating crime rates at the CBSA level, while also leveraging the variation made possible by scaling the minimum wage to a CBSA's median wage. Unlike most papers on the topic, I do not find definitive results of a directional effect of minimum wage changes on crime rates, instead finding nearly no relationship.

This paper will take an econometric approach in evaluating the effect of changes in the minimum-to-median wage ratio on crime rates. Section 2 reviews literature in the fields of criminology and economics, with the relevant economic theory being presented in Section 3. Section 4 provides an overview of the data as well as summary statistics. My contributions to this literature begins in Section 5, which exposits the empirical approach, with a discussion of the results in Section 6. Finally, Section 7 discusses the limitations of the study and potential next steps, while Section 8 concludes with this study's findings.

2 Literature Review

In 1968, Gary Becker laid out a framework for the economics of crime in "Crime and Punishment: An Economic Approach" [5]. He notes that "a person commits an offense if the expected utility to him exceeds the utility he could get by using his time and other resources at other activities" (Becker 9). Specifically he defines the number of offenses a person commits as a function of the probability of conviction, the punishment per offense, and other influences, most notably the income available to them in legal activities. This framework suggests that an increase in income available in legal activities would reduce the number of offenses for a person.

Aside from Becker (1968), there seems to be one other crime main framework that most modern works build upon, and that is Ehrlich (1973). Ehrlich arrives to many similar ideas as Becker (1968) – namely that individuals face a choice between crime and work, with a threat of punishment, and that 's participation in crime depends upon the levels of those factors. His analysis adds to that of Becker's by accounting for both benefits and punishments associated with legitimate and illegitimate activities (rather than simply punishments). He does this by treating the worker's choice as an optimal allocation problem under uncertainty, rather than between a set of mutually exclusive choices. Most importantly for my paper, Ehrlich (1973) finds empirical evidence of a strong positive correlation between income inequality and crimes against property. This is what the theory of minimum wage and monetary crimes would suggest, and provides a direct link to my main specification of using the minimum-to-median wage ratio[2]. Draca, et al. [12] provide a review of various adjustments to the main Becker (1968) and Ehrlich (1973) models including a continuous allocation between time and crime (Lochner 2004), criminal specialization, and criminal human capital build-up (Lochner 2004). Most of these studies arrive to broadly similar conclusions as the initial work by Becker (1968) and Ehrlich (1973).

There is a pretty substantial branch of economics research dedicated to minimum wage research on unemployment, which will not be reviewed in great detail here.[3] Many of the results of that research depend on determining whether the substitution (often called the unemployment) effect or the income effect dominate. The unemployment effect happens

[2]The minimum-to-median wage ratio represents the gap between the minimum wage worker and the median worker, which I assume to be representative of the general population. This makes this ratio a crude measure of income inequality among citizens of an area.

[3]For examples see: Belman and Wolfson (2014) [6]

when firms substitute away from labor due to the higher wages, and results in a loss of jobs (and concurrently, workers are demanding more work since it is now relatively more profitable than leisure). The income effect happens when workers substitute away from working due to the higher wages making it easier to maintain an income for less work. Determining which of these effects dominate allows us to estimate the size of the unemployment that results from changes in the minimum wage. Many of the articles investigating minimum wage and crime (as well as this paper) will use similar methods and theoretical arguments which will be detailed further below.

The literature as it relates to the effects of minimum wage policies on crime rates is rather sparse. Most of the literature is fairly recent, with many citing a 2016 Council of Economic Advisors (CEA) report as the motivation for their work. The report cites growing incarceration rates in the United States despite falling crime rates, which are driven primarily by changes in criminal justice policies. It also mentions the disproportionate impact of criminal policies on people of color, poor people, and people with mental illness. As an alternative to these discriminatory and sometimes ineffective policies, it proposes policies that improve labor market opportunities and educational attainment to reduce crime. In theory, this would help to eliminate crime at its source by eliminating many of its determinants, rather than punishing crime retroactively with additional incarceration. One specific measure they mention is increasing the minimum wage, saying that the "CEA finds that raising the minimum wage to $12 by 2020 would result in a 3 to 5 percent crime decrease (250,000 to 510,000 crimes) and a societal benefit of $8 to $17 billion dollars (CEA 6)."[4] This statement raised some concerns with economists aware of the ambiguous unemployment and income effects associated with changes in minimum wage and prompted the release of multiple articles about the relationship between crime and the minimum wage.

Before I review the papers published in response to the CEA report, it's important to consider the two papers that preceded it. The first relevant paper, and one that most of the

[4] Based on back-of-envelope calculations, using elasticity estimates from Gould, Weinberg, and Mustard (2002).

recent papers draw on, is Hashimoto (1987). Hashimoto looks to expand on the evidence available at the time of the adverse effects of the federal minimum wage on employment levels of young workers. He does this by investigating if an increase in time spent on activities outside of the labor market increases the rate of criminal activities. Using arrest data (which was the most readily available crime data at the time), he finds that minimum wage changes increased property-related crimes for teenagers. This is consistent with economic theory that says in the event of the unemployment effect dominating the income effect, those displaced workers will need to find alternative sources of income – in this case through monetary crimes.

While Hashimoto uses an aggregated, macro-level study, Beauchamp and Chan (2014) consider their study to be Hashimoto's micro-level complement. They use data from the National Longitudinal Survey of Youth 1997 cohort (NLSY97) to examine employment-crime substitution on the individual level. The detailed nature of the NLSY97 data allows them to determine whether or not movement in and out crime is due to employment status. It also allows them to directly identify individuals bound by minimum wage changes rather than approximating the treatment group and controlling for individual-level heterogeneity. Using linear probability and logit models, they find individuals, especially teenagers, commit more crime (both monetary and violent). Overall, their estimates suggest that crime will increase 1.9 percentage points as the minimum wage increases, due to workers becoming unemployed and idle.[5] They find that crime and employment are complements, not substitutes, speculating that this is due to minimum-wage-bound workers being a selected group "more likely to work and less likely to rely solely on crime for income." Like the CEA report, they mention the importance of employment and education options being available to young, unskilled workers, but find that overall, increasing the minimum wage is not an effective method of fighting crime.

[5] They use an indicator for whether an individual was bound by the minimum wage if they met a set of criteria, namely if they were employed at a job at or below the minimum wage prior to the increase in minimum wage. Thus their results for minimum wage increases could be applicable to any changes in wages before/after the increase, and are thus subject to some set of bounds, which they do not disclose.

Other researchers studying the effects of the minimum wage on crime use a number of dependent variables including crime, incarceration, and recidivism rates. Agan and Makowsky (2018) approach the problem from the social support side of the argument by also including Earned Income Tax Credits (EITCs) in their analyses. Instead of focusing on crime rates, they examine the effects of these social support policies on criminal recidivism (rate of returning to prison). They find that ex-offenders' employment is sensitive to even moderate changes in wage policies and to unemployment effects (labor-labor substitution), and better labor market opportunities reduce the probability of returning to prison. While some recidivism is captured in the typical studies using aggregate crime rates, this paper looks at ex-offenders' willingness to substitute away from crime and towards legitimate labor after release. They use administrative prison release records to track individuals over 14 years and conduct a difference-in-differences analysis to identify how changes in minimum wage and social support affect their probability of returning to prison. They find that for revenue-generating crime that might act as a substitute for legal employment, the probability of returning to prison is reduced by 2.8% with a $0.50 increase (the average in their study) in the minimum wage. However, their analysis does not allow for identification of the magnitude of the unemployment vs. the wage effect, so they simply assume that the wage effect dominates. While this tends to be a fairly common assumption in the literature, such an assumption yields biased results, though the magnitude of that bias is unknown. Additionally, by focusing on EITCs (which is skewed in favor of those with children) and rates of return to prison, they are presumably missing a majority of the crime-committing population who are sensitive to minimum-wage changes, which is the younger 16-24 year old workers.

