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The Impact of the Minimum Wage on Employment and Hours Worked for the Young and Low-Educated: An Analysis of the United States' North East

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While writing this thesis, I have not witnessed any wrongdoing, nor have I personally violated any conditions of the Skidmore College Honor Code.

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Abstract*: This paper used individual level data to analyze the impacts of an increase in the minimum wage on hours worked and employment. The demographic analyzed was individuals between the ages of 16 and 29 who don't have a high school degree and live in the United States' North East. This analysis was disaggregated by gender and found heterogeneous impacts on hours worked and employment. The estimated impacts of the minimum wage for men in the analyzed demographic is a slight reduction in both hours worked and the probability of being employed. The estimated impact of the minimum wage for women in this demographic is a small increase in hours worked and a moderate increase in the probability of being employed. Both the effects on hours worked and the employment effect for men are of small magnitudes that they may better be seen as no effect. Only the employment effect for females has a magnitude that is of economic significance.*

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1. Introduction

The topic of increasing the minimum wage is currently contentious within the United States, with this contention being partly facilitated by the lack of consistent findings within the current economic literature on the employment effects of the minimum wage. Some findings suggest large adverse employment effects, while others suggest no employment effects, and some even suggest positive employment effects (Sabia, 2008; Hoffman, 2016; Card and Krueger, 1994). Engendered by this inconsistency of results, I seek to answer the question, what are the effects of the minimum wage on employment and hours worked? By answering this question, I will both be evaluating the neo-classical model of a binding price floor in a labor market, and providing relevant information to politicians who are faced with the choice of whether or not to support an increase in the minimum wage (Dickens et al., 2015).

The array of results that the literature finds for the employment effects of the minimum wage is matched by the myriad of ways the topic has been approached. Hoffman (2016), through the use of a difference in difference approach, analyzed how employment for individuals between the ages of 16 and 29 who don't have a high school degree is affected by the minimum wage. The use of a difference in difference approach is common in the literature (Hoffman, 2016; Card and Krueger, 1994; Sabia et al., 2012; Dickens et al., 2015). Dickens et al. (2015) suggest that not separating the employment effects by gender will not allow for the effects of the minimum wage to be properly seen, and by doing so they found adverse employment effects for part-time women as a result of the U.K's minimum wage. While Hoffman (2016) didn't disaggregate his analysis by gender, neither he nor Dickens et al. (2015) analyzed the lagged effects of the minimum wage. Both Partridge and Partridge (1999) and Sabia (2008) accounted for the lagged effects of the minimum wage in their analysis, but only Partridge and Partridge (1999) found results suggesting that the minimum wage has a negative lagged effect, and that not accounting for the lagged effect would not capture the minimum wage's full employment effect. Sabia (2008) had also analyzed the impact of the minimum wage on hours worked, finding a negative impact in the current year for hours worked and employment in the retail sector. Similar to Sabia (2008), Pratomo (2013) analyzed both the minimum wage's effect on hours worked and employment. However, Pratomo (2013) didn't attempt to capture the lagged effect of the minimum wage, but his analysis did disaggregate the minimum wage's effects by gender, similar to Dickens et al. (2015). Pratomo's (2013) results were similar to Sabia's (2008) in the sense that he estimated negative current year employment effects.

The purpose of this paper is to, through using a micro approach, give a thorough analysis of the impacts that the minimum wage has on employment and hours worked by accounting for both lagged effects and the possibility of heterogeneous impacts by gender. This will be done by running three regressions on individual level data for individuals between the ages of 16 and 29 that don't have a high school degree. The first regression will be an OLS regression on wage/salary income to test whether or not this demographic contains minimum wage earners. The second regression will also be an OLS regression, but on an individual's usual weekly hours worked, to analyze the minimum wage's impact on hours worked. The third regression will be a probit regression model, meant to capture the impacts of the minimum wage on the probability of being employed. The regressions on hours worked and employment will contain lagged variables to account for the lagged effects of the minimum wage, following the hypothesis that the current year effect is a reduction in hours worked, followed by adverse employment effects the following year. Gender interaction terms will be used to account for the possible heterogeneous impacts of the minimum wage by gender.

One of the contributions of this work is the analysis of both the lagged effects and heterogeneous effects of the minimum wage by gender, since as far as I am aware no section of the literature has analyzed both the lagged effects of the minimum wage and its possible heterogeneous impacts by gender. The contributions of this work also include using data from up to 2016, which is more recent than the data used in most of the previous literature and gives a more up to date analysis of the minimum wage's effects, and that its analysis is focused on the North East of the United States. The latter contribution means that my analysis is more specific to the North East of the United States than what is found in the literature.

The results of my analysis show that a large portion of this demographic are minimum wage earners by showing a positive relationship between the minimum wage and wage/salary income, and that this is equally true for men and women in this demographic. However, my results show that the minimum wage affects usual weekly hours and employment differently for men and women in this demographic. I estimate a small reduction in men's hours worked and probability of being employed as a result of minimum wage increasing, with only the lagged effect on hours worked and current year's effect on employment being significant. I also estimate that women experience an increase in the probability of being employed and a small increase in their usual weekly hours worked as the minimum wage increases. Again, for hours worked only the lagged effect is significant, but for employment both the current year and lagged effects are significant.

Section 2 reviews the current minimum wage literature, section 3 describes the data I used, section 4 discusses the econometric models used in my analysis, section 5 presents my results and discusses future research possibilities, and section 6 concludes.

2. Literature Review

2.1. Summary and Critique

2.1.1. *General Concept and Inconsistency of Results*

The empirical evidence on the minimum wage's effect on employment and hours worked varies considerably. Some papers in the literature have found results that are consistent with what neoclassical economic theory would predict; that increasing the minimum wage will decrease employment and hours worked in markets that have the minimum wage serve as a binding price floor (Sabia et al., 2012; Sabia, 2008; Dickens et al., 2015). Other parts of the literature find either that the minimum wage has no significant impact on employment, or in some cases a slight positive impact on employment (Hoffman, 2016; Card, and Krueger 1994). There is seemingly no consensus within the literature as to what the effect of increasing the minimum wage is.

The study conducted by Card and Krueger (1994) is one of the most influential and contentious studies within the literature on the minimum wage's impact on employment. Through the use of a difference in difference approach applied to data they collected through a survey that they conducted on fast-food restaurants in both New Jersey and Eastern Pennsylvania before and after the 1992 increase in New Jersey's minimum wage, Card and Krueger (1994) found a slight positive employment effect on fast-food restaurants in New Jersey as a result of the minimum wage increasing. They then analyzed data from the same survey to see what effect there was on the prices at fast-food restaurants, and found results that indicate that New Jersey's fast-food prices rose when compared to Pennsylvania's fast-food prices. The combination of these two results, both the increase in minimum wage and the increase in prices, is inconsistent with both the neoclassical model, and monopolistic and job-search models, with the later of these models predicting that an increase in the minimum wage will increase employment in markets were the minimum wage is a binding price floor and firms have monopsony power (Card and Krueger, 1994). However, this model doesn't predict a rise in prices, so their results are difficult to reconcile with economic theory.

