## Impacts of Minimum Wage Increases on Teen Employment

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#### Introduction

Throughout the calendar year, more than half of all teenagers in the United States are employed either part- or full-time. Teen employment accounts for a significant portion of the United States economy, particularly in summer months June-August, at which point teen employment rates increased tenfold to nearly 21 million teen employees in 2017 (Bureau of Labor Statistics, 2017). This segment of the American population represents the influx of the next generation's lifetime workforce, and their contributions to and participation in the economy indicate what the future of work looks like in the United States.

Minimum wage is a contentious topic in the United States, where economists and policymakers debate its amount, effects and relevancy. The federal minimum wage is \$7.25 an hour (Department of Labor, 2018) and statewide it is as high as \$11 an hour in Washington and California (Department of Labor, 2018). With the shrinking middle-class, the increasing gap between the rich and poor and the skyrocketing costs of rent, education and living expenses for families nationally, these wages are a determinant for financial stability and an opportunity to reach the mythological American dream.

The convergence of these two sectors makes this topic a critical concern to economists and policymakers alike. Teens' wages can be used to help support their families, in addition to building valuable interpersonal skills and experience outside the home and classroom. Thus, focusing on teen employment is not isolative, but inclusive of the lived experiences of the spectrum of workers in the United States. A change in the minimum wage and its effects on teen employment are both microcosmic—the increase or decrease in a teen's and household's financial stability—and macrocosmic—the change in overall employments rates and its economic consequences—the latter of which this report sought to investigate.

Using March CPS data between 1990 and 2013, this paper utilizes a difference-in-difference methodology to ascertain the impacts of minimum wage increases between states in the midwest that had state minimum wage increases above the federal level, and those that only paid the federal minimum wage.

Beyond the impact on overall employment rates, this paper examines the impacts of minimum wage increases specifically on teens who work full-time, which serves as a proxy for low-income teens who need to work full-time to support their families. The paper also examines differences

in employment rates by race, which is also associated with income levels. We hypothesize that minimum wage increases will lead to a decrease in employment, and that this will disproportionately impact full-time workers.

## Background

The research on impacts of minimum wage on employment rates report varying results due to differences in methodology, data sets, and problem definitions. One of the foundational studies on this question, Card and Kreuger's 1994 study of the impacts of minimum wage increases in New Jersey, used a difference-in-difference model and found that wage increases were not associated with a decrease in employment in the fast food industry. Additional difference-in-difference studies (Card 1992; Card, Katz and Kreuger 1994; Neumark and Wascher, 1992, 1994) honed in on the impact of minimum wage increases for teen employment rates, specifically. These studies used CPS data, and found small, statistically insignificant effects on teen employment (Card, Card et al.), or significant negative effects on teen employment (Neumark and Wascher). Later studies found that the 1991 federal minimum wage increase had positive employment effects in food service for teens (Lang and Kahn, 1998), at the expense of adults in the same industry.

Findings on the impact of age and teen affluence on employment rates given minimum wage increases have also been contradictory at times. Studies using CPS data have shown that a minimum wage increase makes it more likely that older teenagers leave school for employment and that younger, employed teenagers become unemployed (Neumark and Wascher, 1996), and that increases in the relative wages of teenagers led to significant increases in the relative employment of teenagers, especially younger and more affluent teenagers (Giuliano, 2013). Meer and West's 2013 study found that minimum wage reduces job growth over a period of several years, with effects most pronounced for younger workers. Meer's study in particular emphasized that the *rate* of job growth reduction over time was more salient for understanding the impacts of minimum wage increases than the net amount of job growth at any given time. Yet another study found that a higher minimum wage level was associated with higher earnings, lower employment and reduced worker turnover for those in the 14–18 age group (Liu, Hyclak, and Regmi, 2015).

The varying findings in these studies, particularly studies that used the same data (CPS), demonstrate that there is still much work to be done to understand the impact of rising minimum wage on teenagers.

### **Theoretical Framework**

This report investigates the change in part-time teen (ages 16-19) employment rates in treatment states (Minnesota, Iowa, Missouri, Arkansas, Illinois and Wisconsin) compared to control states (North Dakota, South Dakota, Wyoming, Nebraska, Kansas, Oklahoma, Texas and Louisiana) as a result of the 2004, 2005, and 2006 minimum wage increases. The pre-treatment period includes 1990 - 2004, and the post-treatment period includes 2005 - 2013.

We hypothesize that minimum wage increases will lead to a decrease in employment, and that this will disproportionately impact full-time workers.