Ghosh et al. (2020) use incarceration rates as their dependent variable, pointing out that incarceration rates can be affected by policies on law and order, while crime rates stem from individuals' perceptions of those policies. Ghosh et al. focus on finding a causal relationship between incarceration rates and state minimum wage, by using manual task-intensive occupations as an instrument for minimum wage. Using two stage least squares and state fixed effects, they find that increases in the minimum wage leads to fewer incarcerations. But, there is an inherent reverse causality problem when using incarceration rate instead of crime rate, because the same politicians who control minimum wages also control the policies that inform incarceration rates, and controlling for that is very challenging. They attempt to control for this by using an instrument of the long-run quasi-fixed component of employment share of manual task intensive occupations, which is highly correlated with changes in minimum wage. There are likely some specification issues in this instrument, which is beyond the scope of this paper, so their results are of lesser importance to me, though they find that increases in minimum wage leads to fewer incarcerations.

Finally, there are two papers that are most relevant for my paper. Braun (2019) constructs a theoretical model to investigate the relationship between labor market outcomes and crime decisions of young, unskilled workers, and calibrates it using aggregate crime statistics. Her goal is to find the level of minimum wage where each effect (unemployment and income) dominates. This reveals a U-shaped relationship between the aggregate crime rate and the minimum wage. This means that raising the minimum wage up to a certain point decreases the aggregate crime rate, but after that point the crime rate begins to rise again. This relationship shows that aggregate crime responds more to changes in wages than to unemployment for relatively small increases in the minimum wage. She then empirically verifies the existence of this U-shaped relationship through the use of the FBI's crime rate data compared to minimum-to-median ratios of income for various age groups. Using a non-parametric regression of county-level crime rates on state-level variation in the minimum to median wage ratio, she finds that the crime rate is minimized when the minimum wage is 0.91 of the median wage of 16-19 year olds, but that to maximize welfare, this ratio is 0.87.[6] Based on the 2018 median nominal wage of $10, these results suggest that raising the $7.25 federal minimum wage by $1-2 will improve welfare and/or crime rates. In 2022 dollars, this

[6]Intuitively, one would not expect the minimum-to-median wage ratio to exceed 1. It's worth noting that relative to the minimum-to-median wage ratios I observe in my data set (ranging from around 0.3 to 0.5), 0.9 and 0.87 are very large.

would be equivalent to raising the minimum wage by $1.20 to $2.39.

Fone et al. (2020) take a more rigorous approach than Braun by using more granular data, but they are investigating the same basic question: do minimum wage increases reduce crime? Similarly to Braun, they focus on younger, lower skilled laborers for whom the federal minimum wage is more likely to be binding [7]. They use both the 1998-2016 Uniform Crime Reports (UCR) and the National Longitudinal Survey of Youth 1997 (NLSY97) to investigate their question. The use of the UCR data allows identification of intent to treat estimates, while the NLSY data allows identification of effect of treatment on treated and to observe crime that does not necessarily result in arrest, due to the self-reporting nature. They start with using two-way fixed effects through OLS on the UCR data and later use event-study analyses on the NLSY data as robustness tests. They find no evidence that increases in the minimum wage reduce arrests. Instead, they find increased property crime arrests among 16-24 year olds, and estimate externality costs of $15 minimum wage increases of up to $2.5 billion. Note that these results are fairly consistent with the findings of Beauchamp and Chan (2014), which is understandable, since Fone also uses the NLSY data of Beauchamp and Chan as a robustness test (opting for a two way fixed effects model rather than a logit). These results do not extend to older individuals, for whom there is little evidence that minimum wage changes affect net crime.

My contribution to the literature falls somewhere between Braun (2019) and Fone's (2020) approaches. Braun's approach has the advantage in that it is non-parametric and allows for a non-linear relationship between minimum wage and crime rates, which allows us to determine at what levels the income vs. unemployment effect dominates. Her study, however, does not look at crime rate outcomes by age, instead only looking at aggregated rates. Since the model was calibrated for 16 - 24 year olds, if the model holds, then looking at 16 - 24 year-old crime rates should strengthen the U-shaped relationship she observes. Since we know that 16 - 24 year olds commit the highest proportion of crimes, fitting the model to this subset should eliminate some of the noise in the total crime rate and narrow in on the effect on young workers. Knowing what we do about the propensity of 16 - 24 year olds to commit crime and work minimum wage jobs, I argue that it's important to examine how the projections change for this group relative to the overall crime rate. Additionally she only looks at property crimes, which picks up the potential substitution between legal and illegal work, but misses the possibility that violent crime increases due to idleness from unemployment. Fone has the advantage of using a more robust UCR data set (having access to years prior to 2009) and being able to isolate the crime rates for the younger age group, but is somewhat limited in the use yearly level data, even though the minimum wage data that they use from Vaghul (2016) comes in more granular forms. Their use of yearly data complicates the ability to use time trends to account for macroeconomic determinants of employment and crime. Additionally, based on the small degree of variation in minimum wages from 2009 - 2016, Fone's study could perhaps be improved by including median wages for each county relative to the minimum wage, to allow greater variation within a state, and facilitate a more granular analysis.[7] Using data with higher frequency and broader geographic coverage enables greater use of fixed effects to account for potential confounders such as region-specific and time-specific trends, culture, or laws.

3 Economic Theory

3.1 Modeling Crime Decisions

In 1968, Gary Becker famously produced a model of crime derived by taking an economic approach. He argues that at its heart, the decision of a person to commit crime can be boiled down to a model similar to those used to decide on making economic decisions. It assumes

[7]Additionally, I think it may be interesting to see if it is possible to find information on the average punishment for the property-related crimes in a given county or state and incorporate that into the model, following the basic utility functions outlined by Becker (1968), but at this stage I have not conducted that analysis.

that a person chooses to commit a crime if the expected utility gained from the crime is greater than the expected utility from engaging in legal activities.

The decision to commit a crime can be simplified down to a function that considers the expected harm to the victim (for this I will only focus on "harm" as monetary loss), apprehension (modeled as the prevalence and strength of anti-crime tools such as police forces, anti-theft equipment, and court personnel), and conviction (the rates and severity of the punishment for a crime). He then models the subsequent "supply of offenses" as:

$$O_j = O_j(p_j, f_j, u_j),$$

where O_j is the number of offenses, p_j is the probability of conviction per offense, f_j is the punishment per offense, and u_j is a variable representing all other influences. Two of the factors that make up the final term u_j are education (causing an increase in "law-abidingness", according to Becker) and an increase in the income available in legal activities. He assumes that in this equation, all of the parameters have an inverse relationship with O_j, the expected number of offenses. For an increase in any of the inputs; conviction probability, punishment, or the other affecting factors, the number of offenses committed should decrease.

Becker focuses primarily on how changes in the probability of conviction and/or the strength of the punishment changes crime decisions, but other papers, as well as this paper, will focus more on the other inputs covered by u_j.

One of these papers is by Braun (2019). She describes a theoretical model where employed and unemployed workers receive exogenous job and crime opportunities. Her simplest approach models the decision to commit a crime as two functions, one for employed people and another for unemployed, where the expected utility of committing a crime is:

$$K_u(a) = g +_p (a) + (1 - \pi)V_u(a)$$

$$K_e(a, \lambda) = g +_p (a) + (1 - \pi)V_e(a, \lambda).$$

This model succinctly ties together many of the points from Becker (1968) by modeling the crime decision as a function of the instantaneous benefit g of committing the crime and the expected utility of unemployment (V_u), the expected utility of prison (V_p), and the expected utility of employment (V_e). She models people as rational, choosing to commit a crime if the expected benefits are greater than 0.

3.2 Minimum Wage Theory

In the past, and still existent in today's "New Minimum Wage Research," a large emphasis has been put on determining how changes in the minimum wage change labor market outcomes. There are two leading theoretical models in this research – assumptions of competition in the labor market and firms with monopsony power. Of these two models, only the competition model is relevant for this paper.

Figure 1 examines minimum wage effects in a competitive market. A graph of labor demand and supply with labor as the x-axis and wage as the y-axis shows us the equilibrium point q* where the current efficient wage is set. An implementation of minimum wage policy would add a price floor at minimum wage w that results in a gap that one can interpret as unemployment, $q_s - q_d$.