The primary analysis of Card and Krueger's (1994) study looked at the immediate impact of the minimum wage increasing in 1992 on employment at fast-food restaurants belonging to fast-food chains, such as McDonalds, KFC, and Wendy's. Since these restaurants belong to large and profitable multi-national chains, they may not respond to increase in the minimum wage the same way as stores that are locally owned or part of a small domestic chain. Their findings showed that the cost incurred by the increase in the minimum wage was transferred to customers through higher prices on meals, which these restaurants could do due to their market power. Firms that act within markets where they are price takers may not be able to do this, so it may be possible that the lack of a negative impact on employment might not hold for firms who can't affect the price of the goods they sell. Although this, that fast-food restaurants mitigated the negative employment effects of a minimum wage increase by rising prices, being the reasoning for Card and Krueger's (1994) findings is unlikely. As a means of checking the validity of their results, they also analyzed teenage employment rates in New Jersey and Pennsylvania, and found a slight positive effect from the minimum wage increase. This shows that their finding of a positive impact on employment resulting from an increase in the minimum wage wasn't due to some unique aspect of their observations.

One critique of Card and Krueger (1994) that has more credence is their use of a dataset that they collected themselves through a survey they conducted. This could have resulted in measurement issues due to the inaccuracy that self-reported employment figures for each restaurant may have brought. If their dataset was inaccurate due to this reason, then their results would be unreliable. However, other studies have used other sets of data, such as the Current Population Survey data, and have also found a positive impact of the minimum wage increasing on employment (Hoffman, 2016). Other studies finding similar results doesn't prove that Card and Krueger's (1994) dataset wasn't biased due to measurement issues, but rather it says that there is some likelihood that their results may be accurate and not the product of unreliable data.

While Card and Krueger (1994) found a positive impact on employment as a result of the minimum wage increasing, other papers, such as Sabia, Burkhauser, and Hansen (2012), found that the minimum wage negatively impacts employment for younger and less educated people. Sabia, Burkhauser, and Hansen (2012) used both a difference in difference (DD) approach and a difference in difference in difference (DDD) approach applied to data from the 2004 and 2006 Current Population Survey Merged Outgoing Rotation Groups (CPS-MORG) to study what effect the increase in New York State's minimum wage from 2004 to 2006 had on employment for people aged 16-29 who didn't have a high school degree or GED. They found a very prevalent negative impact on employment for this group of people. They estimated that for this specification of people, the 2006 increase in the minimum wage decreased employment by approximately 20%, and they estimate an employment elasticity with respect to the minimum wage of -0.7. This is far larger than the -0.1 to -0.3 estimates that most studies find (Hoffman, 2016).

The results of Sabia, Burkhauser, and Hansen's (2012) analysis would imply that increasing the minimum wage has a large negative impact on employment for people who are young and don't have a high school degree, but there are aspects of their analysis that do stand to be questioned, such as their use of CPS-MORG data instead of the full CPS data. The CPS-MORG data is smaller and inherently has higher variance, leading to what may be less reliable results. This possibility of the CPS-MORG data bringing misleading results was analyzed by Hoffman (2016), who was skeptical of the large negative impacts on employment from the minimum wage increasing that Sabia, Burkhauser, and Hansen (2012) found. He chose to re-examine the 2004 to 2006 New York minimum wage increase's effect on employment for younger and less educated individuals, first by using the CPS-MORG data that Sabia, Burkhauser, and Hansen (2012) had, and then by using the full CPS data. Hoffman (2016) found no fault in Sabia, Burkhauser, and Hansen's (2012) original analysis of the CPS-MORG data, coming up with the same estimates when he performed the same DD and DDD analysis that they had. Hoffman's (2016) findings did differ rather drastically from Sabia, Burkhauser, and Hansen (2012) when he used the full CPS data instead. He estimated a far more modest employment elasticity of -0.15, which is within the range of what previous literature has found. This result can be seen as confirming the appropriateness of using CPS data instead of CPS-MORG data due to the lower variance of a larger dataset leading to more reliable results.

During the same time period that Sabia, Burkhauser, and Hansen (2012) had analyzed, New Jersey, Florida, Illinois, and the District of Columbia had increased their respective minimum wages substantially. Hoffman (2016) expand his analysis to see what impact these minimum wage increases had on employment for younger and less educated individuals living in those areas. Applying the same types of analysis as before, Hoffman (2016) found a slight positive employment impact from the minimum wage increasing in those states and the District of Columbia. These results are consistent with the findings of Card and Krueger (1994) and further show the possibility of Sabia, Burkhauser, and Hansen's (2012) results being unreliable. Another takeaway from this is that New York may not be representative of the rest of the U.S, and may not be the most appropriate subject of analysis since the results from New York were different than those of the other areas that Hoffman (2016) analyzed.

2.1.2. *Lagged Effect*

One thing to note about these studies mentioned above is that they analyzed what the immediate impact on employment was from an increase in the minimum wage and not how hours worked was affected. There is a section of the literature that suggests that the initial impact the minimum wage has isn't on employment, but rather that it affects the hours an employee works. The subsequent affect is then on employment, with this lagged employment effect possibly being the result of higher costs associated with firing employees than reducing employees' hours, leading to hours worked to be reduced initially then employment to be reduced later on (Pratomo, 2013).

One such study was by Partridge and Partridge (1999), whose analysis of the impact that the minimum wage had on employment for the retail sector accounted for the possibility of the minimum wage having a different effect on employment over the long-term when compared to the short-term. They did this by running regressions that included last year's minimum wage and the current year's minimum wage as variables. Their analysis was primarily looking at the effect of the minimum wage on retail employment by seeing how it affected retail employment growth rates between the years of 1984 and 1989 within the 48 contiguous states of the United States. The retail sector was used as Partridge and Partridge's (1999) subject of analysis due to the low wages of retail employees, thusly meaning that their wages are affected by the minimum wage increasing, and that they would then be susceptible to the minimum wage's hypothesized employment effects. They used a pooled panel state level dataset derived from the CPS datasets, the U.S Department of Labor, and the Bureau of Economic Analysis.

Partridge and Partridge (1999) found results that indicates that the minimum wage increasing positively impacts employment growth for the retail sector over a one-year period, but the impact on employment growth as a result of the previous year's minimum wage increase is negative and three times the size of the initial positive impact in magnitude. They conclude that over a two-year period the impact of increasing the minimum wage by 10% is a 1% decrease in the growth rate of employment in the retail sector. Partridge and Partridge's (1999) findings on the initial impact of the minimum wage on employment growth is consistent with both Card and Krueger (1994) and Hoffman's (2016) results. Partridge and Partridge's (1999) findings that the minimum wage increase has a negative lagged effect that is greater than the initial impact would suggest that Card and Krueger (1994) and Hoffman's (2016) analysis didn't fully represent the impact of a minimum wage increase is. Had Card, and Krueger (1994), and

Hoffman (2016) analyzed what the long run impact of a minimum wage increase was, then according to Partridge and Partridge's (1999) finding, they may have found results indicating a negative impact.

Partridge and Partridge (1999) show results of a modest impact of the minimum wage on employment growth, which may be a product of the time period that they studied. The substitutability of capital and labor during the 1980s was less than what it was during the 2000s and even smaller than what it would be during the end of the 2010s. If their analysis was done on the 2010s, then it would be reasonable to suspect that their findings would indicate a larger negative impact on the growth rate of retail employment over a two-year period. The positive impact on employment that Hoffman (2016) found, although his period of study was the mid 2000s, would suggest that Partridge and Partridge's (1999) findings on the initial impact of the minimum wage on retail employment growth wouldn't have changed.

