Econometric Analysis of the US Minimum Wage's Effect on Unemployment and Poverty

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Abstract: In this paper, I study the estimated effects of the minimum wage on unemployment and poverty rates using US state and year fixed effects. Looking at data mostly collected through the Current Population Survey (CPS), I aim to compare effects across age and race demographics. I find a 10% increase in the minimum wage has a positive effect on the unemployment rate between 1.88 and 4.89 percentage points, and a positive effect on the poverty rate of 2.99 percentage points. My estimated effects were found to be widely statistically significant and followed what many past studies looking at the overall US unemployment effects of the minimum wage have found.

I. Introduction and Background

One of the most commonly debated topics between economists, politicians, and many others; is what should be the level of the minimum wage? As an economics student, I have drawn interest in the effects of the minimum wage since taking a course on Labor Economics. In that course we discussed the minimum wage to some extent, as well as other policies such as the Earned Income Tax Credit (EITC) program. Since then, I have been interested in the effects of policies like the minimum wage, and in this paper, I aim to estimate the effect of raising the minimum wage on unemployment and poverty rates. I believe my use of a newer dataset, of the years 2003-2017, will help provide some more recent context to the question of the minimum wage.

Many economists have performed similar studies to mine, and what makes this topic so interesting is the variation amongst their results. Differing results when estimating minimum wage effects on employment can mostly be attributed to the population being used in the model. Most methods have come to the conclusion of negative employment effects when the minimum wage is increased. The methods finding the opposite results tend to use "geographically-close controls", meaning their model focuses on a population that's seemingly very similar but a few key variables are differing. Neumark (2018) argues that this could be caused by geographic areas with many commonalities being more endogenous when it comes to economic shocks. However, there isn't a solid answer as to which method is more reliable; let alone why the methods produce differing results (Neumark, 2018). One of the more famous studies finding no evidence that a rise in the minimum wage had negative employment effects was conducted by Card and Krueger (1994) where their model focused on fast-food chains in New Jersey and Pennsylvania.

Their choice to look at the fast-food industry was an excellent way to try and focus their model on minimum wage workers, and by using a difference-in-difference approach they came to two significant conclusions. By their estimation they were able to conclude that an increase in the minimum wage increased employment and raised the price of the fast-food meals; meaning the cost of the minimum wage increase was seemingly passed onto the consumer (Card, Krueger 1994). While there are varying results when studying the minimum wage's employment effects, the majority of studies have found negative employment effects amongst low-skilled workers.

Neumark and Wascher (2006) came to this conclusion when looking at low-skilled employment. They looked at employment effects incurred by the minimum wage in many different countries across the world, defining "low-skilled" workers in different ways such as teenage workers, blue-collar workers, manufacturing workers, and many more. They arrived at this conclusion about their studies as a whole and indicate that the variation in US state minimum wages is the cause for the many different conclusions between studies focusing on the US minimum wage (Neumark, Wascher 2006). This is partially why I've decided to study this, particularly using US state minimum wage levels.

Wolfson and Belman (2016) took a different approach, by using meta-analysis to study a collection of past research results. By using multiple estimates of the employment effects of the minimum wage they're able to combine them to make an estimate that is better than any of the single estimates it is made up of. They used LASSO to perform their meta-analysis and found that the employment effects of the minimum wage have been becoming less negative and closer to zero, and in fact "the consensus range of -0.3 to -0.1 has shifted considerably toward the

origin: -0.12 to -0.05" (Wolfson, Belman 2016). This is an interesting approach, but as Wolfson and Belman (2016) mentioned in their paper, contains some amount of bias including publication bias. This is the idea that they can only perform their analysis on papers that have been published, although there are countless studies that went unpublished for one reason or another. This indicates that studies taking a meta-analysis approach should be looked at with the assumption of some bias, but their results finding employment effects that are less negative are still important.

