The Impact of Changes in the Minimum Wage on Employment

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Abstract

Early empirical research regarding the effects of minimum wage changes corroborated the classical assumption that the imposition of a price floor will lead to a proportionate reduction in employment. This paper, however, will provide evidence in support of contemporary research that refutes that assumption. With a fixed effects model, we control for time-varying heterogeneity that may ordinarily lead to "spurious" negative employment elasticities. Our findings, while not unassailable, support recent findings that increasing the minimum wage will not necessarily lead to employment loss.

1 Introduction

The debate over appropriate minimum wage policy has intensified in recent years, due in large part to wage stagnations that have plagued the U.S. economy during the current economic recovery. Traditional research concerning the minimum wage has suggested a significant negative impact of the minimum wage on the employment of low-wage workers. However, that consensus view has been challenged in recent years by work that, among other measures, effectively controls for time-varying heterogeneity by the implementation of spatial controls. The aim of this project is to attempt to evaluate these competing claims. To do so, we will use fixed effects regressions to model the effect of changes in the real minimum wage on employment.

To the best of our ability, our analysis is performed in the spirit of Dube, Reich, Allegretto, their rotating set of co-authors, and permutations thereof. Due to limitations of time and expertise, we will focus less on an exact replication of work by these authors. Rather, after a brief survey of compelling aspects of their work, and an overview of context with which to interpret it, we will develop and test two primary models that draw, in part, from their instructive 2013 working paper, Credible Research Designs for Minimum Wage Studies.

In section 2 we will provide a brief survey of the literature that has informed and motivated this project. We will first review the empirical research concerning the effects of minimum wage policy on employment, followed by a review of other economic consequences and implications from welfare theory. In section 3 and 4 we will present our data and methodology. We will overview our data selection process, variable construction, and specifications of our two primary methods. The first method employed in the investigation is a state-level fixed effects regression modeling employment effects on low-wage workers. The regression will be evaluated in different forms in order to assess the validity of various functional form and variable decisions. The second method will assess the treatment effects on employment for high school dropouts, and similar scrutiny will be applied. We will present our results in section 5, which demonstrate modest support for the previous findings that when spatial controls are properly accounted for, minimum wage effects on employment are slightly positive. Lastly, in section 6 we will discuss these findings and potential problems.

2 Literature Review

2.1 Empirical Research on the Minimum Wage and Employment

According to Neumark (2015), the earliest minimum wage empirical research studied only the effect of changes in minimum wage at the national level. Despite, or perhaps because of the lack of rigor employed, the findings supported prevailing assumptions drawn from classical theory. Specifically, as restrictions on the wage floor are imposed, firms choose to no longer employ workers whose marginal product of labor is less than the new mandatory wage floor. The studies found elasticities of labor demand between -0.1 and -0.3 for teens ages $16-19$, and between -0.1 and -0.2 for young adults ages $16-24$.

Studies that followed tended to support these findings, yet with slightly more rigor. For example, the second wave of studies included changes in regional state and local changes minimum wages, which made it possible to study the phenomenon in comparison to locations that did not receive the effect of a nominal minimum wage increase. These studies similarly found negative employment effects associated with nominal minimum wage increases.

However more recently, case studies making direct comparisons between treated and untreated adjacent areas found little to no effect of the treatment on employment. Examples include Card and Krueger (1994, 2000) and Dube, Naidu, and Reich (2007). In fact, Dube et al. (2010) similarly find little to no elasticities and show that "traditional approaches that do not account for local economic conditions tend to produce spurious negative effects due to spatial heterogeneities in employment trends that are unrelated to minimum wage policies."

Allegretto et al. (2013) assess a number of approaches with which to mitigate the problems of time-varying heterogeneity. The first method, which we will employ in this study, is with the use of geographic controls with a fixed effects model. Many early studies on the topic failed to include geographic controls, and hence exposed their parameter estimates to omitted variable bias by failing to account for fundamental place-specific differences. Fortunately, data and software developments make these controls easy to implement. Other methods deemed to be credible remedies for time-varying heterogeneity, but which we will not pursue in this project include: synthetic controls, spatial and temporal lags, and the use of neighboring treated and untreated locality pairs (within same commuting zone) to serve as control and treatment groups.

2.2 Qualitative Analysis

According to Flinn (2010), the effect that a change in the minimum wage has on employment depends on the labor market conditions. Specifically, if the labor market is perfectly competitive and wages are equal to the marginal product of labor, an increased real minimum wage will result in employment termination for all workers producing at a marginal product less than the new minimum wage. However, most labor markets are in fact imperfect or noncompetitive, and either firms or workers earn rents from the employment relationship. In this situation, changing the real minimum wage will not in theory lead to changed unemployment. Rather, changing the real minimum wage will simply reallocate a different portion of the rents to the labor or capital share of profits.

Because no labor market is perfectly competitive, minimum wage policy may play an important role to ease the negative effects caused by the imperfections. In the extreme case of monopsonistic (market of one buyer or employer) imperfection, appropriately levied minimum wage policy has the greatest opportunity to benefit society. According to Stigler (1946), a correctly chosen minimum wage in this situation may increase wages, employment, and output.

2.3 Other Effects

While this study, like much of the minimum wage literature, will only analyze the effect of minimum wage changes on employment, employment is a rather narrow measurement of the welfare consequences of and motivations for minimum wage policy. In effort to provide greater context for our investigation and convey more broadly the effects of minimum wage changes, we will briefly discuss below the impact on other economic variables and related welfare theory.

2.3.1 Impact on Wages and Employment Growth

Flinn (2010) found that increases in the nominal minimum wage lead to modest increases in the proportion of the labor force working for the minimum wage or below. While minimum wage increases sometimes led minimum wage workers to become unemployed, many workers remained employed and saw their wages rise to the new minimum. To illustrate the potential impact of a minimum wage increase on wages, a 2014 report by the nonpartisan Congressional Budget Office estimated that by raising the federal minimum wage to $9 per hour, approximately 7.6 million low-wage workers would experience a pay increase.