Similar to the analysis that Partridge and Partridge (1999) performed, Sabia (2008) had also used state level data from 1979 through 2004 to analyze both the initial one-year impact of increasing the minimum wage on retail employment and the lagged two-year impact. His analysis was also extended to what impact the minimum wage has on the average hours worked by retail employees. Sabia's (2008) models don't indicate a significant lagged impact on the employment or average hours worked of retail employees as a result of the minimum wage increasing, which is inconsistent with Partridge and Partridge's (1999) findings. The wage elasticity with respect to the minimum wage for retail employees that Sabia (2008) estimates is consistent with that of Partridge and Partridge (1999); that a 10% increase in the minimum wage decreases retail employment by 1%. Sabia (2008) also found results that estimate a 1% reduction in the average hours worked by retail employees as a results of the minimum wage increasing by 10%.

There are some issues that may have arisen from Sabia's (2008) use of a panel dataset that spanned over 20 years, most notably how technological developments from the beginning to the end of this time period may have made capital and labor more substitutable. The change in the substitutability of capital and low-skill labor over this time period would also mean that the impact of the minimum wage over this time period might change as well, with the more substitutable the two inputs are the larger an impact the minimum wage might have on employment. While the regression models Sabia (2008) ran used year dummy variables to account for state-invariant time effects and state dummy variables to account for state-specific time-invariant unobserved characteristics associated with unemployment rates, these may have captured how reductions in the cost of capital or how technological advances had reduced employment, but they may not have captured how advanced in technology have changed the effect that the minimum wage increasing has on employment and hours worked.

The invention and implementation of the self-checkout system in the 1990s could be hypothesized to have changed how the minimum wage impacts retail employees by increasing the substitutability of low-skilled labor and capital in the retail sector. Running models on data only for years after self-checkout systems became widespread in retail may cause the coefficient on the minimum wage variable to represent a larger negative impact on employment than models run on data for years before then. Sabia's (2008) results may have shown a modest impact of the minimum wage on retail employment and usual hours worked by including periods where the substitutability of capital and low-skilled labor vary rather substantially, such as before and after the implementation of self-checkout systems, that is, by finding the average effect over this time. This may also be why Partridge and Partridge (1999) found modest results while using a data set that ranges a small number of years, because during the time period they had analyzed, low-skilled labor and capital wouldn't have been as substitutable in the retail sector as they have been more recently.

2.1.3. *Differences by Gender*

Within the current literature on the minimum wage there are some findings that suggest that increases in the minimum wage have different effects on employment for men and women. Dickens et al. (2015), in an analysis of the impact that the U.K national minimum wage's implementation and subsequent increases have had on employment for part-time workers divided into subgroups by gender, found that part-time females were significantly adversely affected by the U.K national minimum wage while part-time males were not. Their method of analyzing the effects of the minimum wage on part-time employees was analyzing individuals' employment retention after the minimum wage implementation or increases, that is, they measured the probability of a person who was employed in year t being employed in year t+1, with year t being before the minimum wage increase and year t+1 being after the minimum wage increase. Dickens et al. (2015) used a difference in difference approach to estimate the minimum wage's impact on employment retention, with the treatment group being those who had their wage increased by the minimum wage and the control group being those who had a wage up to 10% higher than the new minimum wage prior to the new minimum wage being implemented. The negative effects that they found for part-time female employees are substantial and consistent with the standard economic model of labor markets.

Dickens et al. (2015) state that some of the reasons why prior studies on the U.K minimum wage didn't find any negative impact on employment is due to the samples they were analyzing being to aggregated. The effects that the minimum wage has on employment may be lost in more aggregated datasets if only one subdivision of the sample is actually effected while another subdivision isn't. As the evidence provided by Dickens et al. (2015) suggests, part-time males and part-time females are affected differently by the minimum wage. This implies that not dividing a group that is hypothesized by standard economic theory to have adverse employment effects as a result of the minimum wage increasing by gender may underestimate or fail to show the effects of the minimum wage on employment or hours worked. This is one possibility for why some of the literature finds evidence for either there being no impact of the minimum wage on employment, or a modest impact of the minimum wage on employment (Partridge and Partridge, 1999; Sabia, 2008; Hoffman, 2016). This however wouldn't be a likely reason for the positive impacts on employment resulting from increasing the minimum wage that Hoffman (2016), and Card, and Krueger (1994) found, since if women were adversely affected by the minimum wage, then not separating by gender would have also understated the positive impact on employment for males.

2.2. *Analysis*

The time periods that were analyzed in the minimum wage literature are nearly as varied as the results that this literature finds. These time periods range from the 1980s to the mid 2000s, as is the case for Partridge and Partridge (1999), and Hoffman (2016), respectively. As time progresses and technology advances it might be reasonable to expect that the effects of the minimum wage on employment become more adverse as low-skilled labor and capital become more substitutable, but the results of in the literature don't show this trend. While Partridge and Partridge (1999) found negative impacts with the time period of their analysis being the 1980s, Card and Krueger (1994) found positive employment effects from New Jerseys 1992 minimum wage increase. Then Sabia et al. (2012) found large negative employment effects from the minimum wage increasing during the mid 2000s, which without Card and Krueger's (1994) findings might suggest that the minimum wage's employment effects are getting more adverse as time progresses. However, this is complicated by Hoffman's (2016) results that estimate that the minimum wage has positive employment effects using the same time period as Sabia et al.'s (2012) analysis. When analyzing the time periods studied and the results that those respective time periods' studies find, it can't be concluded that there is a clear change in the minimum wage's employment effects as time progresses.

The differences in these studies methodologies for analysis also can't be seen as a clear reason for the differences in their results. The section of the literature that implements a difference in difference approach for their analysis has results that are just as varied as the literature when taken as a whole. While both Sabia et al. (2012), and Dickens et al. (2015) used a difference in difference approach and estimate that the minimum wage has an adverse effect on employment for some demographics, Card and Krueger (1994), and Hoffman (2016) also used a difference in difference approach yet estimated that the minimum wage has positive employment effects. The section of the literature that uses simpler regression analysis has milder variance in their results, but still doesn't arrive at a clear answer. Sabia's (2008) use of a standard regression analysis estimated that the minimum wage had no lagged effect, and that the current year employment effect was negative. Using a similar approach, Partridge and Partridge (1999) found that the minimum wage had a similar overall negative effect to Sabia's (2008) findings, but had found that the minimum wage had a positive employment effect in the current year while having a larger negative lagged effect. The main inconsistency between these two estimates is that one finds a lagged effect while the other doesn't, and these estimates also differ in regards to whether the current year effect is positive or negative. When analyzing the different methodologies used to analyze the minimum wage, standard regression approaches are more consistent in finding an overall negative employment effect for the minimum wage, while difference in difference approached are more varied in their results, and have even found positive employment effects.

3. Data

The dataset that I have used to conduct my research was taken from IPUMS-USA, which provides individual and household level census and survey data for the United States. It is an individual level pooled panel dataset, including information from individuals in the North East of the United States[1] between the years of 2010 and 2016, inclusive. The samples used within this dataset were taken from American Community Surveys (ACS), which IPUMS-USA has for each year from 2000 onward. Additional state level data was taken from the U.S Department of Labor, and then was appended to my data set. The individuals within my data set that were used in my regression analysis were aged 16 to 29, inclusive, and without a high school degree, with this choice of demographic coming from their high likelihood to be minimum wage earners and the use of this demographic to analyze the effects of the minimum wage on employment within the literature (Sabia et al., 2012; Hoffman, 2016). My dataset contains 98,450 observations, and 55% percent of the individuals in my sample are identified as being male.

