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# Determinants of County-Level Poverty Rates in 2017: An Upper-Midwest Comparison

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## Abstract

The American upper-Midwest as a region throughout the 2010s has experienced lower-than-average poverty rates. This paper seeks to uncover the determinants that have the greatest impact on the county-level poverty rates for five states (Iowa, Minnesota, Wisconsin, and the Dakotas). Outcomes for this study came from an Ordinary Least Squares (OLS) regression to estimate the impact each independent variable had on the poverty rate. The empirical results showed the unemployment rate, the percentage of households headed solely by females, and percent of the population that was Native American in 2017 had a significant impact on a county's poverty rate.

## Keywords

poverty, income inequality, unemployment, labor markets

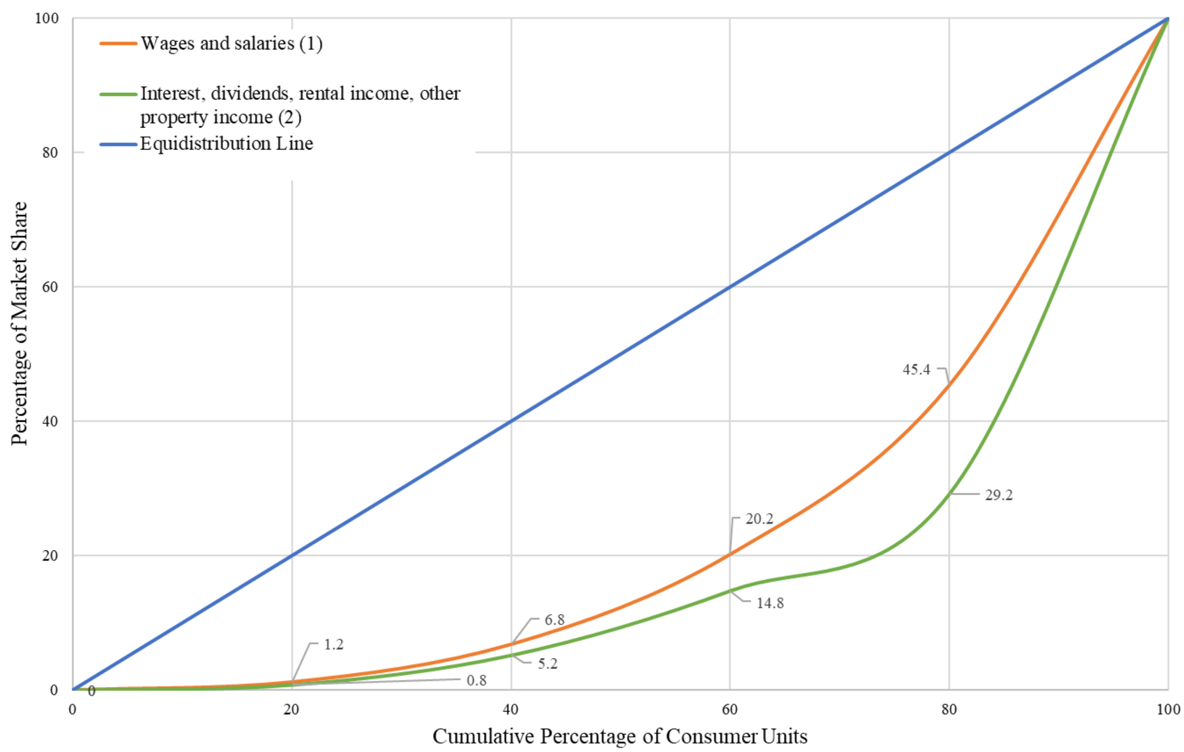
## Cover Page Footnote

I would like to thank Dr. Margaret Lewis for her guidance throughout the process of drafting this paper.

## 1. Introduction

The United States has an income and asset distribution problem. This is not a new issue, as the *New York Times* points out that every state in the U.S. has experienced rising income inequality since the 1970s (Tritch, 2016). But the popular press is not alone in pointing out this issue—according to the Consumer Expenditure Survey, in 2017, 54.6 percent of all income earned in the United States went to the top quintile of earners (Figure 1). This leaves only 45.6 percent of income to go to the remaining 80 percent of earners. This 45.6 percent of income also remains unequally distributed, with the bottom quintile only accounting for 1.2 percent of total income earned in 2017. Assets are even less equally distributed, with only 0.8 percent of income from rental properties, interest on financial accounts, and dividend payouts going to the bottom quintile of earners, while the highest earning quintile brought in an astounding 70.8 percent of the income earned from these assets.

Figure 1: Quintile Comparison of Wage, Salary, and Assets, 2017

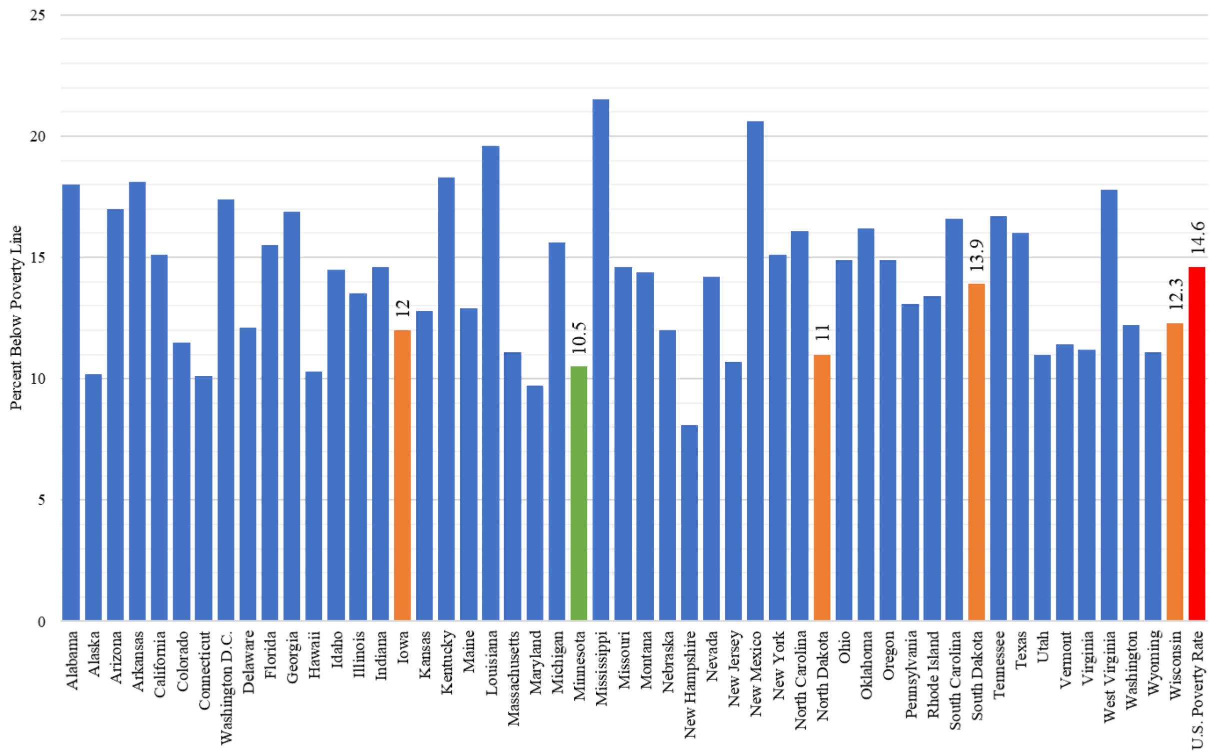



Source: U.S. Department of Labor, Bureau of. Labor Statistics, 2017 Consumer Expenditure Survey, Table 1101: Shares of annual aggregate expenditures and sources of income. Data downloaded on 9/22/19 from https://www.bls.gov/cex/tables.htm#annual.