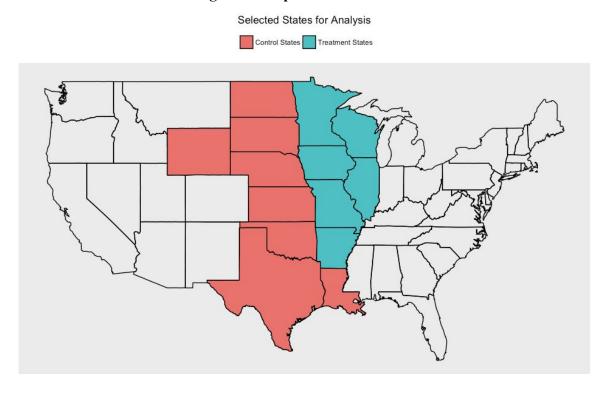


Figure 1. Map of States Selected

This report uses a difference-in-difference (DID) econometric model to calculate and estimate the causal effect of minimum wage increases on employment rates over time. The DID model leverages panel data to examine a treatment and a control group before and after a policy change while holding constant characteristics that are unique to the observed subjects (in this case, states) across time. This effectively overrides the impact of difficult-to-isolate confounding variables on the outcome variable. The DID model is based on the typical OLS assumptions and the parallel trends assumption.

DID's unique characteristics and application make it the ideal econometric model to study this report's research question. The DID model can analyze data in multiple time periods both before and after the minimum wage increase occurred and compare the two groups' change trajectories, and is well suited to utilize the longitudinal data available from the U.S. Census Bureau CPS data (as described below).

#### Data

The data in this report comes from the Current Population Survey (CPS) from the U.S. Census Bureau. The CPS is a monthly survey of labor market outcomes. We rely on the March CPS because each March the survey asks questions regarding labor market outcomes in the previous year and, as such, is a popular data set. Data is aggregated to the state and year level, and we do not have access to more granular data.

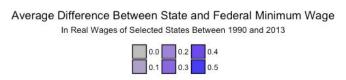
Figure 2. Summary Statistics of Control and Treated States

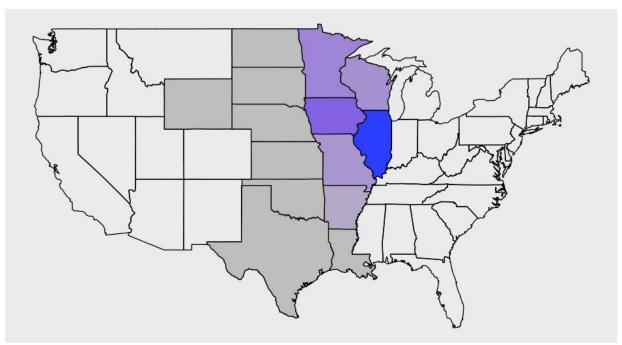
Statistic	N	Mean	St. Dev.	Min	Max
Employed Ages 16-19	192	0.413	0.100	0.171	0.680
Employed Ages 16-17	192	0.319	0.116	0.049	0.614
Employed White Ages 16-	19 192	0.447	0.096	0.184	0.702
Works Full Time	192	0.124	0.037	0.030	0.225
Works Part Time	192	0.289	0.090	0.091	0.531
Treated States Dependen	t Vari	able S	ummary St	atisti	cs
			ummary St		cs Max
	N		St. Dev.		Max
Statistic	N 144	Mean	St. Dev. 0.098	Min	Max 0.664
Statistic Employed Ages 16-19	N 144 144	Mean 0.427 0.341	St. Dev. 0.098 0.117	Min  0.144	Max 0.664 0.644
Statistic Employed Ages 16-19 Employed Ages 16-17	N 144 144 19 144	Mean 0.427 0.341	St. Dev. 0.098 0.117 0.098	Min  0.144 0.106	Max 0.664 0.644 0.678

This report relies data from the years 1990 to 2013 for all 50 states. However, as noted in above, we limit the data to the states in our treatment and control groups. Our outcome or dependent variables are all measurements of fractions of teens that are employed in any given year. "Teens" include those aged 16-19, though some variables split this group into 16 and 17 year olds and 18

and 19 year olds. Other variations in outcome employment variables include the fraction of teens working full or part time, the fraction of females or males that are employed, the fraction of white or minority teens that are employed, and the fraction of those working in retail or restaurants, among others.