To conduct my analysis three dependent variables were used, each with their own respective regression model. The first dependent variable I used was usual $uhrswork_{ist}$, which is the usual number of hours individual *i* in state *s* at year *t* works within a week. Within the literature the relationship between the minimum wage and usual hours worked has been explored, thusly engendering me to explore this relationship in my analysis of the effects of the minimum wage (Sabia, 2008; Pratomo, 2013). The usual hours that an individual works was used instead of the hours they worked last week due to the effect that short-term frictional or seasonal factors, not representative of the effects of the minimum wage, may have on the hours a person worked last week, such as an individual temporarily not being employed for reasons not pertaining to

[1] These states are Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, Pennsylvania, Rhode Island, and Vermont

the minimum wage. Sabia (2008) had also used usual weekly hours worked as the dependent variable in his regression of the minimum wage on hours worked. The usual hours an individual reports working is then a better and more robust measure of their hours worked. A person's usual hours worked was also included to serve as a control variable when testing if increasing the minimum wage is effective at increasing an individual's wage, since when all else is equal increasing hours worked would increase wage income.

The second dependent variable found in my dataset and used in my regression analysis is $employed_{ist}$, that is, a dummy variable taking on the value of 1 if an individual is employed. My decision to use $employed_{ist}$ as the dependent variable in my analysis of the minimum wages effect on employment was derived from Dickens et al.'s (2015) use of employment in $year_{t+1}$ as the dependent variable in their analysis of the minimum wage's effect on employment retention, and the section of Pratomo's (2013) analysis that used employment as the dependent variable in a probit regression model.

The theories that explain the possible effects that the minimum wage has on employment all follow on the baseline assumption that raising the minimum wage raises the amount that employers pay employees that had previously been paid below the new minimum wage. These theories are both the neoclassical model and monopsony job search model (Dickens et al., 2015; Card and Krueger, 1994). This is why a third dependent variable, $incwage_{ist}$, an individual's wage and salary income was included in my dataset. This was meant to be used to test for whether or not a minimum wage increase increases an individual's pay, who is within the demographic I am analyzing and employed. Sabia (2008) used wage as the dependent variable when analyzing if individuals in the retail sector had their wages increase as the minimum wage increased. I used wage/salary income instead of an individual's wage since the data I collected from IPUMS-USA doesn't contain an individual's hourly wage, so I had to proxy a measure for the effectiveness of the minimum wage on increasing wages by observing if wage/salary income increases as the minimum wage does, with all other variables explaining wage and salary income remaining constant.

My dataset contains the following individual level variables that served as independent variables in my regressions; age_{ist} which is the age of an individual, fem_{ist} which is a dummy variable that takes the value 1 if an individual is female, $nchild_{ist}$ which is the number of an individual's own children they have living with in their household, and $married_{ist}$ which is a dummy variable that takes on the value of 1 if an individual is married. The inclusion of these variables in my dataset comes from Pratomo's (2013) use of them as control variables for his probit regression on employment and his OLS regression on hours worked. The statistical significance that these variables had in Pratomo's (2013) models suggests that their exclusion from my models would result in omitted variable bias.

There are also the dummy variables $white_{ist}$, $black_{ist}$, and $hispanic_{ist}$, which take on the value of 1 if an individual identifies as belonging to one of these respective racial or ethnic demographics in my dataset. Their inclusion follows from Kahn and Whittington's (1996) analysis of labor force participation and hours worked for Hispanic women that found differences in both the hours worked and likelihood to participate in the labor force for Hispanic, White, and Black women. The differences between hours worked and labor force participation that exists between these racial and ethnic identifiers may be due to other variables not in my models, or unobservable differences my models wouldn't be able to capture with other variables. The difference between labor force participation is pertinent to my analysis on employment since having a lower likelihood of participating in the labor force also means a lower likelihood of being employed. These variables were also included to control for the possibility of discrimination leading to differences in pay, following Cornwell et al.'s (2017) findings of wage discrimination based on race in Brazil.

The variable $selfemp_{ist}$, which is a dummy variable taking the value of 1 if an individual is self-employed was included for the possible impact that being self-employed may have on both an individual's hours work and their income. The findings of Daly's (2015) analysis provide evidence that self-employed individuals both work more hours and earn more. Although these findings were on a sample with a broader demographic then that of my study, I would expect, following from this literature, that self-employment is an important determinant of both hours worked and wage/salary income.

The independent variables included in my dataset that don't directly follow from the literature that I have read on the subject of the minimum wage are $childlast_{ist}$, which is a dummy variable that takes on the value of 1 if an individual had a child within the last year, $inschool_{ist}$ which is a dummy variable taking the value of 1 if an individual is in school, and $wrklast_{ist}$ which is a dummy variable that takes the value of 1 if an individual worked last year. The inclusion of $childlast_{ist}$ in my dataset comes from my assumption that an individual who had a child within the last year would be likely to substitute their hours worked for hours spent performing childcare, or that they may abandon the labor force to become a full-time parent, either permanently or temporarily. The variable for whether or not an individual is in school comes from the possibility that an individual who is in school may be more likely to work part-time, thus having less hours worked, or not working at all. Both of these predictions follow from the assumption that being in school provides a higher opportunity cost for working, that is, the time spent working costs time that could be used to study. The variable $wrklast_{ist}$ was included under the assumption that individuals who didn't work last year are likely to not be participating in the labor force, and are then likely to report usually working zero hours per week.

Also not coming from the literature, but rather from my own assumptions, was a set of dummy variables for the number of weeks an individual worked last year. This took on the form of several dummy variables instead of being a continuous variable since IPUMS-USA reports an individual's weeks worked as being within a range, and not as a number. The ranges they reported were 0 to 13, 14 to 26, 27 to 39, 40 to 47, 48 to 49, and 50 to 52. A dummy variable was created for every range except 0 to 13 since including a dummy variable for every range in my models would result in perfect multicollinearity. The 0 to 13 range served as the reference range. This variable was included following the assumption that the more weeks an individual works, the more they earn, all else being held constant.

Also in my dataset is $Minwage_{st}$ which is a variable that accounts for the minimum wage in state *s* at year *t* in nominal terms. This is the key explanatory variable within all of the regressions I ran in my analysis. A lagged variable for the minimum wage, $Minwage_{st-1}$, is meant to account for the effect that last year's minimum wage has on employment and hours worked, which when taken with the variable for the current year's minimum wage can be used to evaluate my hypothesis that the initial impact of a minimum wage increase is a reduction in hours worked, and then the lagged effect is a reduction in employment. The lagged minimum wage variable also comes from both Partridge and Partridge's (1999) and Sabia's (2008) use of a lagged minimum wage variable in their regressions on hours worked and employment, respectively.

Every state within the North East or the United States excluding Pennsylvania had a dummy variable meant to capture time-invariant, state-specific, factors that would otherwise be excluded from my models. These states are Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, Rhode Island, and Vermont. Pennsylvania serves as the reference state within my analysis. Observations from New York were taken out of my dataset for several reasons[2]. The first is that Hoffman (2016), in his analysis found that employment for 16 to 29 year olds without a high school degree, the same demographic in my analysis, wasn't affected by the 2004 to 2006 New York minimum wage increase while other states that increased their minimum wage during this time experienced increases in employment for this demographic. Second, a large portion of New York's population lives in New York city where the minimum wage is higher than the state minimum wage, so increases in the state minimum wage would not effect a large section of the observations from New York. Third, I had ran preliminary regressions with and without observations from New York and found evidence that those from New York experienced less wage growth resulting from the minimum wage increasing, when all else was equal, suggesting that more observations from New York were earning more than the state minimum wage than those from other states, possibly due to the higher minimum wage for New York city.