With this inequality in income and wealth distribution, one might wonder how this issue has affected the poverty rate in the United States. The link between income and poverty was created back in the 1960s, when the initial thresholds were established by Mollie Orshansky (Sawhill, 1988). The poverty rate calculation will be discussed later, but the Census uses pre-tax income for a household as the measure to determine poverty status. Minnesota has a lower-than-average poverty rate when compared to the other states in America (Figure 2 displays the poverty rate for each state in the United States, and Washington D.C. for the year 2017). When comparing Minnesota's state-level poverty rate to the U.S.

national poverty rate, Minnesota seems to be doing exceptionally well. However, the upper-Midwest as a whole is not very far behind Minnesota in terms of suffering from generally low rates of poverty.

Figure 2: Poverty Rate for All Persons by State, 2017

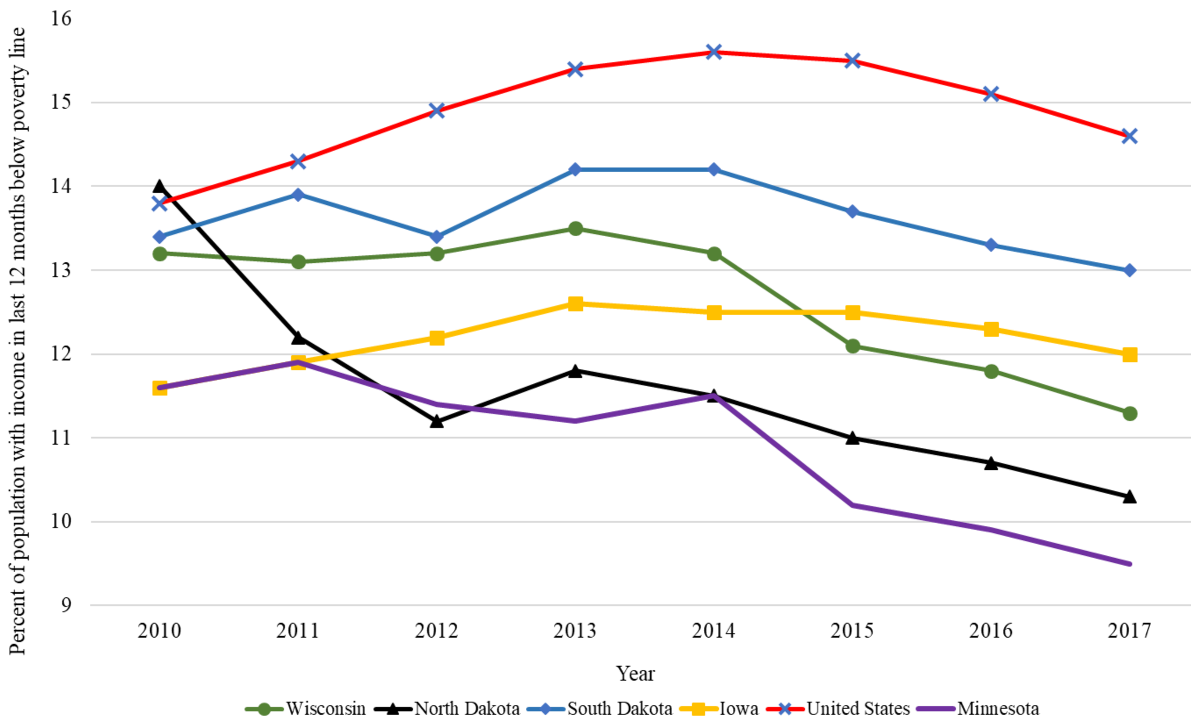



Source: U.S. Census Bureau, 2017 American Community Survey, Table DP03. Data downloaded on 11/15/19. https://data.census.gov/cedsci/table?q=poverty&hidePreview=true&table=DP03&tid=ACSDP1Y2010.DP03&t=Official%20Poverty%20Measure%3APoverty&lastDisplayedRow=

The entire upper-Midwest appears to have lower-than-average poverty occurrences, as for the year 2017, each of the five states this study observes had lower rates than the national average. But if we expand upon this, and look at these states from 2010 to 2017, the trend remains mostly the same (Figure 3). Apart from North Dakota in 2010, Minnesota and its neighbors have continuously remained below the national poverty rate since the year 2010. The oil surge in North Dakota likely assisted them in joining the other states in the region in terms of the poverty rate they experience, but that likely does not explain the entire picture of poverty in the region.

In 2009, Minnesota set out to end poverty in the state, with many religious leaders and community members around Minneapolis coming together to urge the state's legislature to form a commission to fight poverty throughout the state. The commission, according to Senator John Marty, one of leading figures in the fight against poverty in Minnesota, did not lead to any substantial policy initiatives. Although the commission did not get a significant amount done on the policy side, Senator Marty claimed that the real success was getting people to talk about the issue, which raised additional awareness among the faith community around the state. Senator Marty said, "This additional recognition, along with some of the legislation passed in the 1970s, as well as our push to pass a minimum wage increase have all helped keep the poverty rate in Minnesota lower than our neighbors" (Marty, 2019).

Figure 3: Upper-Midwest & U.S. National Poverty Rates, 2010-2017




Source: U.S. Census Bureau, 2017 American Community Survey, Table DP03. Data downloaded on 9/11/19 from: https://data.census.gov/cedsci/table?q=poverty&hidePreview=true&table=DP03&tid=ACSDP1Y2010.DP03&t=Official%20Poverty%20Measure%3APoverty&lastDisplayedRow=144&g=0400000US27,38,46,55&y=2010&moe=false&tp=false.