A worker is then faced with two choices: (1) substitute away from leisure and towards work, since it is more profitable now (substitution effect) or (2) reduce the number of hours worked and make a similar income since wages are higher (income effect). The firm also faces a similar tradeoff when choosing between capital and labor, as shown in Figure 2. The greater the elasticity of substitution of labor for other factors of production, the larger the expected effect of the minimum wage increase on labor hours. Similarly, the greater the magnitude of the price elasticity of demand for the product or service, the larger the expected effect of the minimum wage increase on labor hours. All of these factors are things that prior minimum wage research has attempted to estimate, with little luck in reaching a consensus.

Figure 1: Unemployment in Competitive Market

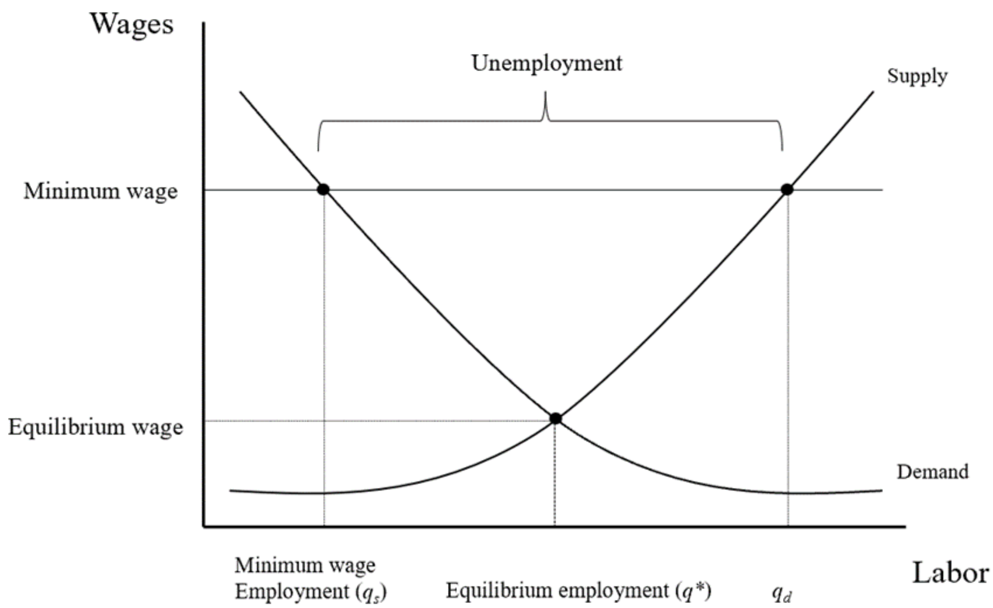
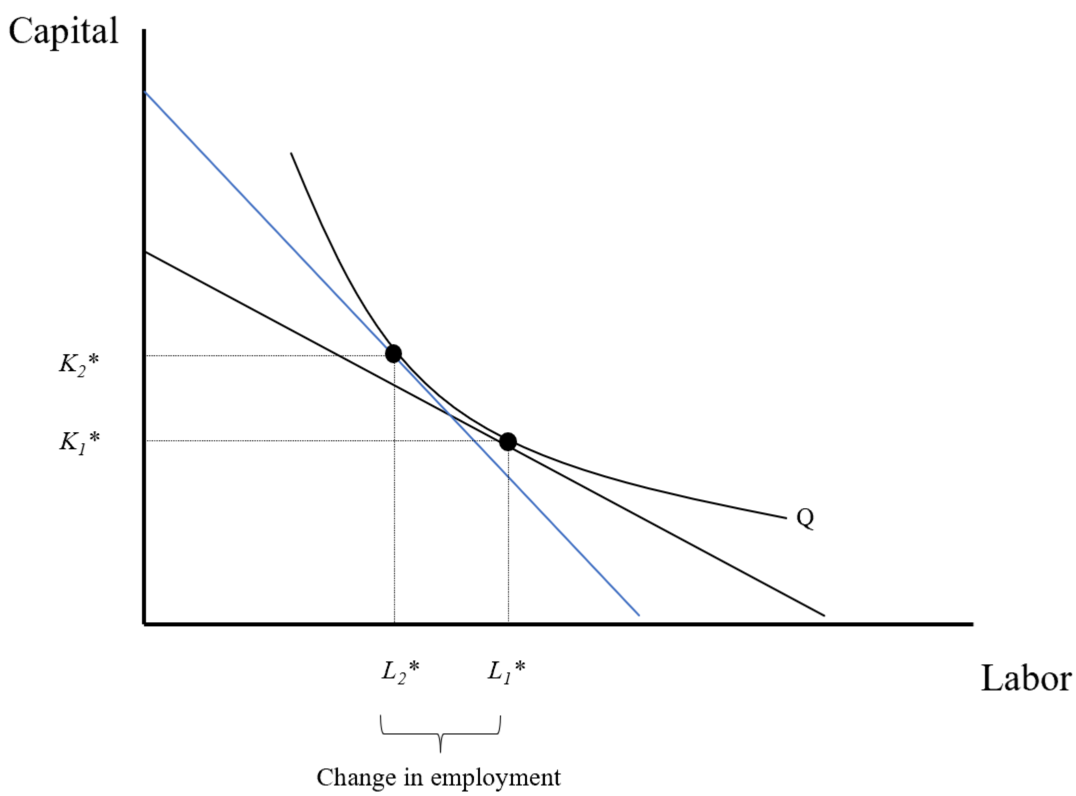


Figure 2: Capital-Labor Substitution



3.3 Combined Theory

With an increase in the minimum wage, there are two possible outcomes, one where the employment effect dominates, and one where the income effect dominates. If the employment effect dominates, people may be being laid off for cost-reduction purposes, there may be internal labor-labor substitution, or there may be a substitution towards automation and away from manual labor. This results in a net loss of jobs given an increase in the minimum wage and may result in people seeking income through illegal avenues. This means that if one can view crime (namely monetary crime) as a substitute for legal work, then the unemployment effect may drive crime up. More specifically, I will begin by investigating how property and other monetary crimes change based on changes in the minimum wage. Since these are revenue-generating crimes, they are most likely to be used in place of legal income. It is also possible that displaced workers may also become idle and engage in violent crime as a result of being out of work, but this paper will not focus on that outcome. On the other hand, an increase in the minimum wage could mean an increase in income for those workers who are not displaced. This increase in income will increase the opportunity cost of crime, and they may no longer need to supplement their income through illegal avenues. This shows us now, that if crime is again a substitute for legal work, the income effect may actually drive crime down.

4 Data and Summary Statistics

4.1 Crime Data

The main data for this project are from the FBI's "Uniform Crime Reporting Program Data: Arrests by Age, Sex, and Race" for the years 2009 - 2016. The data are a compilation of monthly arrest statistics submitted voluntarily by city, county, or state law enforcement

Table 1: Frequency of Number of Offenses in Agency in October 2013

Tabulation of Number of Offenses in Each Agency in 10/2013

	Freq.	Percent	Cum.
1	1626	17.77	17.77
2	2064	22.56	40.33
3	1938	21.18	61.51
4	1896	20.72	82.24
5	1625	17.76	100.00
Total	9149	100.00	

Table 2: Frequency of Crime Types in Agency in October 2013

Tabulation of Crime Type for Agencies with 1 Crime Reported

	Freq.	Percent	Cum.
Burglary-breaking or entering	204	12.55	12.55
Larceny-theft (not motor vehicles)	1226	75.40	87.95
Motor vehicle theft	70	4.31	92.25
Robbery	35	2.15	94.40
Stolen property- buy, receive, poss.	91	5.60	100.00
Total	1626	100.00	

agencies to the FBI. Thus, each observation provides the counts of a specific offense in an agency for a given year and month. For the purposes of this project, I begin by restricting the crimes to be the monetary crimes of burglary, larceny, motor vehicle theft, robbery, and stolen property. A breakdown of the frequencies of these crimes for an example year and month (I arbitrarily chose October 2013) can be found in Tables 1 and 2.