When considering the policy implications of raising the federal minimum wage to \$15, there is anything but a unanimous conclusion on the employment effects. I believe that it can be agreed upon, that the federal minimum wage is "due" for an increase in the coming years, as it has been at \$7.25 since 2009. However, the question is where should the minimum wage be set at in today's day and age? Many politicians have lobbied for a raise to \$15, yet the impact of raising the minimum wage by such a substantial amount is still disputed amongst economists. This is because the current minimum wage (directly) affects younger and lower skilled workers; while raising the minimum wage to the \$15 level would impact a much broader range of workers, particularly in lower-wage states (Neumark, 2018). However, Cooper (2019) argues that such a substantial increase will have the same effects on employment as many economists have found when studying past minimum wage increases. He believes that it will increase income for low-wage workers, with little to no effect (in either direction) on employment. Meaning, the Raise the Wage Act of 2019 would essentially give many low-wage workers the opportunity to rise from poverty with a full-time job (Cooper, 2019). While this is an interesting take on the \$15 minimum wage, I don't believe anyone can make predictions on the outcome of

the policy, or at least accurate predictions. There have been no minimum wage increases of the proposed magnitude in the US, so I don't believe it's wise to try and make claims about the outcome of such a policy.

One slightly comparable policy change in the minimum wage could be implementation of a minimum wage in Puerto Rico following the passing of the US Fair Labor Standards Act (FLSA) in 1938. Castillo-Freeman and Freeman (1992) study the employment effects of such policy change, where over the course of 27 years Puerto Rico had to implement a minimum wage that eventually met the US minimum wage of \$3.35 in 1987. They found evidence that this minimum wage policy implementation had substantial negative employment effects (Castillo-Freeman, Freeman 1992). While the US economy is much different than that of Puerto Rico, it's important to consider this case study in policy that implements significant minimum wage increases, as the US has never implemented such a drastic minimum wage increase.

The use of many different methods, models, and population groups in past studies serves as evidence that there is no "correct" way to go about studying the employment effects of the minimum wage. I will be using US state minimum wage levels to estimate minimum wage unemployment and poverty effects by using unemployment and poverty rate data.

II. Models and Econometric Technique

In order to perform my analysis, I use multiple regression models to show how the coefficients change. First, I used a basic fixed effects model with state and year fixed effects, where the minimum wage was the only explanatory variable included:

total unemployment rate =
$$\beta_0 + \beta_1 log(minimum\ wage)_i + yearFixedEffects +$$

$$stateFixedEffects + u_i$$

Next, I will perform a few fixed effects regressions with state and year fixed effects again, but this time with some control variables, measuring education attainment and race populations in each state for each year. Median household income is not included in the poverty rate regression, because income being below a certain level (depending on the number of people in the household) is what declares a person "in poverty". Below is the regression on the total unemployment rate, including all controls:

total unemployment rate = $\beta_0 + \beta_1 \log(minimum\ wage)_i + \beta_2 \log(household\ income)_i + \beta_3 no$ high school_i + β_4 high school only_i + β_5 bachelors plus_i + β_6 white population_i + β_7 black population_i + β_8 Asian population_i + β_9 two or more races_i + yearFixedEffects + stateFixedEffects + u_i

For the age regressions, the education controls are not used. This is because age is most likely correlated with education attainment. The groups I use, such as teenage unemployment is somewhat of a grey area, as many of them are students as well as work force participants. Below

is the regression on the teenage unemployment rate, where the right-hand side is identical to the regression on the young adult unemployment rate:

teenage unemployment rate = $\beta_0 + \beta_1 \log(minimum\ wage)_i + \beta_2 \log(household\ income)_i + \beta_3$ white population_i + β_4 black population_i + β_5 Asian population_i + β_6 two or more races_i + $yearFixedEffects + stateFixedEffects + u_i$

The race regressions won't include the race controls. Below is the regression on the white unemployment, but this will be repeated where the right-hand side is identical for all the races' unemployment rates (black, Hispanic/Latino, and Asian):

white unemployment rate = $\beta_0 + \beta_1 \log(\min(\max(\max(\beta_i)))) + \beta_2 \log(\max(\beta_i)) + \beta_3 \log(\max(\beta_i)) + \beta_4 \log(\max(\beta_i)) + \beta_5 \log(\min(\max(\beta_i))) + \beta_5 \log(\max(\beta_i)) + \beta_5$

The fixed effects method is very useful here, because through time-demeaning it allows for arbitrary correlation between *stateFixedEffects* and the other independent variables. Because of this, fixed effects has been primarily labeled as the more convincing method to use for ceteris paribus effects, meaning effects with other conditions held constant (Wooldridge, 2015).