3.1. Descriptive statistics

Within my dataset, the average number of usual weekly hours worked for employed men in the demographic I am analyzing was 26.84, while for women in the same demographic it was 19.66. The difference between these two means was statistically significant at the 1% level. This can be seen as implying that more women are part-time employees than men in this demographic. The average wage incomes for men and women in my dataset were $10,880 and

[2] The results from the regressions ran with observations from New York will be provided upon request.

$6,088 if they were employed, respectively, with this difference being statistically significant at the 1% level. This would suggest that women are paid less than men if not for the difference in the number of hours worked by these two groups. There is a higher proportion of women who are employed to those who aren't in my data set than there is for men who are employed to those who aren't, 28.1% and 26.3%, respectively. This difference in the proportion of employed men to women is significant at the 1% level. None of these t-test results can convincingly conclude that the reason previous studied have found more adverse effects from the minimum wage increasing for women than for men is due to women in this demographic earning a lower wage, and thusly being more susceptible to changes in the minimum wage. Also, the average age of an individual in my dataset is 18.39, which would suggest that most of the people in my analysis who don't have a high school degree are still in high school. This is further shown since 93.6% of the individuals in my sample below the age of 19 are still in school. All descriptive statistics are reported in tables 4 & 5.

4. Methodology

4.1. Regression Equations

The statistical methodology I used to conduct my analysis was two OLS regression equations, with $incwage_{ist}$ and $uhrswork_{ist}$ as the two respective dependent variables, and a probit regression model with the dependent variable being $employed_{ist}$. The probit model was used for my analysis on employment due to $employed_{ist}$ being a dummy variable, and the interpretations of the coefficients of the probit model estimates how a change in an independent variable affects the probability of an individual being employed. A probit model with marginal effects is preferred over a linear regression model, an OLS regression with the dependent being a dummy variable, because the coefficients of the probit model with marginal affects can have the magnitude of their respective variable's impact evaluated as well as the sign of the relationship between that independent variable and the dependent variable. While a linear probability model's coefficients can only be interpreted for their sign, if a change in a variable positively or negatively affects the probability of the dependent variable being equal to

1 instead of 0, rather than having the size of the impact being something one can evaluate from that model.

The OLS regression equation that I will be using for my analysis of the minimum wage increasing on an individual's usual hours worked follows the form,

$$uhrswork_{ist} = \beta_0 + \beta_1 Minwage_{st} + \beta_2 Minwage_{st-1} + \beta_3 femMinwage_{st} + \beta_4 femMinwage_{st-1} + \alpha_1 \boldsymbol{x}_{ist} + \alpha_2 \boldsymbol{y}_{st} + \varepsilon_i$$

where $femMinwage_{st}$ is a slope dummy variable derived by multiplying the dummy variable fem_{ist} with the $Minwage_{st}$. And $femMinwage_{st-1}$ is a similar dummy variable for the lagged minimum wage variable. The slope dummy variable was used to capture the possibility that the minimum wage may have different impacts for men and women. I accounted for this due to Dickens et al.'s (2015) finding that the increases in the U.K's national minimum wage only affected part-time women, suggesting that previous studies on the U.K minimum wage didn't find any impact on employment because their analysis was too aggregated. By not disaggregating my analysis among this line, there would remain the possibility that the true impacts of the minimum wage would not be observed. The use of a slope dummy variable is preferred to running my regression equation separately on only male observations, then on only female observations due to the bias that can result from removing observations.

I hypothesize that $\beta_1$will be negative, following the logic that the initial response to the minimum wage increasing for an employer is to cut their employees hours due to larger costs associated with firing an employee (Pratomo, 2013). However, the literature I have read found evidence that women may experience adverse employment effects resulting from increases in the minimum wage, but have remained relatively silent on the possible heterogeneous impacts on hours worked. But if women experience more adverse employment effects, then it would be reasonable to hypothesis that β_3 will be negative, representing that women's hours worked are more adversely affected. If the initial impact on the minimum wage is to reduce hours worked, I then also hypothesize that the coefficients corresponding to the lagged minimum wage variables will not be significantly different from zero, representing no lagged affect, since employment is hypothesized to be what is affected in the year after a minimum wage increase. This also comes from the results of Sabia (2008), where he found that there was no statistically significant lagged effect from the minimum wage on hours worked.

Within the vector of individual level control variables, $\boldsymbol{x}_{ist}$, were the variables age_{ist}, $married_{ist}$, $nchild_{ist}$, fem_{ist}, $white_{ist}$, $black_{ist}$, $hispanic_{ist}$, $childlast_{ist}$, $inschool_{ist}$, and $selfemp_{ist}$. The inclusion of age_{ist}, $married_{ist}$, and $nchild_{ist}$ came from Pratomo's (2013) use of them as controls for his regression on hours worked. The variables $white_{ist}$, $black_{ist}$, and $hispanic_{ist}$ were included to control for the differences in labor supply that Kahn and Whittington (1996) found for these groups. The variable fem_{ist} was included to control for possible differences in the hours worked for men and women (Pratomo, 2013). The variable $selfemp_{ist}$ was included to control for the difference in hours worked by self-employed people and other workers found by Daly (2015), and $inschool_{ist}$ was to account for the possibility of students working less hours on average than non-students. I hypothesize that more students are part-time workers than other groups, so I expect there to be a negative relationship between being in school and hours worked. The variable $childlast_{ist}$ was included to control for the impact that having a child in the last year would have on an individual's hours worked, since having a new child may cause an individual to spend time taking care of their child instead of working. I also hypothesize $childlast_{ist}$ will have a negative coefficient.

The vector of control variables $\boldsymbol{x}_{ist}$ also contained the slope dummy variable $femnchild_{ist}$, the interaction term between the variables fem_{ist} and $nchild_{ist}$. This is meant to account for Angrist and Evans' (1998) findings that women's hours worked are affected by their number of children, while men's aren't. The variable age_{ist}^2, the value of an individual's age squared, was included to account for a possible non-linear relationship between age and hours worked that was present in the results of Pratomo's (2013) regression results on hours worked. Although he segmented age by a series of dummy variables for different ranges, his results show that as individuals age they began to work more hours until a point, then they begin to work less hours. This non-linear relationship could also be controlled for with the inclusion of age_{ist}^2, since if the coefficient on age_{ist} is positive and the coefficient on age_{ist}^2 is negative, then the increase in hours worked to a point, which is followed by a decrease as age continues to increase would be captured within this model.[3] Also, $\boldsymbol{y}_{st}$ is a vector of state dummy variables that take on the

[3] Listed are the expected signs of the variables derived from the literature, following the form, variable (expected sign): age (+), age^2 (-), nchild (not different from zero), femnchild (-), married (+), white (+), black (+), Hispanic (-), fem (-), and selfemployed (+), (Angrist and Evans, 1998; Daly, 2015; Kahn and Whittington, 1996, Pratomo 2013). There expected signs come from their respective article's results.

value of 1 if a person lives in a specific state. Pennsylvania was used as the reference state, so it doesn't have a dummy variable. This is meant to control for any time-invariant state specific factors that would influence an individual's usual hours worked.