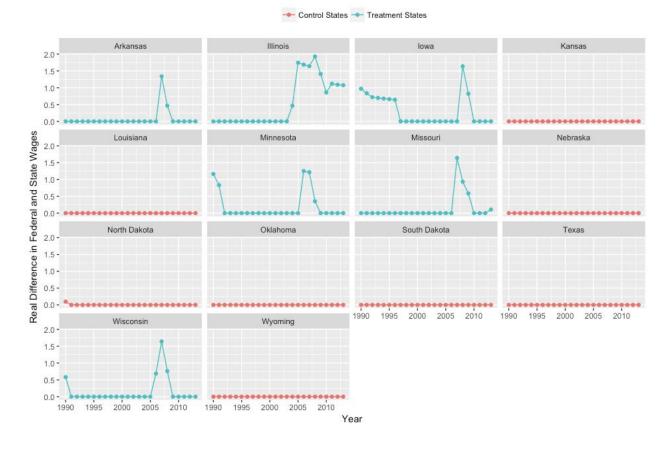
Figure 3. Map of State Minimum Wage Increases





Two other data sets are merged with the CPS data. The first is the minimum wage of each state in any given year, taken from Neumark, Salas and Wascher. The second is the Consumer Price Index (CPI) for March of each given year. This latter data set allows for us to adjust for inflation the minimum wage. Thus, all minimum wages are in real dollars.

Figure 4. Minimum Wage Increases By State Over Time



# Results

**Table 1. Regression Results** 

	Dependent variable:								
	Employed Ages 16- 19			Works Part Time	Employed Ages 16- 17	Employed White Ages			
	(1)	(2)	(3)	(4)	(5)	(6)			
Treatment States	0.030**	0.003	0.004	0.027**	0.043***	0.032***			
	(0.012)	(0.005)	(0.004)	(0.012)	(0.014)	(0.012)			
Post 2004	-0.071***	-0.023***	-0.015***	-0.048***	-0.078***	-0.069***			
	(0.013)	(0.005)	(0.005)	(0.012)	(0.016)	(0.013)			
Treatment X Post 2004	-0.042**	-0.025***	-0.022***	-0.017	-0.070***	-0.048**			
	(0.020)	(800.0)	(0.007)	(0.019)	(0.023)	(0.020)			
n School			-0.333***		0.669***				
			(0.036)		(0.117)				
Constant	0.440***	0.133***	0.400***	0.307***	-0.195**	0.472***			
	(0.008)	(0.003)	(0.029)	(800.0)	(0.094)	(0.008)			
Observations	336	336	336	336	336	336			
R <sup>2</sup>	0.203	0.200	0.364	0.109	0.241	0.218			
Adjusted R <sup>2</sup>	0.196	0.193	0.356	0.101	0.231	0.211			
Residual Std. Error	0.089 (df = 332)	0.035 (df = 332)	0.032 (df = 331)	0.084 (df = 332)	0.103 (df = 331)	0.086 (df = 332)			
F Statistic	28.181*** (df = 3; 332)	27.653*** (df = 3; 332)	47.394*** (df = 4; 331)	13.550*** (df = 3; 332)	26.212*** (df = 4; 331)	30.892*** (df = 3; 332)			
Note:	•	•				p<0.1; <b>p&lt;0.05</b> ; p<0.0			

The specification **employed**<sub>i</sub> =  $\beta_0 + \beta_1$ **treatment**<sub>i</sub> +  $\beta_2$ **post**<sub>t</sub> +  $\beta_3$ **treat\_interact**<sub>it</sub> +  $\alpha$  was significant at  $\alpha$ =.05 (p = .039). States in the treatment group had a lower employment rate than states in the control group by 4.2%, and the overall R-squared was .2.

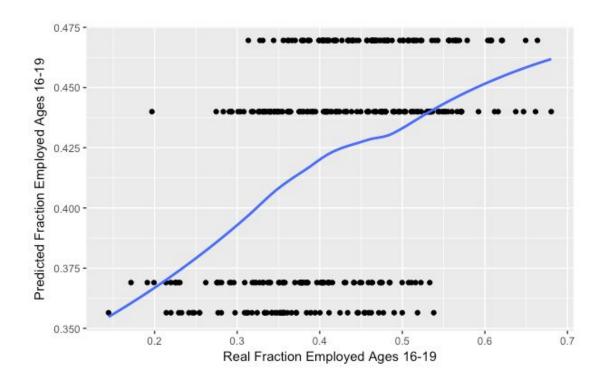


Figure 5. Regression Model 1

To confirm that the difference-in-difference model is valid (i.e. that the control and treatment groups had parallel trends prior to the treatment), we tested the specification **employed**<sub>i</sub> =  $\beta_0$  +  $\beta_1$ **treatment**<sub>i</sub> +  $\beta_2$ **pre**<sub>t</sub> +  $\beta_3$ **pre\_interact**<sub>it</sub> +  $\epsilon_i$ , where pre\_interact was an interaction variable between the pre-period and the treatment. Pre\_treatment tested as statistically insignificant, meaning we can safely assume that if the treatment group's employment trend was measured in the pre-treatment period, it would look identical to that of the control group. However, there was only significance at  $\alpha$ =.1, and not at  $\alpha$ =.05 (p = .074). This will be further explored in the robustness section later on in this paper.