Some variables that could be in my error term u could be policies implemented (other than the minimum wage) aimed to lower unemployment and/or poverty rates. An example of such

policy is the Earned Income Tax Credit (EITC) program many states have implemented. Other characteristics that make a person more or less "employable" could also be in the error term u. With a broad question like this, it can be difficult to accumulate the proper data needed; however, I believe I was able to find some useful data mostly through US government resources.

III. Data Description

This data was collected from a few different sources, where I used Excel and R to clean and merge the data frames for my analysis into a panel dataset. Minimum wage data is from a Kaggle.com dataset which scraped the data from the US Department of Labor (DOL) website. Poverty rate data was collected from the US Census website. Unemployment rate data, as well as education attainment and race population distribution data were collected from the Current Population Survey (CPS). In order to gain a better perspective on the growth or decline of the main variables (minimum wage, unemployment rate, and poverty rate), figures A, B, and C show the trends over time of state averages of those variables. Table 1 also provides the average value for each variable, across all states over the entire time period (2003-2017). Table 1 shows the race with the highest unemployment rate was black or African American, and interestingly the distribution of education attainment was fairly evenly distributed. Also, I'll note the white population was shown to be about 80%, which is higher than the actual distribution, this can be accredited to the CPS being a survey of a sample of 250,000-350,000 people each year. The variables in my dataset along with their description can be found on the next page.

Variable	Description
year	Calendar Year (2003-2017)
state	US State (All 50 and Washington DC, not including territories)
total_unemp	Unemployment Rate for entire population, given state and year (%)
men_unemp	Unemployment Rate for male population, given state and year (%)
women_unemp	Unemployment Rate for female population, given state and year (%)
white_unemp	Unemployment Rate for white population, given state and year (%)
black_unemp	Unemployment Rate for black and African American population, given state and year (%)
hist_lat_unemp	Unemployment Rate for Hispanic and Latino population, given state and year (%)
age_16to19_unemp	Unemployment Rate for population within age range of 16-19 years old, given state and year (%)
age_20to24_unemp	Unemployment Rate for population within age range of 20-24 years old, given state and year (%)
asian_unemp	Unemployment Rate for Asian population, given state and year (%)
min_wage	Minimum wage, given state and year (\$, USD)
poverty_rate	Poverty Rate, given state and year (%)
hh_income	Median Household Income (\$)
no_hs_perc	No High School Diploma Earned (%)
hs_perc	Only High School Diploma Earned (%)
some_col_perc	Some College Completed, less than 4 years (%)
bachelors_plus_perc	Bachelors Degree or more earned (%)
white_perc	White Population (%)
black_perc	Black and African American Population (%)
asian_perc	Asian Population (%)
two_plus_perc	Two or More Race Population (%)

The values within my dataset for unemployment and poverty rates and education and race demographics are not exact values. They were calculated via the survey results from the Census and Current Population Survey (CPS). This means they must be judged with a certain amount of margin for error, as I will be using these estimated values for my analysis. Because they're from surveys of samples of state populations, unfortunately some of my variables contain some NA values, where there was not a large enough subset of that population in the sample. This mostly comes into play with the unemployment rate by race. I will also note that the percentages for the education attainment and race demographics will not add to 100%, as I dropped some of the variables that were not necessary for my analysis. This includes for education attainment, children 0-15 years old (presumable no education completed) and for race, Hawaiian and Native American races which were very small percentages.