Pertaining to my analysis on the employment effects of a minimum wage increase, a probit model with marginal affects was run using the equation function,

$$employed_{ist} = \beta_5 + \beta_6 Minwage_{st} + \beta_7 Minwage_{st-1} + \beta_8 femMinwage_{st} + \beta_9 femMinwage_{st-1} + \alpha_3 \boldsymbol{x}_{ist} + \alpha_4 \boldsymbol{y}_{st} + z_i$$

where $Minwage_{st}$, $femMinwage_{st}$, $Minwage_{st-1}$, and $femMinwage_{st-1}$, are the same variables for the current and lagged minimum wage and their respective gender interaction terms used in the regression equation to estimate the effects of the minimum wage on hours worked. The inclusion of the two lagged minimum wage variables comes from the empirical results of Partridge and Partridge's (1999) analysis that found a positive effect on employment for the current minimum wage and a larger negative effect on employment the following year. This is also consistent with the hypothesis presented in Pratomo's (2013) analysis that the initial impact of the minimum wage increasing would be on hours worked, with the following impact being on employment. The expected sign for β_6 is positive, following from the empirical results presented by Partridge and Partridge (1999). Also following from Partridge and Partridge's results is the expectation that β_7 will be negative and larger than β_6, signifying that the lagged impact of the minimum wage in negative. I expect however that both β_8 and β_9 will also be negative, following from the results of Dickens et al.'s (2015) that found that the U.K minimum wage only adversely affected employment for part-time females.

Also within this regression equation is the vector of state dummy control variables, $\boldsymbol{y}_{st}$, which served a similar role as they did in the regression equation for usual hours worked. They are meant to control for time-invariant, state specific characteristics that affect employment with Pennsylvania serving as the reference state. The vector of individual level control variables $\boldsymbol{x}_{ist}$ within this regression equation contains age_{ist}, $nchild_{ist}$, and $married_{ist}$, following from their inclusion in Pratomo's (2013) regression for employment. The variable age_{ist}^2 was also included to account for any non-linearity in the relationship between age and the probability of being employed, such as it increasing as an individual approaches the age when they should graduate high school, then having a significantly lesser increase after this point. This possible relationship could exist if there are more individuals within the typical high school student age range who are without employment due to their own choice to not enter the labor force than those who are older, with the number of individuals willingly without employment decreasing as they approach the age when a typical person would leave high school and thusly the probability of being employed increases. Then there also would no longer be this same increase in the probability of being employed once an individual is out of this age range.

Additional control variables are present in $\boldsymbol{x}_{ist}$, such as $white_{ist}$, $black_{ist}$, and $hispanic_{ist}$, which were included due to the finding of Kahn and Whittington (1996) which indicated that there were differences between labor force participation for women of these demographics. The slope dummy variable $femnchild_{ist}$, the interaction term between fem_{ist} and $nchild_{ist}$, was also included to account for the differences that fertility may have on labor force participation for men and women (He and Zhu, 2016). The variable $inschool_{ist}$was included to control for the possibility that individuals who are in school are less likely to be employed, due to the opportunity cost of working increasing since it now includes forgone hours of studying. This means that I expect a negative relationship between being in school and the probability of being employed. Included in $\boldsymbol{x}_{ist}$ is also the control variable $childlast_{ist}$, which follows from the assumption that individuals who have had a child within the last year are more likely to drop out of the labor force than if they didn't, so that they can take care for their new child. That is, I also assume this relationship with the probability of being employed to be negative[4].

Given that the economic theory underlying the potential impacts a raise in the minimum wage may have rely on the minimum wage effectively serving to increase the wage of employed individuals who previously earned below the minimum wage, a regression equation following the form

$$\ln(incwage)_{ist} = \beta_{10} + \beta_{11} Minwage_{st-1} + \beta_{12} femMinwage_{st-1} + \alpha_5 \boldsymbol{x}_{ist} + \alpha_6 \boldsymbol{y}_{st} + v_i$$

was implemented to test if the minimum wage was effective at increasing the wage for young and low-educated individuals. Only individuals who were employed were included in the subset of my dataset used for this regression equation. The dependent variable, the natural log of

[4] Listed are the expected signs of the variables derived from the literature, following the form, variable (expected sign): age (+), nchild (not different from zero), femnchild (-), married (+), white (+), black (+), Hispanic (-), and fem (-), (Silles, 2016; He and Zhu, 2016; Kahn and Whittington, 1996, Pratomo 2013). There expected signs come from their respective article's results.

$incwage_{ist}$, was used to test this since my dataset didn't contain a variable for the wage an individual earned. The regression that Sabia (2008) used to estimate the impacts of the minimum wage on wages did use an individual's wage as the dependent variable. My choice of dependent variable was meant to proxy a change in wages given the limitations of my dataset. It can be assumed that if both hours worked and weeks worked were controlled for, then a statistically significant and positive relationship between the minimum wage and an individual's wage/salary income should exist if the new minimum wage raised their wage. The lagged minimum wage variable was used instead of the current year's minimum wage because the earnings an individual reports to IPUMS-USA is from the previous year. The slope dummy variable for the interaction between the gender variable and the minimum wage was included to test whether the heterogeneous impacts of the minimum wage by gender can be explained by whether or not more women have their wage affected by the minimum wage (Pratomo, 2013; Dickens et al. 2015). In other words, is it that more women than men earn the minimum wage. I expect the sign on the gender slope dummy variable to be positive, showing that more women in this demographic are minimum wage earners.

Within the vector of control variables $\boldsymbol{x}_{ist}$ are a series of dummy variables for several ranges of weeks worked last year. This was expressed as dummy variables instead as a continuous variable, with the range 0 to 13 weeks serving as the reference range, because IPUMS-USA reports the number of weeks an individual works in ranges. The expected sign on each of these dummy variables is positive, and I expect the coefficient to be larger for the dummy variables representing more weeks worked. Also within $\boldsymbol{x}_{ist}$ is the variable for the usual hours an individual works. Both the weeks and hours an individual works were included due to a change in either of them while holding an individual's wage constant will result in a change in their wage/salary income. The expected sign of the usual hours worked variable is positive.

Also included in $\boldsymbol{x}_{ist}$ are the variables age_{ist}, age_{ist}^2, $nchild_{ist}$, and the slope dummy for the interaction between gender and number of children, $femnchild_{ist}$. The variable for the number of children and that variable's gender interaction variable were included to control for the wage-penalty that Casal et al. (2013) found for the number of children women have, while the two variables for age were included due to their inclusion in Casal et al.'s (2013) regression analysis on wage. A dummy variable for whether or not an individual is married and a variable accounting for the interaction between being married and a female, the product of the two variables fem_{ist} and $married_{ist}$, were included to control for the marriage-wage premium that de Linde Leonard, and Stanley(2015) found for men. Included also was a dummy variable for whether or not an individual was self-employed, to control for the differences in income for self-employed individual's when compared to individuals who work for someone else (Dolly, 2015). The dummy variables for race from my regressions on employment and usual hours worked were also included in $\boldsymbol{x}_{ist}$ to control for the differences in pay that might exist, partly due to racial discrimination (Cornwell et al., 2017)[5]. The vector $\boldsymbol{y}_{st}$ contained state dummy variables with Pennsylvania serving as the reference state to account for any time-invariant state specific characteristics that affect wage/salary income.

4.2. Robustness Checks

I checked for multicollinearity within each of my models, with the model for employment being ran as an OLS regression instead of a probit regression for the purposes of observing the estimated VIFs for each variable. I didn't find their to be any multicollinearity issues for any of my models, with the highest VIFs in the regressions for wage, usual hours worked, and employment being 2.33, 3.02, and 2.98, respectively[6]. I also performed several Parks tests, using an individual's total income as the sizing variable to test for heteroscedasticity. Each of the parks tests that I ran on each of my three regression models rejected the null hypothesis, showing the presence of heteroscedasticity in each model. This was corrected for in the models for usual hours worked and wage by using the "robust" command after the regressions I ran in STATA to correct the standard errors for heteroscedasticity. This was not performed on the probit regression I ran for employment, but the results of correcting the standard errors for heteroscedasticity in the other models showed that heteroscedasticity had a minimal effect on

[5] Listed are the expected signs of the variables derived from the literature, following the form, variable (expected sign): age (+), age^2 (+), nchild (not different from zero), femnchild (-), married (+), femMarried (-), white (+), black (-), Hispanic (-), fem (-), selfemployed (+) (Daly, 2015; Casal et al., 2013; de Linde Leonard, and Stanley, 2015; Cornwell et al., 2017). There expected signs come from their respective article's results.