The specification **employedw**<sub>i</sub> =  $\beta_0 + \beta_1$ **treatment**<sub>i</sub> +  $\beta_2$ **post**<sub>t</sub> +  $\beta_3$ **treat\_interact**<sub>it</sub> +  $\epsilon_i$  was also significant at  $\alpha$ =.05 (p = .016). In this specification, the percentage of employed white workers aged 16-19 decreased by 4.7% for states in the treatment group, relative to non-white workers aged 16-19. We tested this interaction to see whether employment had a higher impact on white workers than on all employees, and found that this was true (4.7% for white workers, vs. 4.2%

for all). Testing the specification on employedmin did not yield significance. One possible explanation for this is that as labor demand decreases due to minimum wage increases, white workers who have more cross-sector mobility due to social connections will be able to find work in other sectors that have higher labor demand.

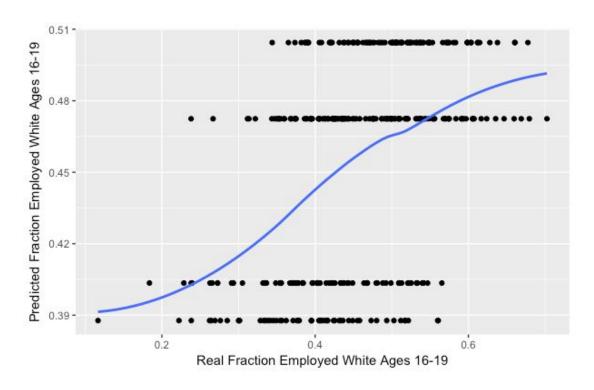


Figure 6. Regression Model 6

The specification  $\mathbf{workpt_i} = \beta_0 + \beta_1 \mathbf{treatment_i} + \beta_2 \mathbf{post_t} + \beta_3 \mathbf{treat\_interact_{it}} + \mathbf{e_i}$  was not significant. In this specification, we attempted to see whether the impact on part-time workers was significant in the treatment group. Teens that work part-time are likely more affluent, and don't need to work full-time to contribute to family finances. By testing this specification, we were checking whether the minimum wage increase particularly impacted employment for those who worked part time. We found that the interaction term was not significant (p = .371), meaning that the minimum wage increase did not particularly impact employment for teens working part time.

Subsequently, we tested **workft**<sub>i</sub> =  $\beta_0 + \beta_1$ **treatment**<sub>i</sub> +  $\beta_2$ **post**<sub>t</sub> +  $\beta_3$ **treat\_interact**<sub>it</sub> +  $\epsilon_i$ , essentially the complementary hypothesis to the previous specification-- that teens working full-time, and therefore more likely to be lower income, would have significantly negatively impacted employment rates due to minimum wage increases. This specification was significant at  $\alpha$ =.01 (p = .002), indicating that full-time teen employment rates were 2.5% lower than overall

employment rates. One possible explanation for this is that as minimum wage increases, low-income students can work less hours, and stay in school for longer.

To test the above possible explanation, we tested the specification  $\mathbf{workft_i} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} \mathbf{treatment_i} + \boldsymbol{\beta_2} \mathbf{post_t} + \boldsymbol{\beta_3} \mathbf{treat\_interact_{it}} + \boldsymbol{\beta_4} \mathbf{inschool_i} + \mathbf{e_i}$ . This was significant at  $\alpha = .01$  (p = .003), and showed that as minimum wage increased, full-time employment reduced by 2.1% among students attending school, relative to those not attending school.