IV. Results

Table 2. Regression Results

	FE	FE	FE	FE	FE	FE	FE	FE	FE
	(total_unemp)	(total_unemp)	(poverty_rate)	(age_16to19_unemp)	(age_20to24_unemp)	(white_unemp)	(black_unemp)	(hisp_lat_unemp)	(asian_unemp)
	1.88	3.21	2.99	4.89	4.04	2.93	2.43	3.89	0.32
log(min_wage)	(.37)	(0.49)	(.53)	(1.07)	(.64)	(.45)	(1.12)	(.86)	(.82)
	t = 5.12	t = 6.51	t = 5.64	t = 4.56	t = 6.28	t = 6.48	t = 2.17	t = 4.53	t = .40
		-15.84		-42.93	-26.43	-14.23	-27.13	-23.32	-13.25
log(hh_income)		(1.04)		(2.90)	(1.76)	(.97)	(2.56)	(1.88)	(1.82)
		t = -15.20		t = -14.80	t = -15.00	t = -14.64	t = -10.60	t = -12.39	t = -7.30
		-0.54	-0.18			-0.53	-0.98	-0.95	-0.59
no_hs_perc		(.12)	(.12)			(.11)	(.30)	(.22)	(.21)
		t = -4.7	t = -1.4			t = -4.99	t = -3.25	t = -4.43	t = -2.74
		-0.44	-0.05			-0.42	-0.85	-0.76	-0.27
hs_perc		(.10)	(.11)			(.10)	(.27)	(.19)	(.19)
		t = -4.19	t =47			t = -4.37	t = -3.16	t = -3.93	t = 1.45
		-0.44	-0.03			-0.45	-0.85	-0.77	-0.46
some_col_perc		(.11)	(.11)			(.10)	(.26)	(.19)	(.18)
		t = -4.08	t =23			t = -4.68	t = -3.22	t = -3.99	t = -2.51
		-0.52	-0.21			-0.5	-0.82	-0.84	-0.35
bachelors_plus_perc		(.10)	(.10)			(.09)	(.24)	(.17)	(.16)
		t = -5.45	t = -1.98			t = -5.76	t = -3.4	t = -4.85	t = -2.16
		-0.01	-0.12	-0.28	0.03				
white_perc		(.06)	(.06)	(.17)	(.10)				
		t =18	t = -1.90	t = -1.70	t = .28				
		-0.24	-0.04	-0.61	-0.45				
black_perc		(.10)	(.11)	(.30)	(.17)				
		t = -2.45	t =38	t = -2.06	t =-2.72				
		0.02	-0.13	-0.27	-0.06				
asian_perc		(80.)	(.09)	(.23)	(.14)				
		t = .26	t = -1.46	t = -1.15	t =45				
		0.02	0.17	-0.09	-0.1				
two_plus_perc		(.09)	(.10)	(.28)	(.16)				
		t = .20	t = 1.70	t =33	t =64				
R-squared	0.04	0.33	0.12	0.28	0.27	0.31	0.2	0.26	0.13
K-squared	0.04				count for serial correlat			0.20	0.1

A larger version of Table 2 with the regression results is included in the appendix. The table includes coefficients followed by clustered standard errors in parenthesis, as well as t statistics for testing statistical significance.

I believe it is important to first mention that these results are estimates, based on samples of the US population. That being said, I found the minimum wage to have a positive effect on the unemployment rate in all of my regressions; and all but the Asian unemployment regression found the minimum wage coefficient to be statistically significant at the 5% level. In my second regression on total unemployment, including all controls, I find that holding all else constant a 10% increase in the minimum wage is expected to lead to a 3.21 percentage point increase in the unemployment rate; this is a larger effect than in my first regression without any controls where

a 10% increase in the minimum wage is expected to lead to a 1.88 percentage point increase in the unemployment rate. I find rather small coefficients from the race controls, which is interested when comparing the race unemployment regressions later on. In my third regression, on the poverty rate, I find that holding all else constant a 10% increase in the minimum wage is expected to lead to a 2.99 percentage point increase in the poverty rate.