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The current study will attempt to determine the major factors in the causes of *county-level* poverty in 2017 for five states in the upper-Midwest: Iowa, Minnesota, North Dakota, South Dakota, and Wisconsin. These states were chosen due to their similar racial and ethnic demographics, being situated in close geographic proximity, and having a near uniform labor force breakdown, with large segments of the population working in education and healthcare, manufacturing, and service industries (Table 1).

| Table 1: Demographic and labor force breakdown by state, 2017 | | | | | | |
|---|---|---|---|---|---|---|
| **State** | **White** | **Black** | **Hispanic** | **Education & Healthcare** | **Manufacturing** | **Services** |
| Iowa | 90.6 | 3.4 | 5.7 | 24.3 | 15.1 | 16.5 |
| Minnesota | 83.7 | 6.0 | 5.2 | 25.0 | 13.5 | 16.5 |
| North Dakota | 87.7 | 2.3 | 3.3 | 24.7 | 6.9 | 17.1 |
| South Dakota | 84.7 | 1.7 | 3.5 | 23.9 | 10.0 | 16.9 |
| Wisconsin | 85.9 | 6.3 | 6.6 | 23.2 | 18.4 | 16.8 |
| Source: Data for race and ethnicity statistics retrieved from U.S. Census Bureau (2017). American Community Survey 5-Year Estimate, 2017 (Table ID: B02001). Data for occupation and labor force composition obtained from U.S. Census Bureau (2017). American Community Survey 5-Year Estimate, 2017 (Table ID: DP03). | | | | | | |

With so many similarities, it begs the question: what are the determinants of county-level poverty rates in the upper-Midwest for the year 2017? The states vary in terms of poverty rate on the state and county levels. This study hopes to determine the factors contributing to the county-level poverty rates for the five Midwestern states it observes.

## 2. Literature Review:

There has been a decided lack of research on the causes of poverty in the United States in recent years. Although three economists studying poverty won the 2019 Nobel Prize in Economics, their research focused on rethinking ways to combat global poverty and centered around India. What was once a thriving body of literature following President Lyndon B. Johnson's 1964 War on Poverty (Gallaway, 1965; Lampman, 1965; Clawson, 1967; Thurow, 1967; West, 1970) has since began to ebb and flow, only producing research when poverty rates increase during recessions (Sawhill, 1988; Glennerster, 2002). Because of this, only Berger, Cancian, and Magnuson (2018), have recently researched anti-poverty policy proposals and explored new, alternative means of fighting poverty in the United States which displayed significant innovations to the existing programs.

The literature produced decades ago provides much of the theoretical background for this research, Thurow (1967) and Sawhill (1988) being the main contributors. This is not to say that there has been no research into the poverty rate over the last fifty years. Gennetian and Miller (2002), for example, investigated whether the Minnesota Family Investment Program (MFIP) reduced instances of childhood poverty in Minnesota compared with the previous program, Aid to Families with Dependent Children (AFDC). They found that the program did have a statistically significant impact on reducing poverty occurrences in single mothers, which in turn also reduced the childhood poverty rates (Gennetian & Miller, 2002).

Results from previous studies vary on certain common variables and their overall impact on the poverty rate in the United States. There is, however, consensus in the literature that increases among a population's formal education and employment levels, especially in certain sectors of the labor force, will cause declines in poverty (Thurow, 1967; Sawhill, 1988; Rodgers & Rodgers, 1993; Caner & Wolff, 2004; Berger et. al, 2018), while increases in crime rate, incidences of single-motherhood, and presence of nonwhite headed households will increase an area's poverty rate (Clawson, 1967; Thurow, 1967; Sawhill, 1988; Rodgers & Rodgers, 1993; Allen & Stone, 1999; Blank, 2002; Gennetian & Miller, 2002).

It seems rational that having a job is key for deterring poverty rates. Thurow (1967) found that in 1963, 48.9 percent of poverty-stricken household had no members in the labor force, while households with only one member employed part-time made up 23.1 per cent of the impoverished population. Thurow also found that farmers had a high rate of poverty 41.2 percent of farmers fell below the $3,000 poverty line in 1963, even after adjusting his model to include income in kind (p. 43). This is not as prevalent today, as far fewer people work in the agricultural industry, and the structure of the economy has changed drastically over the last 56 years. However, the presence of certain occupations does still appear to influence overall poverty rate of a county.

Berger et. al (2018) point out that increases in the availability of construction and manufacturing jobs will tend to lead to lower poverty rates, as these are high-paying jobs that require low levels of education, allowing a large number of (mostly) men to bring in a large income. This is, however, getting more difficult to sustain—globalization, changes in technology, and decreases in union influence have all contributed to a reduction in employment rates and wage-growth for the segment of the workforce that lacks formal education. These factors have all added up to a stagnation in earnings for workers without a college education, restricting their access to work that would allow them to earn their way out of poverty, and leading them toward work in the typically low-wage services sector of the labor market (Berger et. al, 2018). Fortunately for the upper-Midwest, both the construction and manufacturing industries have sizeable labor forces in the observed states, which may contribute to the lower-than-average poverty rates (Table 1).

The education variable has become more important in recent years. Thurow (1967) measured household education based on the heads of the household having eight or more combined years of education. More modern studies discuss the importance of formal education in relation to earning more than the poverty threshold. Berger, Cancian and Magnuson (2018) lay out a situation that some experience in the modern-day United States, saying:

> The low-wage labor market has been characterized by stagnation with little growth in wages and few opportunities for advancement. At the same time, young adults with low levels of education have increasingly transitioned into parenthood in the context of unmarried romantic partnerships that often dissolve shortly after their child's birth (p. 5).

Berger et. al (2018) also mention lack of job security. Whereas lack of employment was a key contributor to poverty in Thurow's day, the late 2000s through today have seen an increase in working poor due to unstable and irregular employment (Berger et. al, 2018; U.S. Department of Labor, 2019). This is due in large part to decreased job tenure, unpredictable work hours, and contingent employment ensuring limited contracts for low-skilled workers, all of which lead to inconstant and insufficient income for these under-educated workers.

Race and ethnicity also play large roles in a household's tendencies toward poverty. Several studies, dating back to the original study on causes of poverty done by Thurow (1967) have found statistically significant poverty rate increases within households headed by nonwhites (Thurow, 1967; Sawhill, 1988; Rodgers & Rodgers, 1993; Blank, 2002; Gennetian & Miller, 2002). Historically differing wage rates for people in minority groups caused this. Prior to the passing of the Civil Rights Act of 1964, wage discrimination was not illegal in the United States. However, black and Hispanic Americans still experience higher rates of poverty today according to Berger et. al (2018); one reason could relate to the crime and incarceration rates in minority communities. Incarceration has immense impact on the poverty rate—evidence suggests that a criminal record produces enormous challenges where employment is concerned. With studies signaling that about half of all black men in America experiencing arrest by age twenty-three, and 68 percent of black men without a high school degree (signaling a lack of education along with a criminal record), it seems that poverty is destined to strike these people in a long-term way (Berger et. al, 2018, p. 6 – 7).

Like households headed by nonwhites, female-headed households (where no husband is present) experience far greater rates of poverty. The Equal Pay Act of 1963 enshrined equal wage rates for women, making gender-based wage discrimination illegal for people working identical jobs. Yet somehow, this group (single-mothers especially) experience higher rates of poverty than many other demographics. Blank (2002) suggests this is due to their inability to enter the labor force while caring for a child. Blank observed the change in caseloads for two programs following the introduction of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA). She concluded that there was a greater increase in labor force participation among low-skilled, less educated, single-mothers following the implementation of the Temporary Assistance for Needy Families (TANF) program, which lead to a 2.0 to 2.2 percentage point decline in the poverty rate among single mothers (p. 1144).