The terms of burglary, larceny, theft, and robbery are often used interchangeably, but there are some distinct differences (though the exact differences do not matter substantially for this paper since I am only focusing on a broader category of monetary crimes). Theft is the most generic term associated with the aforementioned crimes, and its definition can be used interchangeably with larceny. "Theft is taking someone's property with the intent of permanently depriving the owner of its use" and can be classed as a felony if the value of the stolen object exceeds $1,000. Robbery can be classified as a violent crime, and refers to "taking property from a person with force or threat of force", but violence is not necessary to be classified as a robbery. Burglary involves breaking-and-entering into a structure to

Table 3: Punishments by Crime

Crime	Fine Value [a]	Prison Time
Burglary	Up to $35,000	Up to 20 years
Motor Vehicle Theft	Up to $10,000	Up to 5 years
Larceny ($1,000 - $5,000)	Up to $10,000	Up to 5 years
Robbery	Up to $20,000	Up to 10 years

[a]For more information on crime punishments, see: [21], [19], [2], and [11]

commit a crime (but similarly to robbery does not require destruction of property for a crime to be classified as it).[25] The punishments for these crimes can vary by state, their punishments using Minnesota as a reference level, can be summarized as seen in Table 3. It's worth noting that the ideal study design investigating the effects of changes in the minimum wage on property crimes would use data on the value of objects stolen combined with these punishment values to calculate a person's indifference curves and willingness-to-pay for crime. This would lead to the cleanest set-up comparing the costs and benefits with working and committing crimes. Unfortunately, that data is not widely available at a national level, and so I will not be able to do that analysis in this study. However, should that data become more available, it would be a very interesting addition to this paper.

The UCR sample used in this project contains the four above crimes, as well as stolen-property. While these data technically report arrest rates rather than crime rates, they have the advantage of including demographic breakdowns for age, race, and sex for each crime committed. This is an important distinction to the Offenses Known and Clearances by Arrest (often called Return A) data which has no such breakdown. Since evidence (BLS, 2017) has shown that the minimum wage is most binding for young workers, and that those workers are most predisposed to crime (FBI, 2016), I want to be able to separate their crimes from those of the rest of the population. While arrests may be a cruder estimate of crimes committed in an area than the actual Return A data, I choose to assume that it is a sufficient enough proxy to inform us of the level of crime in a given area.

Due to the voluntary nature of the reporting, there is some under-representation of areas of high crime. Most notably, New York City is absent from the data. It is unclear why these agencies choose not to report. But, I do know that in general more agencies report every year, and once they start reporting, they do not tend to stop [20]. More work is necessary to ensure that there is no correlation in lack of reporting and minimum wage levels, though for now I will assume such an association does not exist.

The UCR data is reported at the agency level, and so in order to conduct analysis with outside data sources, I use the Law Enforcement Agency Identifiers Crosswalk (LEAIC) to provide sufficient geographic information for the purpose of merging datasets. The LEAIC Crosswalk data provides common matching keys for socio-demographic data (such as FIPS codes) for the agencies present in the crime data. However, the crosswalk only provides the geographic location associated with the address of the reporting agency. And so, for agencies that span multiple counties, it is impossible to tell which counties it spans – I only know the county the headquarters is located in. This is less consequential than it seems, because the UCR data on its own is somewhat equipped to combat this issue. The UCR data includes a population variable reflecting the population of the agency's jurisdiction. For agencies where there is overlapping jurisdiction (for example: colleges or universities, airports and transit authorities, or wildlife police), their population is assigned to be 0. And so, calculating crime rates based on agency population simply requires summing up the observations and aggregating to some level higher than the agency (for example county or CBSA code). However, this population metric is somewhat flawed in that it only represents the population that lives within an agency's jurisdiction, so for areas with a large number of non-residents (such as Los Angeles or Washington DC) the crime rates reflected may be inaccurate, particularly, the rates are likely overstated.

From the UCR data I generate male, female, total, juvenile, and elderly crime counts by agency. These are later converted to be crime rates after aggregating to the CBSA level to account for the agencies with overlapping jurisdictions whose populations are recorded as 0. My dependent variable of interest, as mentioned before, are the juvenile crime rates of

16-24 year olds, especially how their rate of crime compares to the total rate of crime in an area. Summary statistics of the variables of interest can be found in Table 5 as well as in the Appendix in Tables 6 - 9.

4.2 Wage Data

Supplementing the crime data are the minimum wage data from Vaghul and Zipperer (2016) provided through the Washington Center for Equitable Growth. They provide historical state and sub-state minimum wage levels for the United States. The state-level data is available for the years 1974 - 2016, while the sub-state data are only available for the years 2004 - 2016. The sub-state level minimum wage data reports any minimum wages at the city or county level that are different from the state-level minimum wage. Using the LEAIC crosswalk file I am able to assign to each agency the appropriate city, county, and/or state minimum wages. To create the minimum wage variable I choose the maximum of those three measures. Figure 3 in the appendix shows the variation in minimum wage across CBSAs in an example month of October 2013.

Due to the lack of variation, specifically the lack of variation at the county level, in the minimum wage during the years for which I have data, I chose to also include median weekly earnings as an additional scaling metric. The Current Population Survey is a monthly household survey studying employment and labor markets conducted by the government. They also publish extracts of this survey as part of their Merged Outgoing Rotation Groups (MORGs). The MORGs contain many of the same variables as the larger CPS surveys, such as hours worked, weekly earnings, industry, and occupation status, but for a smaller stratified sample. [8]

Because the MORGs is a survey, there is a noticeable amount of censoring in some of the geographic variables to maintain anonymity. Around two thirds of the data does not have a

[8]For more information on the CPS and MORGs, see: [24]

specific county FIPS code identifier, and is instead coded as a 0. However almost all of the observations retain a Core Based Statistical Area (CBSA) code. A CBSA code is a metric the government uses to describe both Metropolitan Statistical Areas (population of 50,000 or more people) and Micropolitan Statistical Areas (from 10,000 up to 50,000 people in population). It "contains one or more counties with an urban area of 10,000 or more people and the counties that have people which would commute to that area" (GreatData, 1) [16]. There are 927 CBSAs across the US (that do not cover the entirety of the country and can also cross state lines), of which my data has 273. Due to the lack of county-level identifying information in the MORGs, it was somewhat unfortunate, but necessary consequence to aggregate the UCR and minimum wage data from the agency level to the CBSA level in order to include median wage information in the analysis.

My primary independent variable of interest is no longer simply the minimum wage, but rather the ratio of the minimum-to-median wage for each CBSA included in the sample. This allows there to be more context for the minimum wage in each CBSA in the absence of large variation. This metric now informs us of the gap between minimum wage earners and the median earner in a given CBSA. Theory suggests that for larger gaps in the minimum-to-median wage ratio (values closer to 0) there will be higher rates of crime, while for values closer to 1 there should be less of a disparity between minimum workers and the median earner. Summary statistics for all of the variables of interest in my regressions can be found in Table 4 in the Appendix.

5 Empirical Approach

The individual unit in my panel data are distinct state and CBSA combinations, with the time unit being measured in month-years. I have two main dependent variables of interest: the total crime rate in a CBSA's population and the rate of 16-24 year old crimes in a CBSA's population. As such, I estimate the following two two-way fixed effects OLS models:

$$Y^{\mathrm{TR}}_{\mathrm{c,s,t}} = \beta_0 + \beta_1 \ln\left(\frac{\text{Minimum Wage}}{\text{Median Wage}}\right)_{\mathrm{c,s,t}} + \beta_2 \text{Lagged Unemployment Rate} + \alpha_{\mathrm{m}} + \alpha_{\mathrm{y,s}} + \alpha_{\mathrm{c,s}} + \varepsilon$$

$$Y^{\mathrm{YR}}_{\mathrm{c,s,t}} = \beta_0 + \beta_1 \ln\left(\frac{\text{Minimum Wage}}{\text{Median Wage}}\right)_{\mathrm{c,s,t}} + \beta_2 \text{Lagged Unemployment Rate} + \alpha_{\mathrm{m}} + \alpha_{\mathrm{y,s}} + \alpha_{\mathrm{c,s}} + \varepsilon$$

where Y^{TR} is the total crime rate for a population in a CBSA and state and Y^{YR} is the 16-24 year old crime rate for a population in a CBSA and state. My main independent variable of interest is $\ln\left(\frac{\text{Minimum Wage}}{\text{Median Wage}}\right)_{\mathrm{c,s,t}}$, which is the natural log of the maximum of the federal, state, city, or county minimum wage over the median wage of the CBSA. I include the lagged unemployment rate of the prior month of the CBSA to control for the unemployment effect, and I include a variety of fixed effects to act as crude controls. The state-year interaction ($\alpha_{y,s}$) and the CBSA fixed effect ($\alpha_{c,s}$) controls for time-invariant determinants of crime rates that vary at the state level such as state-laws and availability and use of anti-crime tools, and also serves as a crude proxy for broad education levels and demographics of each CBSA. I include month-in-year (α_m) fixed effects to account for the inherent seasonality in crime behaviors.