Meer and West (2013) analyzed the effects of minimum wage on employment growth. According to their research, reduction in employment rate growth is a more significant side effect of an increased minimum wage than is employment loss.

2.3.2 Impact on Prices

Research into the impact of recent nominal minimum wage increases on prices has demonstrated significant and positive relationship between the two. Allegretto and Reich (2015) analyzed over 60,000 online restaurant menus before and after San Jose, CA in 2013 implemented a 25 percent local minimum wage increase. Interestingly, while the study found a significant positive effect on prices among all restaurant types, it did not find a negative impact on employment, suggesting that restaurants, rather than focusing to reduce costs, shifted the increased costs to the consumer. This case study provides evidence for the income inequality-reducing benefits of minimum wage increases, assuming that the wealthy disproportionately comprise restaurant customers in a city like San Jose.

2.3.3 Welfare Theory

Flinn (2010) outlines three more rigorous welfare measurements that are worth contemplation. In the spirit of Hosios (1990), welfare is assessed as four group-weighted welfare averages that are functions of the wage m and are tied to weight functions determined by group sizes. The four groups, assessed at wage m are: individuals who are out of the labor force, individuals who are unemployed, individuals who are employed, and firms with a filled job vacancy. The reason that firms with a job vacancy and those that have not chosen to create a job vacancy are not included is that they make no positive welfare contributions.

Named for the moral philosopher John Rawls, the (supply side) Rawlsian Criterion asserts that welfare is to be measured by its impact on the worse-off members of a population. Under this precept, all population groups are weighted 0 except for the unemployed, who are assigned a weight of 1. Thus welfare in this scenario is equivalent to the welfare of the unemployed, who perhaps stand to lose from an increase in the real minimum wage. Flinn's second measurement of welfare, Total Welfare, assigns equal weight to all groups, times the expected value of being in each state, which is equal to the number of agents in each group. While morally appealing, Total Welfare does not help to guide, on its own, minimum wage policy. The third standard of measurement is Participants Welfare, which assigns weight of 0 to individuals not in the labor force and 1 to each other group, and is the preferred standard of Flinn (2010) and Hosios (1990). The preference stems from the advantages of historical comparability and because welfare estimation of labor force non-participants is highly arbitrary.

3 Data

3.1 Data Sources

The primary data source used for this study is the Current Population Survey (CPS), which, since 1940, has been conducted by the U.S. Census Bureau for the Bureau of Labor Statistics. Since 1948, the CPS has included one month per year the Annual Social and Economic Supplement (ASEC), which is informally referred to as the March CPS. Because the ASEC includes economic information such as employment status and occupation, in addition to demographic details, the majority of the variables used in this study are created from ASEC data. The ASEC data was obtained via the University of Minnesota's Integrated Public Use Microdata Series (IPUMS), which, as described on its website is a project dedicated to integrating and disseminating United States census data, and is free of charge.

Because the CPS employs a complex stratified sampling scheme, all variables constructed with the ASEC data (employment figures and demographic controls) are weighted according to the individual-level inverse probabilities provided by the CPS. According to IPUMS, these inverse probability weights adjust for the following factors: failure to obtain an interview; sampling within large sample units; the known distribution of the entire population according to age, sex, and race; over-sampling Hispanic persons; to give husbands and wives the same weight; and an additional step to provide consistency with the labor force estimates from the basic survey. More information about the weighting scheme can be found by visiting the URL provided in the references.

The data on the state minimum wages was obtained via source author Arindrajit Dube's web page dedicated to providing resources pertinent to replication studies. Because this state-level minimum wage data is available for the years 1977-2014, ASEC data was selected from IPUMS with state-level coding for that span.

The minimum wage variable MW used in our data refers to the real minimum wage at state level between 1977 to 2014. Since the signing of the 1938 Fair Labor Standards Act, the federal minimum wage has risen from \$0.25 to \$7.25 per hour. The federal minimum wage has been legislatively increased at irregular intervals to compensate for higher price levels (see Figure 1), yet since the price level generally increased on an annual basis, there has been a fluctuation of the real value of minimum wage since 1938. In order to reflect the true impact of minimum wage, we adjusted the nominal minimum wage at state level using the Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W) published by the Bureau of Labor Statistics. Real minimum wages were expressed in terms of the 2015 CPI-W index, the latest data available up until now. The adjustment was made according to equation (1):

$$MW_{i,t}^{real} = \frac{MW_{i,t}^{nom} * CPI_{2015}}{CPI_t} \tag{1}$$

We included a per capita income variable (in log form) in our models for each year t and state i to serve as a macroeconomic control. Data were obtained from the U.S. Bureau of Economic Analysis web site and were adjusted manually with the Consumer Price Index to reflect real values with 2015 as a base year.

3.2 Dependent Variable Selection

For consistency with the literature, employment will be measured as such–not as unemployment. In order to spotlight the employment consequences of minimum wage policy, our study utilizes two dependent variables that are similarly constructed to focus attention on the workers most affected by minimum wage-influenced hiring decisions. Each method has its strengths and limitations.

3.2.1 Low-Wage Workers

In the first version of the model, the dependent variable is defined as the employment rate among low-wage workers, and is created yearly for every state in the study. The low-wage label is applied to workers whose occupational designation per the ASEC falls among a list of traditionally low-wage occupations identified by the authors (See Table 1). Our decision to focus primarily on food preparation and serving workers is supported in the literature. Flinn (2010) reported that, according to a 2005 Bureau of Labor Statistics analysis, food and preparation serving includes by far the greatest proportion of minimum wage workers (17.5%). This figure is higher than teenagers–another cohort commonly cited for its predominantly low-wage composition. In 2005, teenagers making equal to or less than minimum wage constituted less than 10% of all teenage workers.