The previous literature has not produced many strong results when trying to find an answer to which types of areas, more urban or more rural, suffer from greater rates of poverty. West (1970) hypothesized that poverty rates would be lower in urban areas. This hypothesis seems logical, based on Thurow's findings from 1967 on the poverty rates of farmers, along with West's assertion that jobs found in more urban areas are typically offer higher wages. This explanation, indeed, makes sense – an abundance of jobs that have higher earnings potential would be an enticing draw to an area for those experiencing poverty. With the poverty threshold being set solely based on pre-tax income, the greater earnings potential of those in cities where larger companies operate, such as Minneapolis, could lead to lower rates of poverty in urban counties. After laying out the reasoning for each variable, it seems appropriate to discuss the theoretical framework that this research will use to obtain its results.

## 3. Theoretical Framework:

While this study uses many sources from several decades ago, there has not been a great deal of research done on the topic as to its effects on the United States. While global poverty remains a popular subject, that same vigor does not seem to have taken hold regarding studying the subject in America. However, based on the few modern sources, along with the literature of the past, this research will use the following theoretical model to study the poverty rate for the upper-Midwest (A discussion of all variables that the current study observes will follow):

***Poverty = f (Unemployment, Non-bachelors, Crime, Con&Man, Hispanic, Black, Native, Urban, Female, IA, ND, SD, WI)***

The theoretical model contains an *unemployment* variable to display the impact of the unemployment rate on the occurrences of poverty in the upper-Midwest. The best-fitting measure for the purpose is the unemployment rate, which economists have traditionally used to assess employment's effect on the poverty rate (Thurow, 1967). This is an effective measure for this study's purposes, as employment leads directly to an increase in income, which logically leads to an increase in income. Due to how the poverty threshold is set, an increase in income will directly lead to a decrease in the poverty rate (the 'Data' section explains this in further detail). However, this is a generalization, as the Bureau of Labor Statistics classified 6.9 million Americans as 'working poor' in 2017 (U.S. Department of Labor, 2019). This ties back to the income inequality issue the United States faces—nearly seven million people are employed but are still too poor to afford necessities, meaning their work is not paying them enough to sustainably survive in their current job. There is not a clear solution for these 'working poor,' and even though these nearly seven million cases exist, indicating that employment does not always equate to decreasing instances of poverty, the *unemployment* variable is predicted to have a positive effect on the *poverty* variable. So, as unemployment increases, *poverty* is predicted to increase, *ceteris paribus.*

Economists have historically theorized that the *education* variable affects a worker's ability to earn in the labor market. This comes from human capital theory, which, holding all else constant, predicts additional formal education will increase a worker's wage rate. More specifically, formal education increases a worker's value to an employer—this occurs through increasing the breadth of knowledge and skills of a student through their years of acquired education. Assuming the wage rate earned by a worker increases that worker's marginal productivity to the firm, it follows that firms will pay more for more highly educated individuals. This study will use the percent of each county's population over the age of 25 who has not obtained a bachelor's degree, and thus we would expect a positive coefficient for the education variable, as more schooling leads to greater income, which decreases the poverty rate (Thurow, 1967; Sawhill, 1988; Berger et. al, 2018). We will expect that the greater the number of people without a bachelor's degree within a county, the higher the poverty rate due to their collective loss in potential earnings.

*Crime* has an interesting relationship with poverty, as it is not certain which seems to create the other. The connection between *crime* and *poverty* comes from a simple risk-benefit analysis. Allen and Stone (1999) discussed four effects that could cause those in poverty to choose crime, or for crime to cause poverty. The first, the earnings effect, comes from an increase in earnings from employment, which in turn leads to a decrease in illegal activity, as the benefits no longer outweigh the risks. The second, the conviction effect, simply states that if an offender is convicted while employed, the higher their earnings, the greater their loss. This is based off basic opportunity cost. They then explain that increases in employment earnings also leads to an increase in cash-on-hand for potential victims of property crimes. This is referred to as the wealth effect. Finally, the tax effect lays out that illegal earnings are not taxed, whereas legal earnings are. All these factors go into the cost-benefit analysis of potential offenders, assuming they behave rationally, and whether they commit a property crime. When looked at through the lens of behavioral economics, people may commit more property crimes when they find themselves in poverty as their potential reward for the risk seems to far outweigh the potential downsides of the act (Allen & Stone, 1999). This relationship is by far the least proven among the variables in the theoretical model, but due to potential increases in poverty rates when crime rate increases, the *crime* variable is predicted to have a positive relationship with the dependent variable.

The *Con&Man* variable is an important one for the model. If a county has a large segment of its labor force working in either construction or manufacturing, there is predicted to be a negative effect on the poverty rate (Berger et. al, 2018). This is due to the high-paying nature of these jobs which require little to no formal education to work. Should a county have, say 40 percent of their labor force being made up of jobs in construction and manufacturing, which Trempealeau County, Wisconsin has, they are predicted to have a lower poverty rate, which Trempealeau also has, with their 9 percent poverty rate being 2.3 percentage points lower than the state's average in 2017. This sizeable proportion of their labor force has jobs that lead to a large income *if* their employment is sustainable. The larger the labor force sector is in each county for these two fields, the lower the poverty rate is projected to be.

Historically, America has experienced income and poverty rate discrepancies across different demographics. For this reason, the model includes the race, ethnicity, and gender variables: *Black*, *Hispanic*, *Native,* and *female*. Poverty rates across these groups in each of the five states clearly indicate the necessity for these variables presence in the model (Table 2).

| **Table 2: State poverty rate by group, 2017** | | | | | | |
|---|---|---|---|---|---|---|
| **State** | **White** | **Male** | **Black** | **Hispanic** | **Native** | **Female** |
| Iowa | 10.5 | 10.8 | 34.1 | 22.7 | 28.1 | 13.2 |
| Minnesota | 7.9 | 9.6 | 31.9 | 20.9 | 31.5 | 11.3 |
| North Dakota | 8.5 | 10.0 | 29.6 | 18.2 | 37.5 | 12.2 |
| South Dakota | 9.6 | 12.6 | 25.6 | 24.8 | 49.3 | 15.2 |
| Wisconsin | 9.8 | 11.2 | 34.3 | 24.8 | 28.1 | 13.5 |
| Source: U.S. Census Bureau (2017). American Community Survey 5-year estimates (Table S1703). Retrieved on Nov. 2, 2019. | | | | | | |

Although laws have outlawed the practice of paying people of different races, ethnicities, and genders different amounts, many believe the practice is still common throughout the United States (Sawhill, 1988; Blank, 2002, Gennetian & Miller, 2002). Historically, these groups have earned less income than white males. Due to this, this study posits that the *Black, Hispanic, Native*, and *female* variables will all be positively correlated with the dependent variable. Therefore, counties which have more households headed by these groups are predicted to have increased poverty rates.

The final non-dummy variable is *urban.* This variable calculates the percentage of each county among the five states that live in urban areas (explained further in the "Data" section). The literature has indicated that more urban counties should experience lower rates of poverty. Thurow (1967) observed that greater poverty rates occurred in rural areas, especially amongst farmers—he explains this occurred due to the limited income opportunities in farming, and due to the lack of availability in alternative, nonagricultural employment opportunities. Following from this, West (1970) explained that urban areas are likely to experience lower rates of poverty—higher instances of poverty in rural areas will create migrations from rural communities to urban communities as people search for higher paying jobs. With this information, the *urban* variable is predicted to have a negative impact on the poverty rate. So, poverty should decline as a county has more of its population living in urban areas, holding all else constant.