I am also interested in estimating the elasticity of crime behaviors with changes in the minimum-to-median wage ratio. To do so, I estimate the same two equations as above, but take the natural log of the dependent variables of interest to instead turn my results into elasticities.

6 Results

The results for my primary two specifications of predicting crime rates and ratios based on the minimum-to-median wage ratio are shown below in Table 9. It is important to note that any interpretations of the coefficient of interest can only refer to the gap between the minimum and median wage. I was unable to specify my estimation in a way that disentangled whether it was the minimum wage or median wage changing, and while this makes interpretations slightly more convoluted, the gap between the two is still an interesting and meaningful measure to study.

One can notice in Table 9 that for a 1% increase in the minimum-to-median wage ratio, we can expect an increase of 0.00593 crimes per 100,000 people. Similarly, I can expect to see an increase in 0.00387 16-24 year old crimes per 100,000 people. Only the coefficient on 16-24 year old crimes is statistically significant, with a weak significance at the 10% level. Thus for these specifications, I do not find that closing the minimum-to-median wage gap reduces crimes at all, instead showing an association of a slight increase in crimes. This suggests that the unemployment effect is dominating the income effect. However, it's worth nothing that as of 2021, the average population of a CBSA was around 900,000 people [23]. And so these estimates of 0.0059 and 0.0039 on average represent less than a 1 crime increase for the average population size of a CBSA.

Additionally, when examining the coefficient on the lagged unemployment rate for both models, I see a negative coefficient. The negative coefficient suggests that for an increase in the prior month's unemployment rate, there is a decrease in the current month's crime rate. However, at least for the 16-24 year olds, there is not sufficient evidence that this number is statistically different from 0. These coefficients do however suggest to us that perhaps our model is misspecified, or that there are omitted variables causing spurious results.

The results of the coefficient on the minimum-to-median wage ratio and the unemployment rate suggest to us that I have not properly fitted our model to fully account for either the unemployment or the income effect. I know that these operate in opposite directions, which could lead to our near-zero estimates if they are both negating each other. I included the lagged unemployment rate to try to control for the unemployment effect, but the positive coefficient on the minimum-to-median wage ratio is opposite to what I expect from our theory if the income effect is dominating. I likely need to add additional controls to isolate the effects of changes in the minimum wage on crime rates. It is worth noting however, that there are significant trends in seasonal and state crime rates found in my fixed effects specification, suggesting that it was important to control for them.

We find similar results when predicting the elasticity of crime on changes in the minimum-to-median wage ratio (Table 10). I estimate a statistically significant 5% level elasticity of 16-24 year old crime rates of 0.017. This means that for a 1% increase in the minimum-to-median wage ratio, there is a subsequent 0.017% increase in the 16-24 year old crime rate. This means that 16-24 year old crime is inelastic, which suggests it does not change much with changes in the minimum-to-median wage ratio, supporting our null results I found above. Similarly to above, in these models, for total crime elasticity and 16-24 year old crime elasticity, the coefficient on the unemployment rate is negative, which seem contradictory to theory. These results suggest again that I am missing controls to isolate either the unemployment or income effect and keep them from operating against each other, leading to near zero results.

6.1 Robustness Checks

As a preliminary robustness check I fit the above specification, but predict elderly crime rates for those aged 65 and above. For the most part, these are people who are likely not in the labor force, and whose actions should not change due to changes in the minimum wage. I find that there is no evidence of a change in the elderly crime rate with changes in the minimum-to-median wage ratio. As seen in Table 12, the predicted coefficient on the logged wage ratio is 0.0047 with a fairly large p-value. This suggests that though our coefficients of interest are small, the ones that are statistically significant, may indicate a relationship between crime and the wage ratio which is not due to any other external changes.

I also fit a few other models to see if removing the control for unemployment rate and also no longer scaling the minimum wage by the median wage affects the results at all. As seen in Tables 9 and 10 in the appendix, for all specifications I find no effect of the minimum wage on crime rates.

My methods fall somewhere between those of Braun (2019), studying the minimum-to-median wage ratio at the year and state level, and Fone (2020) who uses a similar two-way fixed effects specification at a county level. Somewhat coincidentally, my results also fall somewhere in between theirs. Braun (2019) finds a U-shape relationship between the minimum-to-median wage ratio and crime, finding more specifically that increasing the $7.25 federal minimum wage would reduce crimes. On the other hand, Fone (2020) does not find reductions in crime with increases in the minimum wage, finding instead increases in property crimes for 16-24 year olds. I however do not find a directional effect, finding instead an inelastic, near zero response in crime rates for changes in the minimum-to-median wage ratio. It is not surprising that our results are so different, the inconclusive nature of minimum wage research is a defining characteristic.

7 Limitations and Next Steps

The question this paper is attempting to study is a challenging one because there are so many factors that go into determining crime rates that if one were to draw a complete causal graph, there would likely be confounders that I missed in my specification. There are a number of limitations in this project due to time constraints and data availability. Ideally I would have data for both crime and the minimum wage going past 2016, preferably up to 2020, but the crime data is undergoing a transition from UCR to National Incident-Based Reporting (NIBRS), and so finding the 2016 - 2020 data is challenging. Tangentially, it would be most ideal if the theft statistics were reported in terms of the value of the items stolen. This would allow us to much more cleanly see how an increase in income would affect the decision to commit crime. If I had this data I would be able to construct indifference curves and come up with a measure of utility in committing crime.

Additionally, I have not found any county or city level minimum wage data past 2016, so even if I had the more recent UCR data there wouldn't be minimum wage data to supplement. Given more time and resources, it may be possible to assemble that manually, but that is a bit beyond my abilities for this project. This means it is challenging to directly test the CEA's theory about crime in 2020, as well as exploit the variation in minimum wages, because as of 2016 there were not as many sub-state minimum wages different from the state as there are today (only around 1% of the agencies in the data set have a minimum wage different from the state minimum wage). This lack of variation was my primary motivation for using the minimum-to-median wage ratio as my independent variable of interest. This parameter allows me to estimate changes in the gap between the minimum wage and median wage worker. however, due to CBSAs having differing median incomes and even differing median incomes over years, this analysis could be improved by running separate regressions for the bottom 25th percentile and the top 75th percentile of median earnings. I began to run these regressions, but due to time constraints was forced to abandon that aspect.

Many of the other data limitations have been discussed above in Section IV. The censoring in the MORG data seriously restricts our sample size by necessitating an aggregation to the CBSA level, and the unemployment measure calculated there is somewhat crude and is based only on the small sample, and not the entire population. The minimum wage data lacks substantial variation and what variation did exist may have been dwarfed by the need to aggregate up to the CBSA level.

Perhaps the largest limitation to this project, and one of which I was not aware until far too far along in the project, is that criminologists who work with the UCR data often do not recommend aggregating it to the county (or presumably the CBSA) level and advise against using it in policy studies. The data is presented at the agency level, and for some agencies, their jurisdiction is over multiple counties. Not only does the UCR not provide information on those jurisdictions, they also do not break down the distribution of crime across those counties. As such, when attempting to aggregate to the county level, one can end up with very incorrect crime rates. Due to the lack of jurisdiction-identifying information in the dataset, I am unaware if there are any agencies whose jurisdiction spans multiple CBSAs. I am specifying my equations under the assumption that they do not, since CBSAs are larger than counties, but without deeper research into specific agency jurisdictions, I cannot be sure. So, it is important to hold that as a caveat when interpreting results since county-level aggregation is so strongly discouraged among the criminology literature. In his web-book about the UCR data, Jacob Kaplan cites a 2002 paper by Maltz and Targonski, where they say that "until improved methods of imputing county-level crime data are developed, tested, and implemented, they should not be used, especially in policy studies" (Kaplan, 10.4) . Given this statement, my specific model specification, and the general weakness of my results, I hesitate to make any sort of definitive assertions on how changes in minimum wage policy affect crime rates.