Occupational classification has evolved over time in the ASEC, yet the data obtained from IPUMS was harmonized to the 2010 ASEC. Some detail is lost by the harmonization, as specific categories from the 2010 ASEC are combined to form broader ones that can accommodate earlier classification. However, the advantage of consistent analysis over time outweighs this drawback.

The universe of respondents to the ASEC occupation question is limited to working age individuals fifteen and older who have held a job in the past five years, and the respondents are asked to provide their current or past occupation. However, defining an employment rate among individuals classified by occupation poses problems. By limiting the universe to respondents who have worked a job in the past five years, there is a slight upward bias on the employment rate figure. Additionally, there is no way to be sure without deeper analysis to what degree an individual who has previously worked as a specific low-wage employee is as vulnerable to minimum wage-induced employment effects as a present or prospective low-wage employee.

3.2.2 High School Dropouts

The alternative model we employ defines the dependent variable as employment among individuals who did not graduate from high school. This method is meant to serve as a proxy for low-wage workers without the complications outlined above. Similar to the occupation data used, the CPS data on educational attainment obtained from IPUMS is a harmonization of different classifications used over time. To create the high school dropout-based employment variable, an indicator variable signifying diploma received (not just 12th grade completed) is created, and then yearly employment rates among those without diplomas are created for each state (see Figure 4). The major drawbacks to this method stem from the fact that high school dropouts is an imperfect substitute for low-wage workers. Additionally, a majority of high school dropouts are in fact not labor force participants (see Table 2). This fact causes an upwards bias on the employment rate.

4 Methodology

As mentioned above, many early models for the minimum wage research used time-series data without implementing spatial controls. The early studies traditionally found that increasing the real minimum wage resulted in decreased employment, and vice versa. However, without correcting for place-specific differences, the results were likely to be biased.

For this project, the authors were highly motivated by a working paper by Allegretto, Dube, Reich, and Zipperer (2013) about a minimum wage study that used spatial control variables to examine the impact on employment. In their paper, a fixed effect model was used, which took time and place into account in order to eliminate the effect of time-varying heterogeneity.

Therefore, a fixed effect model is used for this analysis, with a year range from 1977 to 2014. Specifically, the model takes time t and state i as two fixed effects.

The primary fixed effect model is expressed as a linear model:

$$Y_{it} = \beta_0 + \beta_1 MW_{it} + \beta_2 X_{it} + \gamma_i + \tau_t + \epsilon_{it} \tag{2}$$

where i is an index for state, with $i = 1, ...51$; t is an index for year, with $t = 1977, ...2014$; Y represents the employment rate of two groups of observations annually in each state i by year t; MW is the real minimum wage in each state i and each year t; X_{it} is a vector of explanatory variables; γ_i is the individual fixed effect, which are indicator variables for each state i; τ_t is the time effect; and ϵ_{it} is the error term.

The secondary fixed effect model is expressed as a linear-log model, which could give the employment elasticity directly. The real minimum wage in log form is used for each state and each year, with all other variables kept the same:

$$Y_{it} = \beta_0 + \beta_1 \log MW_{it} + \beta_2 X_{it} + \gamma_i + \tau_t + \epsilon_{it} \tag{3}$$

For both models, the primary independent variable is the minimum wage (we evaluate in log and linear form). In the linear model, the coefficient estimate β_1 represents that when real minimum wage changes 1 unit, the employment rate would change by β_1 units. In the linear-log model, the coefficient estimate β_1 represents the employment elasticity: when the real minimum wage changes 1%, the employment rate would change by β_1 units. Because the unit of the employment rate is calculated in percentage, β_1 shows the percentage change in employment rate.

The first group of observations for employment rate is low-wage workers in each state, represented as dependent variable Y in the model. As mentioned above in the data section, low-wage labels are created to approximate workers who are earning minimum wage (see Table 1). In addition, the secondary employment classification group is the high school dropout population in each state (see Table 2). Both dependent variables will be included in the analysis and comparisons between these two targeted groups will be made in order to achieve better conclusions.

At first, minimum wage is the only included independent variable in the model with state and time fixed effect. Next, demographic and macroeconomic control variables are included in the model to help better explain the dependent variable Y. The controls are created as state averages for each year observed in the study. They are average age, log real per capita personal income, percentage of white population, percentage of female population, percentage of high school graduates, percentage of college graduates with at least a bachelors degree, and the percentage of the population married in each state. Ones education status is highly considered to be correlated with his or her employment status (Howe, 1988). Gender and age are also commonly used by scholars to analyze the employment rate (Bugudui, 2015). γ_i are indicator variables for each state. Specifically, there are 50 states plus Washington, D.C., and the number of indicator variables γ_i is 51 minus one.

Additionally, one-year and two-year lagged values of the minimum wage are tested as dependent variables. The intuition behind this decision is that perhaps the employment impact of a change in the real minimum wage takes one or two years to adequately show effects. The strategy to test lagged values of employment is supported in the literature (Allegretto, 2013).

Although the model already included fixed effect for both time and state variables, other state-specific time-varying explanatory variables could also be included in the model to help better explain the dependent variable Y. State population could be included as an independent variable. According to Meer and West (2013), total population in each state represent a determinant for both demand and supply of employees. Because states differ non-linearly in their population changes, controlling population by state may be essential. Other macroeconomic condition controls used commonly in the literature can be included as well (Clemens and Wither, 2014). For instance, state macroeconomic conditions such GDP, housing price, or current account deficit or surplus could also be included in the model to explain employment rate.