Comparing the teenage and young adult unemployment rates in my fourth and fifth regressions, the teenage unemployment rate is expected to experience a slightly larger positive effect, from an increase in the minimum wage, which is .85 percentage points larger than that of the young adult unemployment rate. When looking at the race unemployment rates in the remaining regressions, the Hispanic and Latino unemployment rate is expected to experience the largest positive effect from an increase in the minimum wage, followed by the white unemployment rate, and then the black unemployment rate. This is interesting as, the black or African American unemployment rate was the largest on average, implying factors other than the minimum wage and education are driving that high unemployment rate. I believe it's also interesting that median household income has the largest coefficient amongst the race unemployment rate regressions. Where a 10% increase in median household income is expected to lead to a 27.13 decrease in the black unemployment rate. Based on past studies done on the unemployment effects of the minimum wage in the US, looking at it from a broad nationwide angle, I believe these results follow expectations.

V. Conclusion

The minimum wage's effect on unemployment and poverty is a difficult question to answer, because of the many factors that play a role in unemployment and poverty rates. I was able to find evidence of the minimum wage having a positive effect on the unemployment and poverty rates. This positive effect on the unemployment rate, with a 10% increase in the minimum wage, was found to be between 1.88 and 4.89 percentage points (amongst statistically significant results, which was all but one regression, as mentioned before). The positive effect on the poverty rate, with a 10% increase in the minimum wage, was estimated to be 2.99 percentage points, which was also statistically significant. Potential issues with my analysis may be having too many factors in the error term u, as there are many things that impact unemployment and poverty rates. Also, large coefficients for the median household income, could mean a source of bias with that variable. In the future, I'd like to implement some other policies besides the minimum wage that are aimed to impact unemployment and poverty rates, such as the Earned Income Tax Credit (EITC) program which many states have implemented; as well as analyzing a longer time period. With a proposed federal minimum wage level of \$15 in the US, I'd also like to analyze the effects of that policy change in the future. Overall, I believe the results follow the expectations from many prior studies, some of which were referenced in the introduction section.

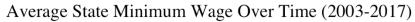
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Appendix

Figure A. Average Minimum Wage Across All States Over Time Period (2003-2017)



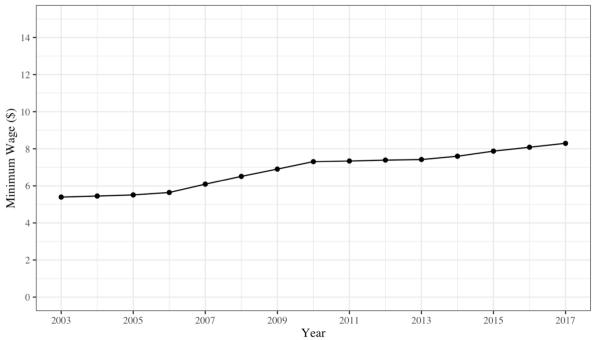


Figure B. Average Unemployment Rate Across All States Over Time Period (2003-2017)

Average State Unemployment Rate Over Time (2003-2017)

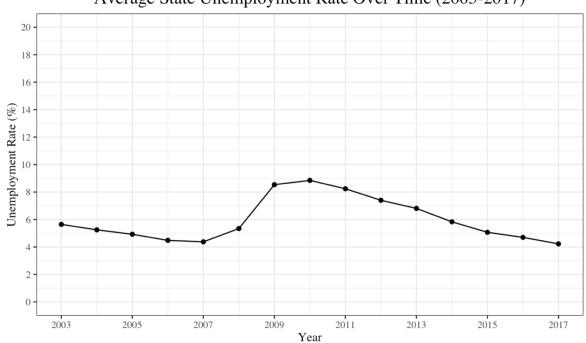


Figure C. Average Poverty Rate Across All States Over Time Period (2003-2017)

Average State Poverty Rate Over Time (2003-2017)

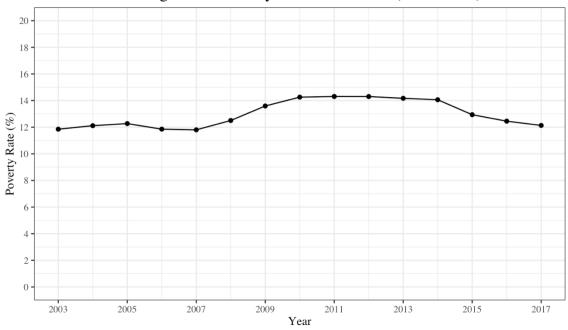


Table 1. Variable Averages, across all states over entire time period (2003-2017)