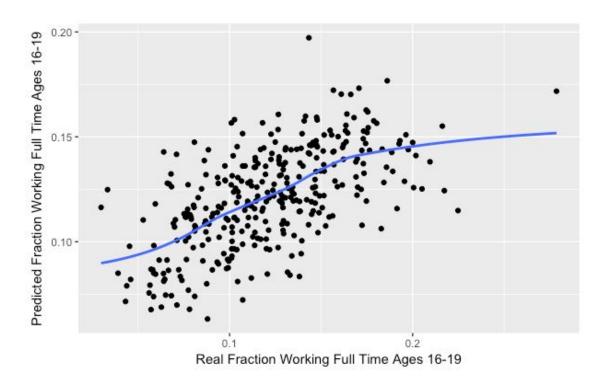


Figure 7. Regression Model 3

Lastly, we tested the specification **employed1617**<sub>i</sub> =  $\beta_0 + \beta_1$ **treatment**<sub>i</sub> +  $\beta_2$ **post**<sub>t</sub> +  $\beta_3$ **treat\_interact**<sub>it</sub> +  $\beta_4$ **inschool**<sub>i</sub> +  $e_i$ . This was significant at  $\alpha$ =.01 (p = .003), indicating that post-minimum wage increases, the employment rate was negatively impacted at a rate of 7% for teens aged 16-17 who were in school, as opposed to employment rates overall. This aligns with our other findings with this study, and adds weight to the theory that teens in school worked less hours, or less overall, once minimum wage was increased and they could afford to spend less time working.

0.2 - 0.4 - 0.6 Real Fraction Employed Ages 16-17

Figure 8. Regression Model 5

#### Robustness

There are some significant limitations to this model. One of the most prominent limitations is that the pre- and post-treatment periods span up until 2004 and after 2004, respectively, but do not actually include the year 2004. When 2004 was included in the analysis, the parallel trends assumption did not hold.

One possible explanation for this is that 2004 was the earliest year that states in the treatment group implemented minimum wage policies that raised wages above the federal minimum wage level, not *all* the states in the treatment group implemented policies during that year. Some states implemented their policies in 2005 and 2006. The fact that the implementation date is inconsistent between states in the treatment group is likely what pulls the parallel trends out of significance when we include the year 2004: Illinois was the only state to raise the state minimum wage in 2004, and the raise was relatively small (\$0.35). This may have caused too much variation compared with the cumulative years pre- and post- 2004.

An additional limitation of the model is the potential for endogeneity bias. Although this model uses panel data, which controls for state-specific features like political orientation, weather, and size of the economy, the data does not include explanatory variables for individual worker characteristics that could impact the variation in employment rate reduction across groups. For

example, CPS doesn't include the number of low-income workers who work part-time vs. full time, and thus this paper relies on full-time teen employment as a proxy for being low-income. Having specific data on the intersection of low-income workers and full-time workers would make the specification that predicts full-time employment effects more accurate, and would allow us to make more accurate statements about the impact of minimum wage increases on low-income workers.

Omitted variable bias is also a concern with this model, because the data does not have individual fixed effects, only fixed effects for states. This means that there is a possibility of omitted variable bias around individual employee characteristics, such as poverty, family characteristics, and education. Additionally, findings could be biased by time-variant unobservables, like the strength of the economy in any given state during a given year.

### Conclusion

This report sought to investigate the effects of the minimum wage on teen employment in two groups of states, utilizing the difference-in-difference econometric model and CPS data from 1990 to 2013. A treatment group of six states was compared to a control group of eight states that shared similar regional and demographic characteristics. Analysis found several significant results, including a significant decrease in employment rates for white workers, full-time teen employees and employed teens ages 16-17, all compared to the employment rate for all teen workers, regardless of race, age, or part/full-time employment status. Limitations to this analysis include the omission of treatment data in 2004, potential endogeneity bias and potential omitted variable bias.

The results indicate that an increase in minimum age can shift the number and demographics of teen employment. Considering the need for teenagers to earn a high school diploma to ensure future upward mobility and financial stability, these results are important for state and federal policymakers who seek to ensure American youth are prepared for individual success and meaningful contribution to the economy.

### **Works Cited**

Card, David. 1992. Using regional variation in wages to measure the effects of the federal minimum wage. Industrial and Labor Relations Review 46, no. 1:22–37.

Card, David, Lawrence F. Katz, and Alan B. Krueger. 1994. Comment on David Neumark and William Wascher, "Employment effects of minimum and subminimum wages: Panel data on state minimum wage laws." Industrial and Labor Relations Review 47, no. 3:487–96.

Card, David, and Alan B. Krueger. 1994. Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania. American Economic Review 84, no. 4:772–93.

Giuliano, Laura. 2013. Minimum wage effects on employment, substitution, and the teenage labor supply: Evidence from personnel data. Journal of Labor Economics 31(1): 155–94.

Liu, Shanshan, Hyclak, Thomas J., Regmi, Krishna. 2016. Impact of the minimum wage on youth labor markets. LABOUR30: 18–37.

Meer, Jonathan, and Jeremy West. "Effects of the Minimum Wage on Employment Dynamics." NBER Working Paper No. 19262. Issued in August 2013, Revised in January 2015.

Press Office, Bureau of Labor Statistics. 2017. "Employment and Unemployment Among Youth." U.S. Department of Labor. Issued in August 2017.