5 Results

Traditionally, studies without spatial controls that examined the employment effects of real minimum wage increases found that higher minimum wages generally reduced employment of low-skilled workers (Allegretto, 2013 and Neumark, 2015). However, based on recent research which used a spatial-control approach and informed this project, our expectations were that the addition of time and state controls should partially (or completely) offset the negative effect of a real increase in the minimum wage on employment for each of our populations. Based on the data collected and a variety of models, our analysis provides some evidence in support of the counter-intuitive recent findings that higher minimum wages may increase employment of low-skilled workers.

For the low-wage worker population, twelve different models were analyzed separately for non-control groups and demographic control groups (see Table 5). Columns (1) to (3) represent the state and time fixed effects regression without controls for linear models with no lag, and one-year lag, and a two year lag, respectively, while columns (4) to (6) show the results for models with controls. However, only the coefficient estimate of minimum wage in the two-year lag with control variables is statistically significant at 5% level of significance, which means that increasing the average real minimum wage by 1 dollar would increase employment rate of low-wage workers by 0.005%.

For the linear-log models, results are shown in column (7) to (12), with non-lagged, one-year lag and two-year lag without and with controls separately. For the log models, three out of six have statistically significant coefficient estimates on log of minimum wage. They are two-year lag without controls, one-year lag with controls, and two-year lag with controls, implying that increasing the minimum wage by 1% would increase the next years employment rate of low-wage workers by 0.0382% and increase the employment rate two years after the enactment of a higher minimum wage of by 0.0376%. In other words, employment elasticity on minimum wage for one-year lag dependent variable is 0.0382 and the employment elasticity for two-year lag dependent variable is 0.0376.

Besides the effect of minimum wage on employment rate of low-wage workers, some of the other demographic control variables are also worth mentioning for this study. The coefficient estimates of log of per capita income and percentage of college graduates in the population are statistically significant in every model with 1% level of significance. Specifically, log of per capita income has a positive effect while percentage of college graduates has a negative effect on the employment rate for low-wage workers. The coefficient estimates of average age on employment rate of low-wage workers and percentage of females also show some significant effects.

For the high school dropouts population, twelve different models were analyzed respectively for non-control groups and demographic control groups (see Table 6). Although some of the control variables obtained significance in these models, coefficient estimates of the minimum wage variable repeatedly failed to reach significance at a 10% level. Significant control variables in these models included: percentage of high school graduates with a negative sign, percentage of college graduates with a negative sign, and log of per capita income with a positive sign, which are statistically significant in every model. The coefficient estimates on percentage of married population are also significant with a positive sign in linear and log-linear non-lagged models.

6 Conclusions

6.1 Discussions

The goal of this research project is to analyze the effect of real minimum wage on the employment rate for certain population groups. Multiple regression results show that, on average, minimum wage has a positive impact on the employment rate, which is consistent with literature that include state and time fixed effects. The main independent variable in our empirical project, real minimum wage at state level, has positive coefficient estimates for both low-wage workers and high-school dropouts. This finding is in support of the argument that raising minimum wage is not a trade-off for increasing unemployment. In particular, the coefficient estimates of real minimum wage for low-wage workers are generally higher than those of high-school dropouts, suggesting that a rise in the minimum wage would in fact have a larger effect on the employment status of workers in low-wage occupations.

Moreover, it is worth noticing that in the low-wage worker population regressions, all significant coefficients of real minimum wage resulted from lagged regression models (4 out of 12). This result is crucial and reasonable because in reality, it generally takes months or years for the effect of increase in minimum wage to be fully absorbed. By giving firms of different sizes sufficient time to adjust for an increase in minimum wage, states are allowing the newly established regulation to be adjusted incrementally.

The regression results indicate that the coefficients for percentage of college graduates in both low-wage worker and high school dropouts population are all negative and significant at 5% or even 1% level. In the scenario where our population of interest is high school dropouts, states with higher percentages of college graduation rates are comparably more literate. As minimum wages increased in these states, people who dropped out from high school are therefore more vulnerable towards such effect, thus the chance of them being employed would decrease. This explains the negative sign of the independent variable percentage of college graduates. The population of low-wage workers across the states also experience similar negative impact, thus the coefficients of percentage of college graduates in the low-wage workers population are negative as well. There exists similar pattern for the independent variable percentage of high school graduates. For people who dropped out from high school and people who earn low wages, as minimum wage increases, higher high school graduation rates put these people in a greater competitive disadvantage due to the lack of education and/or skills, thus explaining the negative coefficient of percentage of high school graduates.

In the case of the independent variable log of per capita income, our regression results show that it is significant at a 1% significance level among all models for both population groups. In addition to there being more jobs available in a healthy economy, we believe that as per capita income increases in population groups that are sensitive to an increase in minimum wage, it would serve as an incentive for workers to stay employed in the job market.

6.2 Limitations

There are many limitations of this study that are worthy of note. Below, we will address some of them.

The first problem with this study relates to our inability to completely control for time-varying heterogeneity. Use of county-level border discontinuity approach was desired in order to allow variations of time effects at the level of commuting zones, since neighboring cities or counties tend to share the same geographic characteristics. The logic follows that the portion of commuting zones that experienced a change in minimum wage would be the treatment groups, whereas the neighboring locality without a minimum wage change would be the control groups. However, the problem with using counties and commuting zone controls was that it was difficult to obtain such fine minimum wage and demographic data. Additionally, many counties had small sample sizes, and more than half of the county labels were removed by the Census Bureau to preserve the privacy of respondents. These problems posed a dilemma to the data-cleaning process. Hence, without the presence of the border discontinuity approach, or other methods referenced in part 2, we were unable to completely control for time-varying heterogeneity among geographic levels.

An additional problem associated with our decision to use state-level data is that we sacrifice variation characteristic to finer county or metropolitan area-level analysis. For instance: since 2014, cities such as San Francisco, Los Angeles, and Seattle passed bills that allow minimum wage to increase to $15 incrementally. Models based on state level instead of more well-defined regions such as counties and/or metropolitan areas could be a generalization of the fact that minimum wage does not increase altogether within the state.