[6] All regressions ran to get the estimated VIFs were in their linear form with none of the gender interaction or lagged variables.

the standard errors. Estimated VIFs and each parks test's results are reported in tables 6 & 7, respectively.

5. Results

5.1. Estimated minimum wage effects

The results of my regression for the effects of the minimum wage on wage growth, that is, the regression ran to check if the minimum wage successfully raised the wage for young and low educated individuals within the North East of the United States, are reported in table 1. The coefficient on last year's minimum wage estimates that a $1 increase in the minimum wage is responsible for a 10.6% increase in how much a male individual earned last year from employment, and this is significant at the 1% level. My results estimate that a $1 increase in last year's minimum wage increases the amount a female individual earned last year from employment by 11.1%. Although the slope dummy variable $femMinwage_{ist-1}$ is not statistically significant, suggesting that both men and women between the ages of 16 and 29, that don't have a high school degree, and are employed have their wage/salary income increase by 10.6% for every $1 increase in the minimum wage. These results suggest that the minimum wage increasing does increase the pay of young and low-educated employed individuals within the state that increased the minimum wage.

The results of my regression on usual hours worked is presented in table 2. The results of my regression analysis estimate that for young and low-educated men, a $1 increase in the minimum wage decreases their usual hours worked in a week by 0.02 hours. My results also estimate that a $1 increase in the minimum wage results in the usual hours worked in a week by a woman is decreased by 0.03 hours. Neither of these estimated effects are statistically significant however. My regression also estimates that for men the lagged effect of the minimum wage increasing by $1, that is, the minimum wage increased by $1 last year, is a 0.4 decrease in their usual hours worked. The estimated lagged effect of a $1 increase in the minimum wage for a woman is that their usual hours worked within a week will increase by 0.01 hours. Both of these lagged effects, for men and women, are statistically significant at the 1% level. These results suggest a positive relationship between last year's minimum wage and hours worked for women, while suggesting a negative relationship between last year's minimum wage and hours worked for men. The magnitude of both of these effects are small, a decrease of 24 minutes per week and an increase of 6 minutes per week, respectively, which could be interpreted as their being no impact of the minimum wage on hours worked, even though these relationships are statistically significant.

The estimated employment effects from my probit model are found in table 3. These results estimate that the impact of increasing the minimum wage causes the probability of a man who is young and without a high school degree being employed decreases in the current year (marginal effect, -0.004). My probit regression results also estimate that an increase in the minimum wage causes the probability of a woman who is young and without a high school degree being employed increases in the current year (marginal effect, 0.003). The current year employment effect of a minimum wage increase for men is statistically significant at the 1% level. The coefficient on the slope dummy variable $femMinwage_{st}$ is also statistically significant at the 1% level. This suggests that the relationship between the current year's minimum wage for men and women is opposite in sign, positive for females and a negative for males, but while they are statistically significant the magnitudes of these employment effects are small.

The estimated lagged employment effect of a minimum wage increase for men who are young and without a high school degree is an increase in the probability of being employed (marginal effect, 0.001). These results also estimate that the effect of the minimum wage increasing last year results in the probability of a woman who is young and doesn't have a high school degree having an increase in her probability of being employed (marginal effect, 0.026). The lagged employment effect for males in this demographic isn't statistically significant, however, the coefficient on the slope dummy variable $femMinwage_{st-1}$ is statistically significant at the 1% level. These estimates of the employment effects of the minimum wage suggest that only women of this demographic experience a lagged employment effect from the minimum wage increasing, and that this lagged effect is positive. The only statistically significant negative relationship between employment and the minimum wage is the decrease in the probability of a young and low-educated man being employed as a result of the current year's minimum wage increasing. The magnitude of these current effects however are small, less than a 1% increase or decrease for every $1 increase in the minimum wage, which may suggest that there isn't any relationship between the current year's minimum wage and employment. The only statistically significant lagged employment effect is the increase in employment for women of this demographic as a result of the minimum wage increasing in the previous year. The positive lagged employment effect for women of this demographic is nearly 5 times larger than the negative current year employment effect that men of this demographic experience. This may be seen as suggesting that the total impact of the minimum wage on employment is positive.

5.2. Some findings from the control variables

The regression that I ran to test if wages are increased by an increase in the minimum wage found no evidence of wage discrimination by race, since none of the coefficients for the race variables were statistically significant, which is contradictory to Cornwell et al.'s (2017) findings. This is also true for the female variable; the coefficient wasn't statistically significant. This model also suggests that men receive a marriage wage premium of a 16% increase, which is statistically significant at the 1% level, while women receive a marriage wage premium of an 8.1% increase, which is nearly half of the premium men receive. This is consistent with de Linde Leonard, and Stanley's (2015) results. The variable for the interaction between gender and marriage is only significant at the 5% level. The model also suggests that women receive a wage penalty for the number of children they have, that is, a decrease in wage income of 3.4% per child, which is statistically significant at the 5% level. This is consistent with Casal et al.'s (2013) findings. Inconsistent with Daly's (2015) is the estimated decrease in wage income of 14.3% for self-employed individuals. Both hours worked and weeks worked were shown to positively affect wage income and were significant at the 1% level. The lack of discrimination by race or gender for this demographic might not be present due to these individuals earning the minimum wage, and thusly can't have their wages be any lower.

The regression ran for usual hours worked confirms a nonlinear relationship between age and hours worked, where hours worked increase then decrease as age increases. This is consistent with Pratomo's (2013) regression results. These results also estimate that men work more hours per child they have and that women work less hours per week per child they have, and that both of these results are statistically significant at the 1% level. The effect of fertility on women's hours worked is consistent with Angrist and Evan's (1998) findings. These results also suggest that married people work more, which is consistent with Pratomo's (2013) regression results and is significant at the 1% level. However, the results suggest that Hispanics individuals work more weekly hours than individuals who are white or black, which is not consistent with Kahn and Whittington's (1996) findings. Being in school reduces hours worked and is statistically significant at the 1% level, consistent with the sign I expected for that variable. Having worked last year is statistically significant at the 1% level and increases usual weekly hours worked by 20 hours, which confirms my hypothesis that having worked last year is a good indicator of whether or not an individual will have a non-zero number of usual weekly hours worked. These results also find no statistically significant impact of being self-employed on hours worked, which is inconsistent with Daly's (2015) findings.

The probit model I ran on employment finds evidence of the nonlinear relationship with age and the probability of being employed that I hypothesized, that the number of children a woman has decreases her probability of being employed, while the number of children a man has increases his probability of being employed, and that there is a statistically significant negative relationship between being female and being employed. The relationship between being female and employed for a person in this demographic is statistically significant at the 1% level. The effects of an individual's number of children on their probability of being employed is significant at the 1% level, and the effect for women is consistent with He and Zhu's (2016) findings. These results also suggest that being married increases the probability of being employed, while having a child last year decreases the probability of an individual being employed. Both of these estimates are statistically significant at the 1% level, with the latter estimate confirming my hypothesis about the effect of having a child in the last year on employment. These results also show differences between the probability of being employed between white, black, and Hispanic individuals who are between the ages of 16-29 and don't have a high school degree. These coefficients on the variables $White_{ist}$ & $Black_{ist}$ are statistically significant at the 1% level, while the coefficient on the variable $Hispanic_{ist}$ is only significant at the 5% level. These results also show that being in school decreases the probability of an individual being employed. This estimate is statistically significant at the 1% level and confirms the hypothesis I had, that students are less likely to be employed than non-students.