8 Conclusion

The CEA (2016) has argued for increases in the minimum wage to serve as an anti-crime tool, while other authors have found that minimum wage increases actually reduce crime. Using a two-way fixed effects framework, I fit a number of specifications estimating the impacts of changes in the minimum-to-median wage ratio on various crime rates. In this paper, I find next to no effect of changes in the minimum-to-median wage ratio on crime rates, suggesting that contrary to the CEA's claims, minimum wage policies would not be an effective crime-deterring tool. That is not to say that minimum wage policies would not be beneficial in other regards or for other applications – this study is not designed in a way to assess that, but for crime-deterrence alone it would not be enough. Additionally, criminologists have expressed an inadequacy in county-level UCR data for informing policy decisions, and so while my results do not support using minimum wage policy to affect crime rates, other papers who do find distinct relationships may be misguided in their policy recommendations. There are a number of limitations to my study described above that leave substantial room for further investigation, but at this point, I find no clear effect of changes in the minimum-to-median wage ratio on crime rates.

References

[1] Agan, Amanda Y., and Michael D. Makowsky. The Minimum Wage, EITC, and Criminal Recidivism. vol. w25116, National Bureau of Economic Research, Inc, NBER Working Papers: 25116, 2018. ProQuest, https://www.proquest.com/working-papers/minimum-wage-eitc-criminal-recidivism/docview/2160366633/se-2?accountid=12205.

[2] "What is the Punishment for Theft in Minnesota?" Arechigo Stokka, 2022. https://arechigo-stokka.com/blog/punishment-for-theft/#:~:text=As%20a%20general%20rule%20in,up%20to%20a%20%2410%2C000%20fine

[3] Baker, Dean. "CORRECTION: This is What Minimum Wage Would Be If It Kept Pace with Productivity." Center for Economic and Policy Research, 2020.

[4] Beauchamp, Andrew, and Stacey Chan. "The Minimum Wage and Crime." B.E.Journal of Economic Analysis and Policy, vol. 14, no. 3, 2014, pp. 1213-1235. ProQuest, https://www.proquest.com/scholarly-journals/minimum-wage-crime/docview/1700657689/se-2?accountid=12205.

[5] Becker, Gary S. "Crime and punishment: An economic approach." The economic dimensions of crime. Palgrave Macmillan, London, 1968. 13-68.

[6] Belman, Dale and Paul J. Wolfson. 2014. "What Does the Minimum Wage Do?" Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://doi.org/10.17848/9780880994583

[7] "Characteristics of minimum wage workers, 2016." BLS, 2017. https://www.bls.gov/opub/reports/minimum-wage/2016/

[8] Braun, Christine. "Crime and the Minimum Wage." Review of Economic Dynamics, vol. 32, 2019, pp. 122-152. ProQuest, https://www.proquest.

com/scholarly-journals/crime-minimum-wage/docview/2196512472/se-2?accountid=12205,doi:http://dx.doi.org/10.1016/j.red.2019.02.002.

[9] Cooper, David. "Raising the federal minimum wage to $15 by 2024 would lift pay for nearly 40 million workers." Economic Policy Institute, 2019.

[10] Council of Economic Advisers. 2016. "Economic Perspectives on Incarceration and the Criminal Justice System." Available at: https://obamawhitehouse.archives.gov/the-press-office/2016/04/23/cea-report-economic-perspectives-incarceration-and-criminal-justice.

[11] "Defense of Minnesota Armed Robbery Charges." Devore Criminal Defense.

[12] Draca, Mirko, and Stephen Machin. "Crime and economic incentives." economics 7.1 (2015): 389-408.

[13] Ehrlich, Isaac. "Participation in illegitimate activities: A theoretical and empirical investigation." Journal of political Economy 81.3 (1973): 521-565.

[14] Fone, Zachary S., Joseph J. Sabia, and Resul Cesur. "Do Minimum Wage Increases Reduce Crime?" vol. w25647, National Bureau of Economic Research, Inc, NBER Working Papers: 25647, 2019. ProQuest, https://www.proquest.com/working-papers/do-minimum-wage-increases-reduce-crime/docview/2314545374/se-2?accountid=12205.

[15] Ghosh, Pallab K., Gary A. Hoover, and Zexuan Liu. "Do State Minimum Wages Affect the Incarceration Rate?" Southern Economic Journal, vol. 86, no. 3, 2020, pp. 845-872. ProQuest, https://www.proquest.com/scholarly-journals/do-state-minimum-wages-affect-incarceration-rate/docview/2427229872/se-2?accountid=12205.

[16] "CBSA Codes Documentation." GreatData.com. https://greatdata.com/pdf/Doc-CBSACodes.pdf

[17] Hashimoto, Masanori. "The Minimum Wage Law and Youth Crimes: Time-Series Evidence." The Journal of Law Economics, vol. 30, no. 2, 1987, pp. 443–64. JSTOR, http://www.jstor.org/stable/725504.Accessed14Sep.2022.

[18] "Federal poverty level (FPL)." HealthCare.gov.

[19] "Theft of a Motor Vehicle." James Blumberg Law, 2023. https://www.jamesblumberglaw.com/criminal-defense/theft-and-property-crimes/theft-of-a-motor-vehicle/#:~:text=Motor%20vehicle%20theft%20is%20punishable,fine%20of%20up%20to%20%2410%2C000

[20] Kaplan J (2021). Uniform Crime Reporting (UCR) Program Data: A Practitioner's Guide. https://ucrbook.com/.

[21] "When Breaking and Entering Becomes Burglary." Keller Law Offices, 2017. https://kellerlawoffices.com/breaking-becomes-burglary/#:~:text=Burglary%20Charges%20in%20Minnesota&text=Penalties%20range%20from%20fines%20up,to%20one%20year%20in%20prison

[22] "Census Core-Based Statistical Area (CBSA) to Federal Information Processing Series (FIPS) County Crosswalk." NBER.

[23] "Metropolitan and Micropolitan Statistical Areas Population Totals and Components of Change: 2020-2021." https://www.census.gov/data/tables/time-series/demo/popest/2020s-total-metro-and-micro-statistical-areas.html

[24] "Current Population Survey (CPS) - Merged Outgoing Rotation Group Earnings Data." NBER.

[25] "The Difference Between Theft, Larceny, Burglary, and Robbery." Smith Giles Attorneys at Law, 2023. https://www.smithgileslaw.com/blog/robbery-theft-larceny-burglary

[26] United States. Federal Bureau of Investigation. Uniform Crime Reporting Program Data: Arrests by Age, Sex, and Race, United States, 2009-2016. Inter-university Consortium for Political and Social Research [distributor], 2011-09-30. https://doi.org/10.3886/ICPSR30761.v1

[27] United States. Bureau of Justice Statistics. Law Enforcement Agency Identifiers Crosswalk, United States, 2012. Inter-university Consortium for Political and Social Research [distributor], 2018-09-18. https://doi.org/10.3886/ICPSR35158.v2

[28] "FBI Releases 2016 NIBRS Crime Statistics in Report and CDE, Promotes Transition of Agencies." U.S. Department of Justice - Federeal Bureau of Investigation, 2017.

[29] Vaghul, Kavya, and Ben Zipperer. "Historical state and sub-state minimum wage data." Washington Center for Equitable Growth (2016).