Furthermore, from our construction of the low-wage worker panel group, there could exist potential bias. From the ASEC data, the coding of occupation is defined as an individual's last job in the 5-year period preceding her or his interview, which means that the individuals were not necessarily employed when the data collection took place. Thus, it is uncertain that workers we designated as low-wage were in fact low-wage workers during the year a minimum wage increase occurred. We are uncertain to what extent this complication has biased our results. It is also worth noting, however, that, to the best of our knowledge, there is no large-scale database of minimum wage workers. Hence, population selection will always be a limitation for much minimum wage research.

Finally, this research analysis might benefit from further exploration of functional forms. Half of the models included are simple linear forms, and the other half are linear-log forms. However, other functional forms, such as polynomial forms, forms with interacted variables, or reciprocal forms might also be applied to this analysis.

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Appendices

Figure 1: National Employment Rate and State Minimum Wage

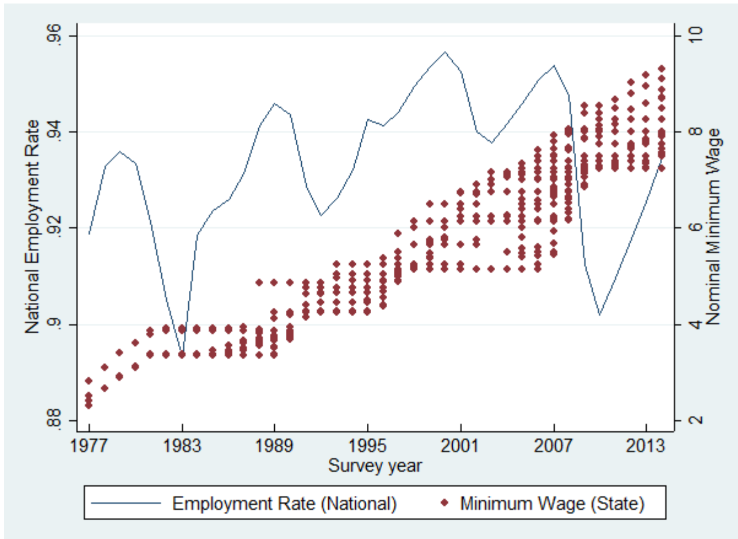

Figure 2: Employment Rate by Worker Type

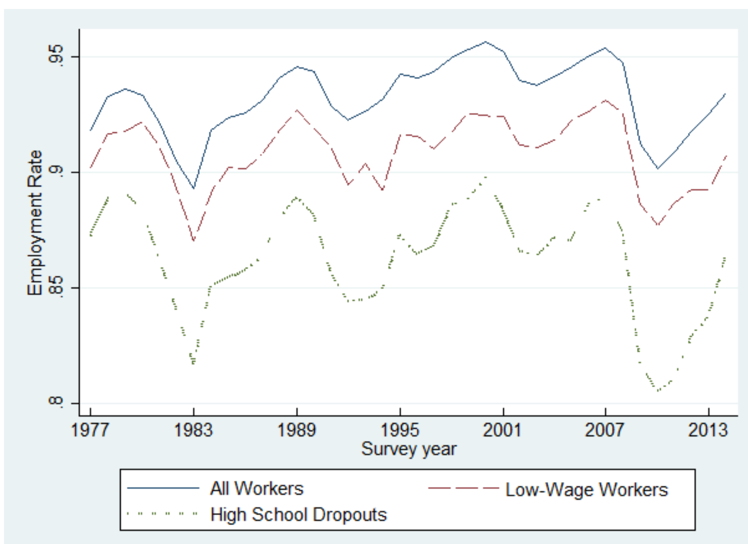

Figure 3: Employment Rate of Low-wage Workers

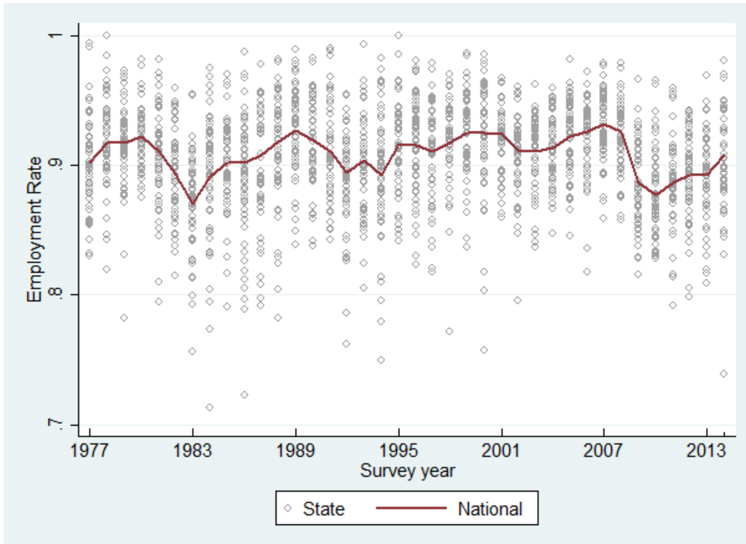

Figure 4: Employment Rate of High School Dropout Workers

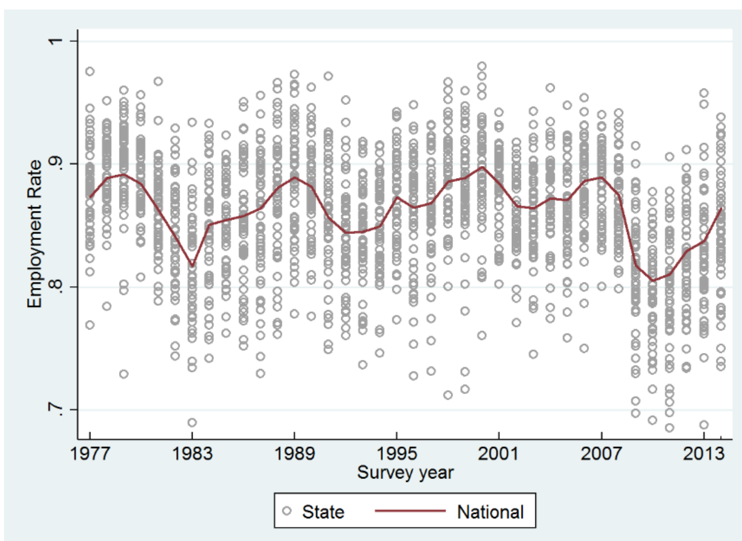

Figure 5: Employment Rate by Minimum Wage Increase Status

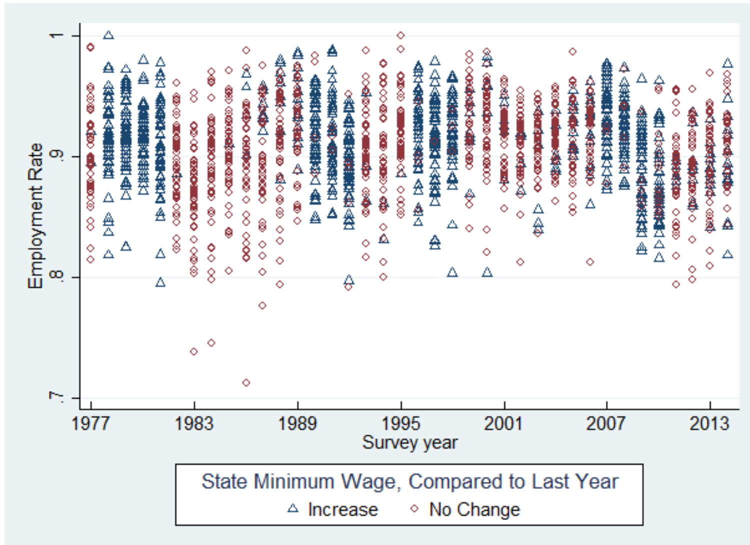

Table 1: Composition of Low-Wage Population

Low Wage Occupation (2010 AESC Designation)	Frequency	Percentage
Food Preparation Workers	10,437	0.20%
Counter Attendant, Cafeteria, Food Concession, and Coffee Shop	11,841	0.23%
Waiters and Waitresses	46,829	0.90%
Food Servers, Non Restaurant	1,693	0.03%
Food Preparation and Serving Related Workers	26,801	0.51%
Dishwashers	5,477	0.10%
Host and Hostesses, Restaurant, Lounge, and Coffee Shop	2,577	0.05%
Janitors and Building Cleaners	61,705	1.18%
Maids and Housekeeping Cleaners	44,859	0.86%
Cashiers	76,295	1.46%
Retail Salespersons	64,451	1.23%
Other Occupations	4,874,352	93.25%
Total	5,227,307	100.00%

Source: 1977-2014 Current Population Survey

Table 2: Composition of High School Dropout Population

		Armed Forces	Employed	Unemployed	NILF	Retired
Non-Graduate	Frequency	562	484405	75973	724097	95498