Variable	Average, All States (2003-2017)
total_unemp	5.98%
men_unemp	6.28%
women_unemp	5.63%
white_unemp	5.19%
black_unemp	11.61%
hist_lat_unemp	7.84%
asian_unemp	4.76%
age_16to19_unemp	18.57%
age_20to24_unemp	10.30%
min_wage	\$6.85
poverty_rate	12.97%
hh_income	\$58,045.94
no_hs_perc	13.71%
hs_perc	23.92%
some_col_perc	21.76%
bachelors_plus_perc	20.75%
white_perc	80.27%
black_perc	11.27%
asian_perc	3.81%
two_plus_perc	2.52%

Table 2. Regression Results

es	310	/11	1/	-	ul	ıs						_			_																		_
	R-squared		two_plus_perc			black_perc asian_perc				white_perc			bachelors_plus_perc			some_col_perc			hs_perc			no_hs_perc			log(hh_income)				log(min_wage)				
	0.04																												t = 5.12	(.37)	1.88	(total_unemp)	FE
Standard E	0.33	t = .20	(.09)	0.02	t = .26	(.08)	0.02	t = -2.45	(.10)	-0.24	t =18	(.06)	-0.01	t = -5.45	(.10)	-0.52	t = -4.08	(11)	-0.44	t = -4.19	(.10)	-0.44	t = -4.7	(.12)	-0.54	t = -15.20	(1.04)	-15.84	t = 6.51	(0.49)	3.21	(total_unemp)	HE
Errors are clustere	0.12	t = 1.70	(.10)	0.17	t = -1.46	(.09)	-0.13	t=38	(.11)	-0.04	t = -1.90	(06)	-0.12	t = -1.98	(.10)	-0.21	t =23	(.11)	-0.03	t =47	(.11)	-0.05	t = -1.4	(.12)	-0.18				t = 5.64	(.53)	2.99	(poverty_rate)	FE
ed at the State level to a	0.28	t =33	(.28)	-0.09	t=-1.15	(.23)	-0.27	t = -2.06	(.30)	-0.61	t = -1.70	(.17)	-0.28													t = -14.80	(2.90)	-42.93	t = 4.56	(1.07)	4.89	(poverty_rate) (age_16to19_unemp)	FE
Standard Errors are clustered at the State level to account for serial correlation and heteroskedasticity	0.27	t =64	(.16)	-0.1	t=45	(.14)	-0.06	t=-2.72	(.17)	-0.45	t = .28	(.10)	0.03													t = -15.00	(1.76)	-26.43	t = 6.28	(.64)	4.04	(age_20to24_unemp)	FE
tion and heteroske	0.31													t = -5.76	(.09)	-0.5	t = -4.68	(.10)	-0.45	t = -4.37	(.10)	-0.42	t = -4.99	(.11)	-0.53	t = -14.64	(.97)	-14.23	t = 6.48	(.45)	2.93	(white_unemp)	FE
dasticity	0.2													t = -3.4	(.24)	-0.82	t = -3.22	(.26)	-0.85	t = -3.16	(.27)	-0.85	t = -3.25	(.30)	-0.98	t = -10.60	(2.56)	-27.13	t = 2.17	(1.12)	2.43	(black_unemp)	FE
	0.26													t=-4.85	(.17)	-0.84	t = -3.99	(.19)	-0.77	t = -3.93	(.19)	-0.76	t = -4.43	(.22)	-0.95	t = -12.39	(1.88)	-23.32	t = 4.53	(.86)	3.89	(hisp_lat_unemp) (asian_unemp)	FE
	0.13													t = -2.16	(.16)	-0.35	t = -2.51	(.18)	-0.46	t = 1.45	(.19)	-0.27	t = -2.74	(21)	-0.59	t = -7.30	(1.82)	-13.25	t = .40	(.82)	0.32	(asian_unemp)	FE