9 Appendix

Figure 3: Minimum Wage by CBSA in October 2013

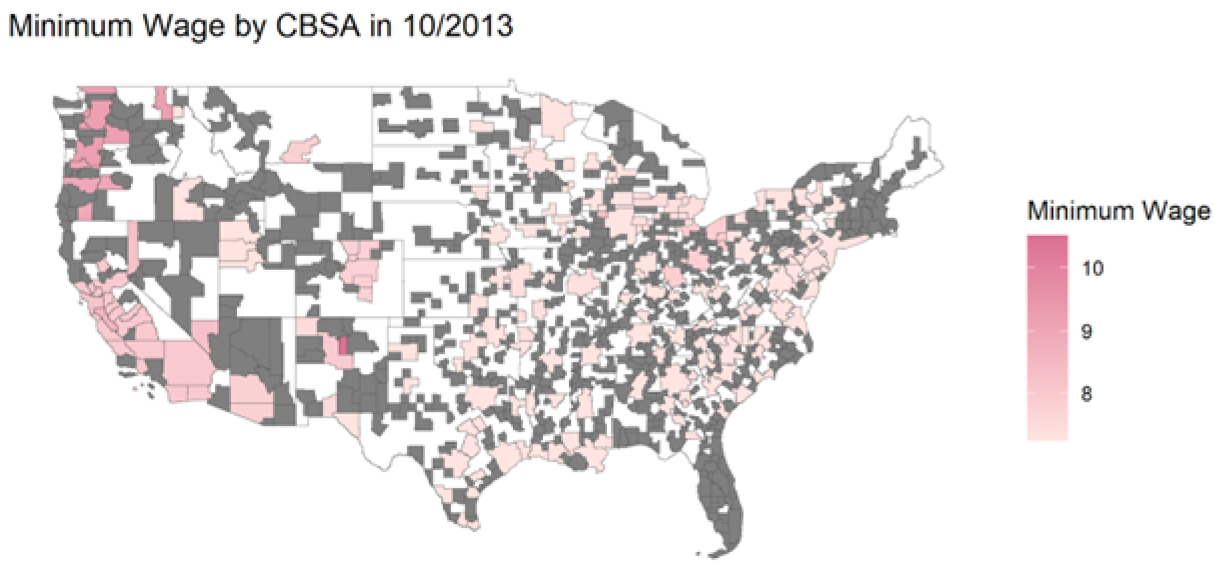


Table 4: Sample Summary Statistics

VARIABLES	(1) N	(2) mean	(3) min	(4) max	(5) p25	(6) p50	(7) p75
Total Crimes per Agency	22,384	1,373	1	33,327	33,327	33,327	33,327
16 - 24 y/o Crimes per Agency	22,384	547.0	0	14,791	14,791	14,791	14,791
Male Crimes per Agency	22,384	888.8	0	21,860	21,860	21,860	21,860
Female Crimes per Agency	22,384	484.4	0	14,897	14,897	14,897	14,897
Crimes Over 65 per Agency	22,384	2.282	0	316	316	316	316
Minimum Wage	22,384	7.547	6.550	10.91	10.91	10.91	10.91
Median Weekly Earnings	22,384	684.5	27.65	2,885	2,885	2,885	2,885
Hours Worked	22,384	39.30	1	99	99	99	99
Minimum-to-Median Wage Ratio	22,384	0.479	0.0136	67.69	67.69	67.69	67.69
% Unemployed in CBSA	22,384	6.550	0	75	75	75	75
Median Weekly Wages in 2023 Dollars	22,384	898.7	34.98	3,769	3,769	3,769	3,769
totCrime	22,384	62.29	1.431	1,727	1,727	1,727	1,727
rate16_24	22,384	24.65	0	600.6	600.6	600.6	600.6
Male Crime Rate	22,384	39.29	0	1,126	1,126	1,126	1,126
Female Crime Rate	22,384	23.00	0	686.1	686.1	686.1	686.1
Proportion of Male Crimes	22,384	0.638	0	1	1	1	1
Proportion of 65+ Crimes	22,384	1.09e-06	0	0.000122	0.000122	0.000122	0.000122
Number of panelid	315	315	315	315	315	315	315

Table 5: Summary Statistics for Variation in Crime Frequencies Across States

Descriptive statistics - by(FSTATE)

	Total Crimes per Agency	16 - 24 y/o Crimes per Agency	Male Crimes per Agency	Female Crimes per Agency	Crimes Over 65 per Agency
Alabama	723	281	468	255	1.38
Arizona	4453	1678	2884	1569	14.5
Arkansas	729	299	453	276	.385
California	2271	867	1510	761	2.97
Colorado	1523	569	931	592	3.58
Connecticut	902	285	611	291	.861
Delaware	958	358	602	356	1.21
District of Columbia	64	37.1	54.9	9.06	0
Georgia	1406	583	970	436	1.49
Hawaii	817	251	580	237	2
Idaho	510	223	310	201	.701
Illinois	6647	2835	5121	1526	26.5
Indiana	755	312	474	281	1.11
Iowa	438	178	252	186	.983
Kansas	338	129	200	138	.19
Kentucky	880	304	551	329	2.72
Louisiana	1561	611	1001	560	2.35
Maine	288	87.1	186	102	0
Maryland	1889	788	1325	563	2.77
Massachusetts	945	269	656	289	.14
Michigan	717	328	471	246	.413
Minnesota	1790	751	1100	690	3.26
Mississippi	740	323	480	260	.126
Missouri	1993	824	1303	689	2.23
Montana	220	82.5	118	102	0
Nebraska	1892	854	1129	763	8.44
Nevada	3594	1301	2389	1205	12.3
New Hampshire	426	142	248	178	.431
New Jersey	1462	556	1010	452	.897
New Mexico	925	334	566	360	2.42
New York	2168	861	1396	772	5.82
North Carolina	1391	575	940	451	1.77
North Dakota	376	163	223	153	.229
Ohio	1074	395	714	361	.575
Oklahoma	1507	607	875	632	2.46
Oregon	1314	430	828	486	3.55
Pennsylvania	763	297	514	249	.817
Rhodes Island	859	290	573	286	.828
South Carolina	1038	390	688	351	1.14
South Dakota	518	210	296	222	.917
Tennessee	1745	673	1081	664	2.89
Texas	1940	835	1241	699	3.53
Utah	1682	601	1052	630	3.88
Vermont	158	37.4	93	64.9	0
Virginia	1429	640	895	535	2.73
Washington	1542	543	1004	539	2.23
West Virginia	216	71.2	122	93.7	.12
Wisconsin	730	315	453	277	1.58

Table 6: Summary Statistics for Variation in Crime Rates Across States

Descriptive statistics - by(FSTATE)

	Total Crime Rate (%)	16-24 Crime Rate (%)	Male Crime Rate (%)	Female Crime Rate (%)
Alabama	.0908	.0359	.0591	.0316
Arizona	.0566	.0212	.0365	.0201
Arkansas	.0871	.0357	.0552	.0319
California	.0435	.0166	.0286	.0149
Colorado	.05	.0197	.0303	.0196
Connecticut	.0446	.0138	.0307	.0139
Delaware	.078	.0301	.0495	.0285
District of Columbia	.	.	.	.
Georgia	.0687	.0286	.0462	.0225
Hawaii	.0421	.0131	.0299	.0122
Idaho	.05	.0211	.0314	.0187
Illinois	.111	.0463	.0762	.0343
Indiana	.0679	.0279	.0413	.0266
Iowa	.0746	.0311	.0427	.0319
Kansas	.0412	.016	.0266	.0146
Kentucky	.0803	.0277	.0497	.0307
Louisiana	.0836	.0327	.0535	.03
Maine	.0576	.018	.0365	.0212
Maryland	.0731	.0294	.0485	.0245
Massachusetts	.0343	.00966	.0228	.0115
Michigan	.0363	.0157	.0229	.0133
Minnesota	.0699	.0293	.0428	.0271
Mississippi	.0723	.0319	.046	.0263
Missouri	.0756	.0306	.0487	.0269
Montana	.0483	.0183	.0256	.0227
Nebraska	.0693	.0313	.0416	.0277
Nevada	.0614	.0226	.0405	.021
New Hampshire	.0526	.0173	.0305	.0222
New Jersey	.0616	.0237	.0397	.0219
New Mexico	.0685	.0246	.0427	.0259
New York	.0707	.0279	.0455	.0252
North Carolina	.0624	.025	.0423	.0201
North Dakota	.0677	.0297	.04	.0277
Ohio	.0545	.0196	.0351	.0194
Oklahoma	.0644	.0257	.0378	.0266
Oregon	.0728	.0251	.0457	.0272
Pennsylvania	.0567	.0223	.0378	.0189
Rhodes Island	.0303	.0103	.0202	.0101
South Carolina	.0585	.0221	.0386	.0199
South Dakota	.0671	.0272	.0382	.0289
Tennessee	.0745	.027	.0449	.0297
Texas	.0593	.0253	.0366	.0227
Utah	.0679	.0254	.0427	.0252
Vermont	.046	.011	.0268	.0192
Virginia	.0484	.0194	.0292	.0192
Washington	.0603	.0223	.0383	.022
West Virginia	.0849	.0271	.048	.0368
Wisconsin	.07	.0302	.0424	.0276