This model includes four dummy variables for the following states: Iowa, North Dakota, South Dakota, and Wisconsin. These have been included to capture differences between the county-level poverty rate for counties in each state that have not been accounted for by the other variables in the model. After laying out each variable's place in this research, through both use in prior research along with their theoretical relationship with the poverty rate, it is now time to discuss the empirical methods this research will use to obtain results.

## 4. Empirical Methods:

The decision to include five states from the upper-Midwest (Iowa, Minnesota, North Dakota, South Dakota, and Wisconsin) maintains a similar demographic composition. As shown earlier in Table 1, these states all have similar ethnic racial and backgrounds, with a majority white population. They also have similar economies, with large manufacturing and service sectors, along with a sizeable workforce participating in education and healthcare (Table 1). One might look to the GDP per capita for the states to see that each are like one another, apart from North Dakota. Below, Table 3 displays each state with its population, per capita GDP, and ranking among all U.S. states in 2017.

| **Table 3: 2017 population estimates, GDP per capita, and position ranking** | | | |
|---|---|---|---|
| **State** | **Population (estimates)** | **GDP per capita** | **Ranking among states** |
| Iowa | 3,118,102 | $53,547.00 | 21st |
| Minnesota | 5,490,726 | $58,235.00 | 14th |
| North Dakota | 745,475 | $66,099.00 | 6th |
| South Dakota | 855,444 | $51,832.00 | 22nd |
| Wisconsin | 5,763,217 | $50,496.00 | 26th |
| United States | 321,004,407 | $55,515.00 | - |
| Source: Data for Population estimates obtained from the U.S. Census Bureau (2017). American Community Survey 5-year estimates (Table B02001). Data retrieved on October 19, 2019. Data for GDP per capita obtained from the U.S. Department of Commerce (2017). Bureau of Economic Analysis. Per capita real GDP by state, 2017 (Table SAGDP10N). Data retrieved October 19, 2019. | | | |

It seems fair to say that North Dakota is a slight outlier in this measurement. This is due in part to their small population, as well as the presence of substantial amounts of oil in the state, leading to an excess of high-paying, but volatile employment opportunities.

| **Table 4: Variable Description and Expected Relationship** | | | |
|---|---|---|---|
| **Variable** | **Abbreviation** | **Description** | **Expected Relationship with *poverty*** |
| *Poverty* | *P* | County-level poverty rate for all persons in each observed state in 2017. | - |
| *Unemployment* | *Unemp* | Unemployment rate for each county in 2017. | Positive (+) |
| *Education* | *Edu* | Percentage of total population 25 and older without a bachelor's degree or higher in 2017. | Positive (+) |
| *Crime* | *Cri* | Property crime rate for observed counties in 2017. | Positive (+) |
| *Con&Man* | *C&M* | Percentage of a county's labor force in 2017 consisting of construction and manufacturing jobs. | Negative (–) |
| *Hispanic* | *Hisp* | Percentage of total county population that was Hispanic in 2017. | Positive (+) |
| *Black* | *Bla* | Percentage of total county population that was African-American in 2017. | Positive (+) |
| *Native American* | *NA* | Percentage of total county population that was Native American in 2017. | Positive (+) |
| *Urban* | *Urb* | Ratio of urban-to-rural population per county as of the 2010 Census. | NA (+/ –) |
| *Female* | *Fem* | Percentage of households headed by females without a husband present in 2017. | Positive (+) |
| *Iowa* | *IA* | Iowa state binary variable. | NA (+/ –) |
| *North Dakota* | *ND* | North Dakota state binary variable. | NA (+/ –) |
| *South Dakota* | *SD* | South Dakota state binary variable. | NA (+/ –) |
| *Wisconsin* | *WI* | Wisconsin state binary variable. | NA (+/ –) |

Moving passed the decision on the states to observe, we must also discuss the reasoning behind observing county-level data. This decision to focus on the county-level not only provides the 30 observations required to run an Ordinary Least Squares (OLS) regression—it also creates more numerical variation within the data set, which will better display the effects each independent variable has on the poverty rate inside each county. Using the five-year estimates for each county will help mitigate encountering outliers as it will create an average for the county; however, increasing the data set to a size of 377 observations (counties) may also open this study to outliers.

As this research hopes to measure the determinants of poverty using the counties of the five observed states, there will not be a focus variable. Instead, this study seeks to identify those independent variables which have a statistically significant effects on the poverty rate. The current study will estimate an OLS regression. The statistical model below will be used to structure the OLS estimators and to determine the effect each variable has on the poverty rate (Table 4 above describes all variables in greater detail).

$$\begin{aligned} \boldsymbol{P_i} &= \boldsymbol{\beta_0 + \beta_{Unemp}Unemp_i + \beta_{Edu}Edu_i + \beta_{Cri}Cri_i + \beta_{C\&M}C\&M_i + \beta_{Hisp}Hisp_i + \beta_{Bla}Bla_i} \\ &\quad \boldsymbol{+ \beta_{NA}NA + \beta_{Urb}Urb_i + \beta_{Fem}Fem_i + \beta_{IA}IA_i + \beta_{ND}ND_i + \beta_{SD}SD_i + \beta_{WI}WI_i + e_i} \end{aligned}$$

The model does not take the natural log of any variables, as the expected relationship between each determinant and the poverty rate should be linear. Because of this, the form of this Ordinary Least Squares model is ‘lin-lin.’ None of the variables can use the natural log, as they are all either percentages, or dummy variables, neither of which can use the natural log. For many of the variables used, a percentage point change in the independent variable is predicted to lead to a certain percentage point change in the dependent variable. This should lead to easy analysis, as, *ceteris paribus,* a one percentage point change in, say the *education* variable, will lead to a certain percentage point change in the poverty rate (Lewis, 2012).

The dummy variables differ slightly from the other variables present in the model. The dummy variables indicate the state that each county is in. Minnesota does not have a dummy variable as it will be the base group for this study. This decision came about after looking at Figure 3 and realizing that Minnesota routinely had a lower poverty rate than its neighbors. With these dummy variables (*IA, ND, SD, WI*), counties for each state will have a one (1) or a zero (0) to indicate which state the county lies in. For example, Adair County, Iowa will have a 1 denoted for the *IA* variable, but a 0 for each other dummy variable. After performing the regression, the dummy variables will display additional information about the poverty rate due in each state that was not covered by the determinants laid out in this study.
As previously stated, this study will use an OLS regression—a statistical method used to estimate unknown parameters in a model. OLS models are where most economists begin their research, and with the challenges present in this study, such as limited time and knowledge, the OLS regression model will suffice for our purposes. After discussing the empirical methods this study will use to uncover the estimated results, it now seems important to discuss the sources for the data of this research, and the specific measurements used to reveal those results.