	Percentage	0.04%	35.09%	5.50%	52.45%	6.92%
Graduate	Frequency	25587	2617109	149572	766871	287519
	Percentage	0.67%	68.04%	3.89%	19.94%	7.47%
Total	Frequency	26149	3101514	225545	1490968	383017
	Percentage	0.50%	59.33%	4.31%	28.52%	7.33%

Source: 1977-2014 Current Population Survey

Table 3: Average Variable Values Per State MW Characteristics

Variable	$MW_{State} = MW_{Fed}$	$MW_{State} > MW_{Fed}$	$MW_t = MW_{t-1}$	$MW_t > MW_{t-1}$
Real PCI	34243	43986	36525	36726
Percent College Grad	11.13	18.29	12.87	12.86
Percent HS Grad	58.01	64.34	59.69	59.37
Percent Married	44.2	41.25	43.49	43.46
Percent White	84.69	79.19	82.74	84.18
Percent Female	51.14	50.89	51.06	51.1
Average Age	34.7	36.17	35.06	35.1
LW Emp Rate	90.62	90.72	90.31	91.09
Dropout Emp Rate	86.19	84.78	85.49	86.34

Table 4: Likelihood of Increasing MW by State Income Ranking

Per Capita Income	
Bottom 25%	0.44
Top 25%	0.45

ΔPCI Past 4 Years	
Bottom 25%	0.37
Top 25%	0.5

Table 5: Regression Results for Low-Wage Workers

	Minimum Wage, *Non-Log*						Minimum Wage, *Log*					
Lag		*t-1*	*t-2*		*t-1*	*t-2*		*t-1*	*t-2*		*t-1*	*t-2*
Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Minimum Wage	0.002	0.004	0.003	0.0017	0.003	0.003	0.020	0.031	0.026	0.019	0.028	0.025
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.028)	(0.026)	(0.024)	(0.029)	(0.026)	(0.023)
Average Age				0.001	0.0003	0.0003				0.001	0.003	-0.0001
				(0.002)	(0.002)	(0.002)				(0.002)	(0.002)	(0.002)
Log Per Capita Income				0.179***	0.184***	0.158***				0.179***	0.184***	0.158***
				(0.027)	(0.026)	(0.025)				(0.027)	(0.026)	(0.025)
Percent College Grad				-0.306***	-0.280***	-0.260***				-0.309***	-0.282***	-0.261***
				(0.068)	(0.055)	(0.068)				(0.068)	(0.055)	(0.068)
Percent HS Grad				-0.255***	-0.211***	-0.171**				-0.253***	-0.215***	-0.170**
				(0.059)	(0.056)	(0.067)				(0.059)	(0.056)	(0.067)
Percent Female				0.123	0.269*	0.016				0.123	0.269*	0.016
				(0.147)	(0.140)	(0.134)				(0.147)	(0.140)	(0.133)
Percent White				0.049	0.043	0.0000				0.05	0.043	0.0003
				(0.051)	(0.047)	(0.046)				(0.051)	(0.047)	(0.046)
Percent Married				0.259***	0.010	0.125				0.261***	0.1000	0.126
				(0.090)	(0.082)	(0.068)				(0.091)	(0.082)	(0.087)
Overall R-squared	0.260	0.261	0.262	0.235	0.217	0.239	0.258	0.261	0.262	0.232	0.216	0.239

Minimum wage and per capita income are included as real values.
Asterisks indicates level of significance: ***=1% level, **=5% level, *=10% level.
Values in parentheses are robust standard errors.