Table 7: Summary Statistics for Crime Proportions Across States

Descriptive statistics - by(FSTATE)

	Proportion of 16-24 Crimes	Proportion of Crimes Committed by Males	Proportion of Over 65 Crimes
Alabama	.359	.639	.00094
Arizona	.376	.646	.00433
Arkansas	.411	.627	.00046
California	.377	.66	.00087
Colorado	.397	.625	.00173
Connecticut	.313	.696	.00173
Delaware	.382	.636	.00105
District of Columbia	.	.	.
Georgia	.41	.671	.00084
Hawaii	.308	.712	.00144
Idaho	.422	.622	.00112
Illinois	.405	.628	.00135
Indiana	.413	.623	.00068
Iowa	.419	.58	.00184
Kansas	.389	.642	.00043
Kentucky	.347	.629	.00185
Louisiana	.387	.645	.00114
Maine	.312	.633	0
Maryland	.399	.672	.00113
Massachusetts	.281	.67	.00012
Michigan	.429	.659	.00028
Minnesota	.402	.627	.00108
Mississippi	.439	.639	.00015
Missouri	.398	.649	.00089
Montana	.38	.531	0
Nebraska	.45	.606	.00398
Nevada	.362	.661	.00267
New Hampshire	.332	.581	.00097
New Jersey	.387	.652	.00067
New Mexico	.357	.627	.00182
New York	.392	.645	.00121
North Carolina	.399	.686	.00075
North Dakota	.434	.59	.00059
Ohio	.36	.644	.00055
Oklahoma	.39	.595	.00098
Oregon	.34	.627	.00221
Pennsylvania	.393	.668	.00088
Rhodes Island	.339	.666	.00107
South Carolina	.379	.663	.00102
South Dakota	.401	.57	.00162
Tennessee	.36	.603	.0015
Texas	.423	.62	.00125
Utah	.372	.632	.00183
Vermont	.236	.581	0
Virginia	.406	.606	.00162
Washington	.37	.64	.00061
West Virginia	.336	.584	.00025
Wisconsin	.426	.608	.00157

Table 8: Wage and Employment Summary Statistics Across States

Descriptive statistics - by(FSTATE)

	Minimum Wage	Median Weekly Earnings	Median Weekly Wages in 2023 Doll	Hours Worked	Minimum-to -Median Wage Ratio	% Unemployed in CBSA
Alabama	7.22	673	865	39.4	.451	6.64
Arizona	7.67	663	869	39.1	.489	7.06
Arkansas	7.31	643	842	39.9	.479	6.1
California	8.38	721	945	39.1	.518	8.27
Colorado	7.68	769	1011	39.8	.425	6.67
Connecticut	9.19	858	1083	38.6	.515	4.73
Delaware	7.46	687	902	39.9	.457	5.82
District of Columbia	8.7	1042	1366	40	.339	7.42
Georgia	7.2	649	853	39.2	.492	6.74
Hawaii	7.91	694	877	40	.473	3.11
Idaho	7.2	642	838	39.4	.467	6.34
Illinois	8.12	661	866	39.2	.514	8.05
Indiana	7.2	674	883	39.3	.542	6.68
Iowa	7.27	693	910	39.6	.442	4.24
Kansas	7.2	679	892	39.6	.446	5.32
Kentucky	7.21	652	853	39	.48	6.65
Louisiana	7.2	661	868	39.9	.476	6.49
Maine	7.55	678	855	38.2	.473	4.07
Maryland	7.45	800	1047	39.7	.405	5.39
Massachusetts	9.09	815	1029	38	.472	4.31
Michigan	7.63	680	892	38.8	.497	7.82
Minnesota	7.37	682	901	38.8	.452	4.42
Mississippi	7.2	653	860	39.7	.47	7.18
Missouri	7.33	680	896	39.4	.461	5.55
Montana	7.62	649	851	39.6	.487	3.5
Nebraska	7.43	698	916	39.8	.435	3.86
Nevada	8.05	638	841	39.9	.515	9.23
New Hampshire	7.25	794	1003	39.6	.39	3.15
New Jersey	7.59	786	1033	38.6	.435	7.45
New Mexico	8.24	662	870	39.4	.535	6.1
New York	7.7	722	945	39	.454	6.04
North Carolina	7.2	660	865	39.3	.468	6.8
North Dakota	7.2	689	903	39.9	.425	2.63
Ohio	7.68	667	877	39.3	.492	7.43
Oklahoma	7.2	637	838	39.9	.481	5.59
Oregon	8.81	641	840	38.8	.574	8.11
Pennsylvania	7.24	697	912	39.1	.443	5.96
Rhodes Island	8.97	717	905	39.9	.506	4.42
South Carolina	7.2	644	842	39.4	.478	6.88
South Dakota	7.46	632	829	39.9	.48	3.29
Tennessee	7.2	640	837	39.5	.487	6.7
Texas	7.2	630	825	39.6	.514	5.56
Utah	7.2	685	896	39.7	.453	4.42
Vermont	9.19	813	1027	40	.456	1.88
Virginia	7.2	723	947	39.4	.459	6.01
Washington	8.98	745	981	38.8	.512	7.26
West Virginia	7.52	768	1003	39.5	.421	5.77
Wisconsin	7.19	699	920	39.1	.434	5.5

Table 9: Regression Output for Crime Rates as the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Total CR	16-24 CR	Total CR	16-24 CR	Total CR	16-24 CR	Total CR	16-24 CR
Logged Minimum-to-Median Wage Ratio	0.593	0.387*	0.605	0.423*				
	(0.589)	(0.223)	(0.589)	(0.250)				
% Unemployed in CBSA = L,	-0.0392*	-0.00796			-0.0345*	-0.00819		
	(0.0222)	(0.00840)			(0.0192)	(0.00840)		
Minimum Wage					-0.278	0.762	0.609	1.467**
					(1.243)	(0.543)	(1.417)	(0.601)
Constant	57.15***	19.39***	57.01***	19.30***	59.05***	12.98***	51.64***	7.221
	(0.918)	(0.344)	(0.914)	(0.388)	(9.968)	(4.354)	(11.37)	(4.819)
Observations	22,384	21,844	22,384	22,384	21,844	21,844	22,384	22,384
R-squared	0.080	0.191	0.080	0.157	0.101	0.191	0.080	0.157
Number of panelid	315	314	315	315	314	314	315	315
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x State Interaction	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: Regression Output for Elasticity Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Total CR	16-24 CR	Total CR	16-24 CR	Total CR	16-24 CR	Total CR	16-24 CR
Logged Minimum-to-Median Wage Ratio	0.00738	0.0171**	0.00833	0.0177**				
	(0.00648)	(0.00785)	(0.00652)	(0.00787)				
% Unemployed in CBSA = L,	-0.000624**	-0.000494*			-0.000623**	-0.000501*		
	(0.000244)	(0.000296)			(0.000244)	(0.000296)		
Minimum Wage					-0.0300*	0.0138	-0.0155	0.0298
					(0.0158)	(0.0191)	(0.0157)	(0.0189)
Constant	3.937***	2.841***	3.934***	2.838***	4.171***	2.718***	4.051***	2.585***
	(0.0100)	(0.0121)	(0.0101)	(0.0122)	(0.127)	(0.153)	(0.126)	(0.152)
Observations	21,844	21,767	22,384	22,292	21,844	21,767	22,384	22,292
R-squared	0.145	0.247	0.141	0.241	0.145	0.247	0.141	0.240
Number of panelid	314	314	315	315	314	314	315	315
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x State Interaction	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: Robustness Test Results

VARIABLES	(1) 65+ Crime Rate	(2) Male Crime Rate
Minimum-to-Median Wage Ratio	0.00471	-0.0154
	(0.00396)	(0.217)
Constant	0.0686***	36.60***
	(0.00928)	(0.509)
Observations	22,384	22,384
R-squared	0.023	0.078
Number of panelid	315	315
Month FE	Yes	Yes
CBSA FE	Yes	Yes
Year x State Interaction	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1