## 5. Data:

We now move to discussing the data used for this study. All data measures used have come from insights from the literature on the topic of poverty. While not all measures are ideal, the best available measures for each observed variable have been used. Data for this research has come the United States Census Bureau and the Federal Bureau of Investigation (FBI). This study has used the 2010 Census, 2017 American Community Survey Five-Year Estimates, as well as the FBI’s Uniform Crime Reporting (UCR) program to ensure accuracy among the data.

The total poverty rate in a county for the year 2017 was used as it encompassed the totality of those affected by poverty—while children do not work, they still suffer from the negative harms of poverty. To understand the poverty measure, one must understand how the threshold is determined. In 1963, the Census Bureau set the initial poverty thresholds by determining the average cost for food for all family compositions (and age and number of members) and multiplied that value by three, based on evidence that families at that time spent approximately one-third (1/3) of their income on food. One and two-person households have their income multiplied by a slightly larger factor due to the diseconomies of small scale (Sawhill, 1988). These thresholds are constant across geographies but continue to be updated yearly using the Consumer Price Index for All Urban Consumers (CPI-U). If the cumulative pre-tax money income for all members of a household over age 15 is below the threshold for that family's configuration, the Census lists all members of the household as 'in poverty.' To display the current rates used to determine the poverty rates for this study, Table 5 displays the poverty thresholds as they were set in 2017.

**Table 5: Poverty Thresholds for 2017 by Family Size and Number of Children Under 18 Years**

| **Size of family unit** | **Related children under 18 years** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | None | One | Two | Three | Four | Five | Six | Seven |
| **One person:** | | | | | | | | |
| Under age 65 | 12,752 | | | | | | | |
| Aged 65 and older | 11,756 | | | | | | | |
| **Two people:** | | | | | | | | |
| Householder under age 65 | 16,414 | 16,895 | | | | | | |
| Householder aged 65 and older | 14,816 | 16,831 | | | | | | |
| **Three people** | 19,173 | 19,730 | 19,749 | | | | | |
| **Four people** | 25,283 | 25,696 | 24,858 | 24,944 | | | | |
| **Five people** | 30,490 | 30,933 | 29,986 | 29,253 | 28,805 | | | |
| **Six people** | 35,069 | 35,208 | 34,482 | 33,787 | 32,753 | 32,140 | | |
| **Seven people** | 40,351 | 40,603 | 39,734 | 39,129 | 38,001 | 36,685 | 35,242 | |
| **Eight people** | 45,129 | 45,528 | 44,708 | 43,990 | 42,971 | 41,678 | 40,332 | 39,990 |
| **Nine people or more** | 54,287 | 54,550 | 53,825 | 53,216 | 52,216 | 50,840 | 49,595 | 49,287 |

Source: U.S. Census Bureau. Obtained on Nov. 29, 2019 from https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html

So, in 2017, for a household composed of three people with one related child under the age of 18 to not be listed as in poverty, all household members over the age of 15 would have to have earned greater than $19, 730 in terms of pre-tax income.

A county's unemployment rate was chosen above other employment measures as it is a very standard, traditional economic measure. It seems a good measure for the *unemployment* variable as economists have traditionally used the unemployment rate when measuring poverty (Thurow, 1967; Sawhill, 1988; Rodgers & Rodgers, 1993). While there may be other employment variables that would provide similar estimation results, but those measures have not been used as frequently in past research. Because of the lack of prior research into measures, such as labor force participation, or the employment-to-population ratio, this study decided to use the traditional measure used when studying poverty, the unemployment rate.

The percentage of each county's population 25 and older without a Bachelor's degree or higher was used to measure the effects of formal education on the poverty rate. The American economy has changed significantly since Thurow (1967), who used a similar measure but only required eight years of total schooling for both heads of a household. In modern-America, a high school diploma, for most, leaves only a select few jobs to work—most of which are low-paying and may lead to the person contributing to the 6.9 million occurrences of 'working poor' mentioned earlier (U.S. Department of Labor, 2019). A four-year degree requires a massive amount of debt, but also increases their earnings potential, as described earlier through human capital theory.

The *crime* variable selected for this study was the property crime rate in each of the observed counties. The FBI's Uniform Crime Reporting program provided the data for this study. Unfortunately, the FBI does not collect or release data for all counties in the five observed states. Because of this, some counties were removed from regressions involving the *crime* variable (Table 6 provides a list of the removed counties).

**Table 6: Removed Counties**

| **State:** | **Removed Counties:** |
|---|---|
| Iowa | Adams; Allamakee; Bremer; Greene; Hancock; Hardin; Jones; Mitchell; Montgomery; Pocahontas; Poweshiek; Ringgold; Winnebago |
| Minnesota | Polk; Sibley |
| North Dakota | Bowman |
| South Dakota | Aurora; Beadle; Brule; Buffalo; Campbell; Clark; Day; Dewey; Douglas; Fall River; Faulk; Grant; Gregory; Haakon; Hand; Hanson; Harding; Hutchinson; Hyde; Jackson; Jerauld; Jones; Kingsbury; Lyman; Mellette; Miner; Oglala Lakota; Potter; Stanley; Sully; Todd; Ziebach |
| Wisconsin | Oconto |
| **Total Removed Counties: 49** | |

There are 377 counties across the five states, and although data for 49 counties (32 of which were from South Dakota) was unavailable for the *crime* variable, more than 30 observed counties remain for each state; therefore, omitting individual counties rather than the state or the *crime* variable seems like a viable first option. If the *crime* variable does not appear to be statistically significant, however, these observations will be added back in, and the study will continue from that point.

To calculate the property crime rate in each county, the number of property crime incidents (burglaries, larceny-theft, motor vehicle theft, and arson) was divided by the total population for each county. This is a better measure than simply taking the occurrences of property crime due to the wide variance in populations in various counties throughout the study. Expectations would be that more crimes occur in more populated counties. This is mostly due to the increased number of high-paying employment opportunities within urban areas and closer proximity of other people and property, which may sway potential offenders toward committing property crimes. To eliminate potential bias against these counties, the current study uses the property crime rate.

Data for the *Black*, *Hispanic*, and *Native* variables came from the Census Bureau. It would have been ideal for this study to have the percentage of households operated by each of these group. This is because of the way the poverty rate is measured—since the Census Bureau poverty rates are calculated using households, that would have been a more accurate measure for the poverty rate; however, due to lack of data, the percentage of the population for each county was used to denote the effects instead. The percentage of each county's population comprised of black, Hispanic, and Native American persons measures those three variables, and those measures should suffice for this study's needs.

The use of a variable to distinguish between urban and rural counties was deemed necessary based on the literature (Clawson, 1967; Thurow, 1967; Tweeten, 1969; West, 1970). The *urban* variable is predicted to have a negative (–) sign, as there is evidence from scholars that counties that have more urban populations experience lower rates of poverty (Thurow, 1967; West 1970). This study will use the Census Bureau's ratio of urban-to-rural population for each county. To calculate this, the Census took the total population and used that to divide the population they determined to be living in 'Urban Areas,' which they described to be areas with populations of 50,000 or more people. This seems an appropriate measure as it effectively distinguishes between those counties that have no cities at all from those which have nearly their entire population centered in large cities (such as Hennepin County, Minnesota, which has 97.78 percent of its population living in urban areas). Distinguishing between percentage of population seemed to be a far more effective way of determining the actual effects on the poverty rate than the alternative, which would have been using a binary variable and determining whether more people lived inside or outside of these urban areas for each county, denoting a one (1) for those that had a majority living inside, and a zero (0) for those whose majority lived outside of urban areas.