Table 6: Regression Results for High School Dropouts

	Minimum Wage, *Non-Log*						Minimum Wage, *Log*					
Lag		*t-1*	*t-2*		*t-1*	*t-2*		*t-1*	*t-2*		*t-1*	*t-2*
Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Minimum Wage	0.002	0.004	0.003	0.003	0.004	0.005*	0.019	0.031	0.028*	0.026	0.038*	0.038**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.018)	(0.019)	(0.017)	(0.019)	(0.020)	(0.019)
Average Age				0.003**	0.0008	-0.0009				0.003**	0.0007	-0.001
				(0.001)	(0.001)	(0.002)				(0.001)	(0.001)	(0.002)
Log Per Capita Income				0.103***	0.103***	0.088***				0.103***	0.103***	0.089***
				(0.020)	(0.019)	(0.018)				(0.020)	(0.019)	(0.018)
Percent College Grad				-0.217***	-0.210***	-0.177***				-0.220***	-0.212***	-0.179***
				(0.053)	(0.061)	(0.050)				(0.054)	(0.061)	(0.049)
Percent HS Grad				-0.068	-0.036	0.010				-0.066	-0.035	0.011
				(0.054)	(0.056)	(0.062)				(0.053)	(0.055)	(0.061)
Percent Female				0.143	0.257*	0.074				0.143	0.257*	0.074
				(0.141)	(0.135)	(0.140)				(0.141)	(0.135)	(0.140)
Percent White				0.071	0.044	0.0320				0.071	0.044	0.032
				(0.038)	(0.055)	(0.042)				(0.037)	(0.055)	(0.042)
Percent Married				0.001	-0.031	0.004				0.002	-0.0300	0.005
				(0.065)	(0.060)	(0.076)				(0.065)	(0.060)	(0.076)
Overall R-squared	0.133	0.134	0.133	0.151	0.138	0.146	0.133	0.133	0.133	0.151	0.138	0.146

Minimum wage and per capita income are included as real values.
Asterisks indicates level of significance: ***=1% level, **=5% level, *=10% level.
Values in parentheses are robust standard errors.

```
*****************************************************************
//The Impact of Increases in the Minimum Wage on Employment
//Group 4: Reese Crispen, Jiayu Li, and Lin Shi
*****************************************************************

//Group members: Reese Crispen, Jiayu Li, Lin Shi



sort statefip year

******DEMOGRAPHIC AVERAGES****

// PERCENT WITH BACHELORS DEGREE BY STATEFIP AND YEAR

 gen college = 0
 replace college = 1 if inrange(educ, 111,125)
 label variable college "bachelors degree dummy"
 by statefip year: egen avcollege=mean(college)

 // STATEFIP-WIDE EMPLOYMENT RATE BY STATEFIP AND YEAR

  gen laborforce = 1 if inrange(emp,10,22)
  gen employed = 1 if inrange(emp,10,12)
  by statefip year: egen LF = total(laborforce)
  by statefip year: egen EMP = total(employed)
  gen er = EMP/LF
  label var er "employment rate by statefip, year"

 // AVERAGE AGE BY STATEFIP AND YEAR

  by statefip year: egen avage = mean(age)
  label var avage "average age by statefip, year"

 // PERCENT FEMALE BY STATEFIP AND YEAR

  gen female =0
  replace female=1 if sex==2
  by statefip year: egen avsex = mean(female)
  label var avsex "percent female by statefip, year"

 // PERCENT WHITE BY STATEFIP AND YEAR

 gen white = 0
 replace white = 1 if race==100
  by statefip year: egen pcwhite = mean(white)
  label var pcwhite "percent white by statefip, year"
```

```
// PERCENT MARRIED BY STATEFIP AND YEAR

  gen married = 0
  replace married =1 if inrange(marst,1,2)
  by statefip year: egen pcmarried = mean(married)



*Low-wage Worker Indicator Variable
 gen lowwage = occ2010 if occ2010==4030| occ2010==4060
| occ2010==4110| occ2010==4120| occ2010==4130
| occ2010==4150| occ2010==4220| occ2010==4230
| occ2010==4720| occ2010==4760| occ2010==4140

replace lowwage = 1 if lowwage !=.
replace lowwage = 0 if lowwage ==.
label var lowwage "low-wage worker dummy"

*Employment rate of Low-Wage Workers (state)

sort statefip year
//Part 1: To create the low-wage employment rate, we created 2 indicators to label individuals as 1) in
the laborforce and 2) employed
gen lw_laborforce = 1 if inrange(empst,10,22) & lowwage ==1
  gen lw_employed = 1 if inrange(empst,10,12) & lowwage ==1

//Part 2: The indicators from Part 1 are summed to create variables totaling the laborforce and
employment for each statefip and year
 by statefip year: egen lw_LF = total(lw_laborforce)
  by statefip year: egen lw_EMP = total(lw_employed)

 //Part 3: By statefip and year, total employment is divided by total laborforce to generate a variable
depicting the employment rate of individuals in low-wage professions
  gen lw_er = lw_EMP/lw_LF
  label var lw_er "low wage worker employment rate by statefip, year"

*Employment rate of Low-Wage Workers (national, by year)
sort year

gen lw_laborforce = 1 if inrange(empst,10,22) & lowwage ==1
gen lw_employed = 1 if inrange(empst,10,12) & lowwage ==1
  by year: egen lw_LFn = total(lw_laborforce)
  by year: egen lw_EMPn = total(lw_employed)
gen lw_er_n = lw_EMPn/lw_LFn
label var lw_er_n "national low wage worker employment rate by year"
```

*High School Diploma Received Indicator Variable

```
gen hsdep = educ
replace hsdep = 0
replace hsdep = 1 if educ >72
```

*Employment Rate of Individuals without a High School Diploma

```
sort statefip year
//Part 1: To create the dropout employment rate, we created 2 indicators to label individuals as 1) in the laborforce and 2) employed
gen nohsd_laborforce = 1 if inrange(empst,10,22) & hsdep ==0
  gen nohsd_employed = 1 if inrange(empst,10,12) & hsdep ==0

//Part 2: The indicators from Part 1 are summed to create variables totaling the laborforce and employment for each statefip and year
 by statefip year: egen nohsd_LF = total(nohsd_laborforce)
  by statefip year: egen nohsd_EMP = total(nohsd_employed)

 //Part 3: By statefip and year, total employment is divided by total laborforce to generate a variable depicting the employment rate of individuals without a high school degree
  gen nohsd_er = nohsd_EMP/nohsd_LF
  label var nohsd_er "no hs diploma employment rate by statefip, year"
```

******Merge with minimum wage dataset****

```
 //Part 1: To stardize the two datasets, we renamed the state variable in the using dataset (mw_annual_1974_2014).
  // code entered in mw_annual_1974_2014: "gen statefip = statenum"

 //Part 2:
 merge m:m year statefip using mw_annual_1974_2014, keepusing(year statefip mw fed_mw)

 drop if mw==.
```

***Numbering wihtin each year group

```
  by year: gen num = _n
```

***Numbering within each unique state-year group

```
 sort statefip year
 by statefip year: gen numstateyear = _n

 sort numst statefip year
 by statefip year: gen id = _n
```

*****Minimum Wage Change From Previous Year Indicator

```
 sort numst statefip year
 gen changed_mw = 0 if mw[_n] ==mw[_n-1]
 replace changed_mw = 0 if id ==1
 replace changed = 1 if changed ==.
 label var change "mw change from last year dummy"

 ***********
 //Reduce Dataset to one observation per state per year
  drop if numst !=1

//Create lagged DVs

. sort year statefip
. sort statefip year
. by statefip: gen lw_erL1 = lw_er[_n-1]
. by statefip: gen lw_erL2 = lw_er[_n-2]
by statefip: gen nohsd_erL1 = nohsd_er[_n-1]
by statefip: gen nohsd_erL2 = nohsd_er[_n-2]

. by statefip: gen loglw_erL1 = loglw_er[_n-1]
. by statefip: gen loglw_erL2 = loglw_er[_n-2]
by statefip: gen lognohsd_erL1 = lognohsd_er[_n-1]
by statefip: gen lognohsd_erL2 = lognohsd_er[_n-2]

 //Redo Dependent variables with weights
    by statefip year: egen nohsd_LF = total(nohsd_laborforce)
  by statefip year: egen nohsd_EMP = total(nohsd_employed)

    by statefip year: egen lw_LF = total(lw_laborforce)
  by statefip year: egen lw_EMP = total(lw_employed)

  Preserve
  collapse (sum) nohsd_LF nohsd_EMP lw_EMP lw_LF[pw=wtsupp], by(statefip year)

 *Next, must divide new weighted totals of employed/laborforce and merge new variables into master
set

 //Redo Lags and logs

 .
preserve
sort year statefip
. sort statefip year

gen logerLW = log(erLW)
gen logerNOHSD = log(erNOHSD)

by statefip: gen lw_erL1 = erLW[_n-1]
```

```
by statefip: gen lw_erL2 = erLW[_n-2]
by statefip: gen nohsd_erL1 = erNOHSD[_n-1]
by statefip: gen nohsd_erL2 = erNOHSD[_n-2]

by statefip: gen loglw_erL1 = logerLW[_n-1]
by statefip: gen loglw_erL2 = logerLW[_n-2]
by statefip: gen lognohsd_erL1 = logerNOHSD[_n-1]
by statefip: gen lognohsd_erL2 = logerNOHSD[_n-2]

label var logerLW "Log of low-wage employment rate"
label var logerNO "Log of no-hsd employment rate"
label var lw_erL1 "Low-wage employment rate 1-year lag"
label var lw_erL2 "Low-wage employment rate 2-year lag"
label var nohsd_erL1 "No-hsd employment rate 1-year lag"
label var nohsd_erL2 "No-hsd employment rate 2-year lag"

label var loglw_erL1 "Log of low-wage employment rate 1-year lag"
label var loglw_erL2 "Log of low-wage employment rate 2-year lag"
label var lognohsd_erL1 "Log of no-hsd employment rate 1-year lag"
label var lognohsd_erL2 "Log of no-hsd employment rate 2-year lag"

  ***********
  *FIGURES
  ***********
//low wage employment rate against all
sort year
line lw_er year if num==1 || line er_nat year if num==1

//low wage employmentrate state vs national
scatter lw_er year if numst==1 || line lw_er_n year if num==1

//emplyment rate vs mw increases
twoway line er_nat year if num==1, yaxis(1) || line nohsd_er year if num==1, yaxis(1)|| scatter mw year
if numst ==1, yaxis(2)

//employment by minimum wage change dummy
scatter lw_er year if numst==1 & changed==1 || scatter lw_er year if numst==1 & changed==0
```