The final variable, *female,* will use the percentage of families with children headed by females without a husband present. This study chose this measure for several reasons. First, not having a second earner in the household will automatically decrease the household income, as it more than likely cuts the number of income-earners for the household from two people to one individual. Second, females have historically earned a lower income than males in the United States, which would also lead to a higher poverty rate based on how poverty status is determined. The third and final reason to measure the *female* variable in such a way is that, according to Blank (2002), low-skilled mothers have traditionally been one of the largest sufferers of poverty. An increase in out-of-wedlock births and declining marriage rates were major concerns back in 2002, and this was especially prevalent among low-income earners of both sexes (Blank, 2002, p. 1153). This is the most appropriate measure available for the *female* variable.

**Table 7: Descriptive Statistics**

| Variable | Mean | Standard deviation | Median | Quartile 1 | Quartile 3 | IQR |
|---|---|---|---|---|---|---|
| *Poverty* | 0.1218 | 0.0658 | 0.1110 | 0.0890 | 0.1345 | 0.0455 |
| *Unemployment* | 0.0404 | 0.0312 | 0.0350 | 0.0260 | 0.0460 | 0.0200 |
| *Nonbachelors* | 0.7766 | 0.0705 | 0.7925 | 0.7529 | 0.8224 | 0.0695 |
| *Crime* | 0.0043 | 0.0041 | 0.0034 | 0.0018 | 0.0057 | 0.0040 |
| *Con&Man* | 0.2629 | 0.0699 | 0.2638 | 0.2147 | 0.3073 | 0.0926 |
| *Hispanic* | 0.0372 | 0.0363 | 0.0270 | 0.0180 | 0.0420 | 0.0240 |
| *Black* | 0.0130 | 0.0212 | 0.0069 | 0.0036 | 0.0145 | 0.0109 |
| *Native* | 0.0456 | 0.1394 | 0.0049 | 0.0026 | 0.0223 | 0.0197 |
| *Urban* | 0.3297 | 0.2999 | 0.3291 | 0.0000 | 0.5776 | 0.5776 |
| *Female* | 0.0814 | 0.0428 | 0.0752 | 0.0604 | 0.0912 | 0.0308 |
| **Number of observations: 377 (328 observations for *Crime*)** | | | | | | |

Before moving to the discussion of the results obtained from the Ordinary Least Squares regression, it is important to also observe the descriptive statistics for each variable in the model to better understand the data we are working with. This will provide a further look into the average rate for each variable in the model over the 377 (only 328 for the *crime* variable) observed counties. Table 7 displays the mean, standard deviation, median, quartile breakdown, and interquartile range for each non-binary data measure used for this research. Using the above information, it was next necessary to find outliers present in the data to ensure that there were not too many grievous outliers in any variables, which may have precluded any insights being gained from their use. Table 8 displays number of outliers for each variable, and the critical value to consider a data point an upper-end or lower-end outliers, calculated using the following four equations:

An observation is a **moderate outlier** if

$X_i < Q_1 - (1.5 * IQR)$ Or $X_i > Q_3 + (1.5 * IQR)$

An observation is an **extreme outlier** if

$X_i < Q_1 - (3.0 * IQR)$ Or $X_i > Q_3 + (3.0 * IQR)$

**Table 8: Outliers**

| | Lower-end | | | | Upper-end | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Moderate if $X_i$<** | **Extreme if $X_i$ <** | **# moderate** | **# extreme** | **Moderate if $X_i$>** | **Extreme if $X_i$>** | **# moderate** | **# extreme** |
| *Poverty* | 0.0208 | -0.0475 | 0 | 0 | 0.2028 | 0.2710 | 20 | 13 |
| *Unemployment* | -0.0040 | -0.0340 | 0 | 0 | 0.0760 | 0.1060 | 17 | 9 |
| *Nonbachelors* | 0.6487 | 0.5445 | 19 | 8 | 0.9266 | 1.0308 | 0 | 0 |
| *Crime* | -0.0040 | -0.0099 | 0 | 0 | 0.0115 | 0.0173 | 15 | 4 |
| *Con&Man* | 0.0758 | -0.0631 | 1 | 0 | 0.4461 | 0.5850 | 4 | 0 |
| *Hispanic* | -0.0180 | -0.0540 | 0 | 0 | 0.0780 | 0.1140 | 30 | 17 |
| *Black* | -0.0127 | -0.0291 | 0 | 0 | 0.0308 | 0.0472 | 36 | 17 |
| *Native* | -0.0270 | -0.0567 | 0 | 0 | 0.0520 | 0.0816 | 52 | 39 |
| *Urban* | -0.8664 | -1.7328 | 0 | 0 | 1.4440 | 2.3104 | 0 | 0 |
| *Female* | 0.0142 | -0.0321 | 2 | 0 | 0.1375 | 0.1837 | 18 | 11 |
| **Number of observations: 377 (328 observations for *Crime*)** | | | | | | | | |

The data with most of the outliers according to Table 8 are the race and ethnicity variables. It seems that the considerable number of counties with less than one (1) percent of their population being Hispanic, African American, or Native American skewed the calculation so that counties with slightly higher populations of these groups are listed as outliers. For reference, there were 27 counties within these five states that had less than one percent Hispanic populations, but there were 239 counties with less than one percent of their population being African American, and 241 counties that had less than one percent of their population as Native American back in 2017. This large number of counties with less than one percent of their populations making up each of these groups minimizes the requirement for other counties to be considered 'upper-end outliers.'

There are a few counties in South Dakota that do appear to be legitimate outliers, such as Oglala Lakota county. This county has a staggering 92 percent of its population being Native American, along with females without a husband present leading 40.6 percent of the county's households. They also have the second highest poverty rate seen in the study, with 51.9 percent of their population earning less than the poverty threshold.

## 6. Empirical Results & Interpretation:

Now that the more general statistical information around the study has been displayed, we can move to the statistical and economic analysis gained through the multiple regressions run for this study. The findings for this research came from applying the Ordinary Least Squares regression to estimate the effects of each determinant on the poverty rate. Table 9 displays the final regression results for each variable that remained in the model.

| **Table 9: Regression Results** | | |
|---|---|---|
| Dependent Variable: *Poverty* | | |
| **Independent Variable** | **Coefficient** | **Standard Error** |
| *Intercept* | 0.0124 | 0.0363 |
| *Unemployment* | 0.5609*** | 0.1623 |
| *Nonbachelors* | 0.0814** | 0.0490 |
| *Con & Man* | -0.0773** | 0.0303 |
| *Hispanic* | 0.0428 | 0.0560 |
| *Black* | -0.0552 | 0.0769 |
| *Native American* | 0.1829*** | 0.0510 |
| *Urban* | -0.0046 | 0.0100 |
| *Female* | 0.3382** | 0.1628 |
| *IA* | 0.0091** | 0.0043 |
| *ND* | -0.0042 | 0.0063 |
| *SD* | 0.0162** | 0.0066 |
| *WI* | 0.0052 | 0.0042 |
| Observation | 377 | |
| R-squared statistic | 0.7707 | |
| Adjusted R-squared statistic | 0.7632 | |
| F-statistic | 101.9672*** | |
| ***1 percent level of significance, **5 percent level of significance. | | |

The results from all regressions can be found in the statistical appendix at the end of the essay. Before displaying the regression results, one thing must be said to clarify the absence of the *crime* variable. The initial regression, which included *crime*, was not an ideal model. After running the initial regression, this study removed the *crime* variable as it was not statistically significant. Still using the 328 counties that the *crime* variable had data for, the regression was done over, omitting *crime*. This resulted in a higher adjusted R-squared statistic, indicating that the model without crime explained more variation within the dependent variable than the model with *crime.* After discovering this, the additional 49 counties were added back into the study.

All results obtained the sign that was predicted by the literature apart from the *Black* variable. Looking to the *unemployment* variable, which was statistically significant at the one-percent level, this model predicts that a one percentage point increase in a county's unemployment rate will increase the poverty rate for that county by 0.5609 percentage points, *ceteris paribus.* This is both statistically and economically significant, as a one percentage point increase in the independent variable is predicted to increase the poverty rate by a substantial amount, more than half a percentage point. This indicates that the structure and stability of a county's labor force are a key factor in determining the poverty rate for that county. If too many of a county's citizens are unemployed, we would expect a higher-than-average poverty rate in that county based on this model.

The *nonbachelors* variable was found to be statistically significant at the five-percent level. With a coefficient of 0.076, a one percentage point increase in the county's population 25 and older without a bachelor's degree is predicted to, *ceteris paribus*, increase the poverty rate of that county by

0.0814 percentage points. Although this is statistically significant, it is hard to determine the economic significance of this variable. While increasing educational attainment in a county is certainly an admirable goal, counties may struggle to ensure their populations acquire formal education, as they do not really have any ability to control their populations level of formal education. As the coefficient is also fairly small, being less than one-tenth of one percentage point, the education variable may not have the same economic significance that other variables, such as *unemployment* hold.

The *Con&Man* variable was statistically significant at the five-percent level. With the coefficient of -0.0773, a one percentage point increase in a county's labor force working in the construction and manufacturing fields is predicted to decrease the poverty rate by 0.0773 percentage points, holding all else constant. Although this is statistically significant, it is less economically significant than the *unemployment* variable. With its small coefficient, it would be hard to say that bringing in more construction and manufacturing job opportunities in a county would efficiently reduce the poverty rate. The *urban* variable was not found to be statistically significant by any traditional economic level, and *urban's* coefficient of -0.0046 indicates that even if it had been statistically significant, there does not be to any economically significant difference between counties that are more urban or rural in terms of the poverty rates that they experience. The outcome of this result goes somewhat against the theory of West (1970), where he stated some individuals might flock to cities, enticed by high-paying, vacant jobs which they can fill. It appears that the economy in 2017 did not experience much, if any, real difference between rural and urban rates of poverty in the upper-Midwest.

The results did not show statistically significant differences in poverty rates for counties with greater populations of African Americans or Hispanics, and the *black* variable did not obtain the predicted sign based on past literature on the subject. The *Native* variable, however, was statistically significant at the one-percent level. With a coefficient of 0.1829, the model predicts that a one percentage point increase in a county's population of Native Americans will increase that county's poverty rate by 0.1829 percentage points, *ceteris paribus*. This study believes this is very significant, as it shows that the Native American population still seems to suffer from abnormal rates of poverty compared to other races and ethnic groups. While the other racial and ethnic variables were not statistically significant, the low populations of these groups found in these five states could be a potential cause for this.

The state dummy variables displayed some interesting results. This study included these variables to display additional information regarding each state and the poverty rates they experience. This, theoretically, helps indicate some of the factors and determinants not directly included within this study. Two states, Iowa and South Dakota, displayed statistically significant differences from the focus state, which was Minnesota. However, with Iowa (0.0091) and South Dakota (0.0162) each having extremely small coefficients, there does not seem to be much economic significance among these variables. With North Dakota and Wisconsin failing to meet the traditional economic measures of significance, the state dummy variables failed to provide any valuable insight into the poverty rates within the upper-Midwest.

This model initially had an income variable in it. This introduced issues, however; while running the regression with the income variable (measured using median household income to combat the average being increased due to income inequality), the sign for the *education* variable would flip. After using the 'corr' and 'pcorr' functions, STATA displayed that there was high correlation between the variables (and the *unemployment* variable). As this study lacked the time and economic know-how to fix the issue of multicollinearity properly, the *income* variable was dropped for simplicity. This model also suffered from heteroskedasticity. This study discovered heteroskedasticity after using the 'estat imtest, white' function, used to conduct a white-test following a regression. The final regression corrected for this issue using the 'robust' function on STATA. Although some results still lacked statistical significance, some results did improve slightly in this area.

Finally, we can cover the adjusted R-squared statistic. With an adjusted R-squared of 0.7632, this model covers 76.32 percent of the variation within the dependent variable. This, along with the F-statistic of 101.9672 indicate that the model as a whole is a fairly accurate estimation of the poverty rates for counties in the upper-Midwest in 2017. Although some data used was not ideal, the model as a whole produced mostly reliable results, and holds important implications for combating poverty in the United States in the future, both in terms of signaling those variables which are likely to increase the rate, and by indicating certain sections of the labor market, construction and manufacturing, that seem to decrease the occurrence of poverty in counties in the upper-Midwest.

## 7. Conclusion:

It is important to determine which variables have the greatest impact on the poverty rate so states can consider policies that might best combat poverty. While it seems impossible to end poverty outright, lessening the harmful societal effects of poverty should be a goal any society finds admirable. Although attempts have been made since the threshold was first established by Mollie Orshansky in 1965 (Sawhill, 1988), no significant impact has been made in terms of eliminating poverty outright, as the U.S. national poverty rate experienced a rise from 2010 through 2014 (Figure 3). The intent of this study was to see if there are variables that had significant statistical and economic impacts on the county poverty rate for counties in the upper-Midwest. While several variables were shown to meet these standards, there is still considerable work to be done in terms of determining what factors lead to some counties experiencing extreme rates of poverty, such as Todd County in South Dakota, which experienced the highest rate of poverty in the observed states in 2017, with 52 percent of its population falling below the poverty threshold.

While anecdotal evidence is by no means economically significant on its own, high rates such as that witnessed in Todd County should draw eyes toward the prevalence of poverty in the United States. These high rates of poverty likely stem from the rampant income inequality present in the United States, and while programs have been used to assist people who are struggling with the issues poverty presents, welfare initiatives do not seem to have worked. It remains to be seen if American society will be able to face the problem of poverty in the twenty-first century, but those who suffer under the current economic structure will continue to endure additional economic hardships until the issue has been addressed. Luckily for those in the upper-Midwest, poverty has not had a strong foothold in the region historically, but it remains to be seen how true this will hold in the future.

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