5.3. Comparing my results with the literature

My findings suggest that the minimum wage increasing has a positive impact on the probability of a woman who is young and without a high school degree being employed in the current year and that their also is a statistically significant positive lagged employment effect for women of this demographic. The results of my analysis also suggest that the only statistically significant employment effect for men of this demographic is a small decrease in the probability of being employed in the year that the minimum wage was increased. My findings also suggest that the minimum wage increasing negatively impacts the usual hours worked by men who are young and without a high school degree in the following year, while also in the following year increasing the usual hours worked for women in the same demographic.

These findings on the impact that the minimum wage has on employment are inconsistent with the results of both Pratomo (2013) and Dickens et al. (2015). Pratomo (2013) had found that as the minimum wage increased, the probability of a woman being a paid employee decreased in urban areas, with a marginal effect of 0.029, while women in rural areas aren't affected. The magnitude of the positive current year employment effect I find is smaller than the negative one Pratomo (2013) found, but the positive lagged effect I estimate is only slightly smaller than the negative current year employment effect he found. Pratomo (2013) also estimated a decrease in the probability of being a paid employed for men in rural areas that is larger than the slight negative impact on employment for men I estimate. My estimate may be better interpreted as no employment effect for men, which would also be contradictory to Pratomo's (2013) findings. One possible reasoning behind the difference between Pratomo's (2013) findings and my own is that Pratomo's (2013) analysis was conducted with observations from individuals in Indonesia, a developing nation, while mine was conducted with observations from individuals in the United States. The moderate negative effect that Pratomo (2013) found, and that I didn't find for my sample, could be due to employers in Indonesia, a poorer nation than the United States, not being able to pay the higher minimum wage, while employers in the United States may be able to.

The results of my regression analysis brought estimates that are contradictory to what Dickens et al. (2015) found were the results of the U.K national minimum wage. While Dickens et al. (2015) found that part-time female employees were adversely effected by the minimum wage, I found that women from another demographic expected to be susceptible to the minimum wage's impacts on employment experienced a positive employment effect. Unlike Pratomo's (2013) analysis of Indonesia, Dickens et al.'s (2015) analysis was of the U.K, another wealthy country, so differences in employment effects resulting from differences in the wealth of the U.K and United States seems unlikely. My results are also partly inconsistent with both Sabia (2008) and Sabia et al.'s (2012) results that estimate negative impacts on employment, with Sabia et al (2012) having analyzed the same age and education demographic that I did in my analysis. The results I find for the employment effects of men in this demographic are negative, but far smaller than those found by Sabia et al. (2012), and as I have already mentioned, the small magnitude of this effect could be interpreted as their being no employment effect. The positive and much larger lagged employment effect I estimate for women of this demographic is the main inconsistency between my findings and both Sabia (2008) and Sabia et al.'s (2012) results.

The employment effects that I estimate are however somewhat consistent with what Card and Krueger (1994) and Hoffman (2016) have found. While neither of these papers disaggregated their analysis by gender, they did find positive employment effects resulting from the minimum wage increasing. While Card and Kruger (1994) had analyzed the employment effects in the fast-food industry resulting from the 1992 New Jersey minimum wage increase, Hoffman (2016) had analyzed the same age and education demographic I have in my analysis. So apart from the slight negative impact on the probability of males in this demographic being employed from the minimum wage increasing, my results on the employment effects of the minimum wage are consistent with Hoffman's (2016) results. My results could be seen as consistent with Hoffman's (2016) due to the positive employment effects I estimate being larger than the negative one, which could suggest that if this demographic was analyzed in aggregate, then I may have only found a positive impact on employment. My results are also partly consistent with Partridge and Partridge's (1999) analysis of the retail sector, since they found a small positive employment effect resulting from the minimum wage increasing in the current year. My results differ from theirs in that they found a negative lagged effect on employment, while I found a statistically significant and positive lagged employment effect for women.

The effects on the usual hours an individual works within a week due to an increase in the minimum wage that I estimated are consistent with what I have found within the literature I have read. Sabia (2008) had found that the current year's minimum wage increasing results in a decrease in usual weekly hours worked within the retail sector. My analysis found results for men who are young and don't have a high school degree that were consistent with the negative relationship Sabia (2008) found. However, the positive relationship between the minimum wage and the usual weekly hours worked by women who are young and don't have a high school degree is not consistent with this. What is also inconsistent between my results and Sabia's (2008) is that I only found statistically significant lagged effects, while Sabia (2008) didn't find a statistically significant lagged effect. My findings however aren't comparable with Pratomo's (2013) findings, even though he found a positive impact of the minimum wage for women's hours worked, since Indonesia's minimum wage is by month instead of by hour. So an employer's strategy for adjusting their employees' hours in response to the minimum wage increasing is fundamentally different.

The choice of the demographic that I have analyzed may also be a reason for why my results do diverge from some of those found in the literature. This may be why I found results that are the opposite of Dickens et al.'s (2015) results, that is, the effect of the minimum wage on employment for women may be different for part-time employees than for young and low-educated women without separating out part-time from full-time employees. Employers may be more inclined to fire part-time employees than full-time employees, so perhaps if I disaggregated my analysis further by part-time and full-time employees, I may find results which are consistent with Dickens et al.'s (2015) results. The method I used for analyzing the heterogeneous impacts of the minimum wage on employment by gender differed from that used by Dickens et al. (2015). They had run their difference in difference regressions on datasets for men and datasets for women, while my method of analysis used pooled panel data and estimated the heterogeneous impacts with the inclusion of a slop dummy variable. This may be another reason why my results differ from Dickens et al.'s (2015).

The choice of demographic I used in my analysis differed from Sabia (2008) and Partridge and Partridge (1999) by what states I used in my analysis. Sabia (2008) and Partridge and Partridge (1999) also included the rest of the continental United States in their panel data sets. This means that my results are more specific, and when Sabia (2008) and Partridge and Partridge's (1999) results are taking into consideration may indicate that these effects aren't consistent among every region of the United States. However, the analysis that Sabia (2008) and Partridge and Partridge conducted didn't look at individual regions of the United States in addition to their aggregated analysis. This could mean that my results don't contradict theirs, but rather that heterogeneity for the impact of the minimum wage on hours worked and employment may exist between regions of the United States. That is, some regions, such as the North East, may experience more favorable employment effects from increases in the minimum wage, while other regions may experience more adverse employment effects.

Comparing my results and analysis to that from the literature I have read, my analysis used the relatively most current time period. Sabia (2008) had analyzed the period from 1979 to 2004, Partridge and Partridge (1999) analysis used observations from the late 1980s, and the most current period of analysis from the literature I have read was 2004 to 2006 (Sabia et al., 2012; Hoffman, 2016). My analysis had looked at observations from 2010 to 2016, the most recent year available from IPUMS-USA. I had hypothesized that my results would have shown a more adverse effect on employment resulting from the minimum wage increasing due to advances in technology increasing the substitutability of low-skill labor and capital. This was not the case. My analysis showed results that indicated only a small adverse employment effect for men that could be seen as essentially no effect due to its small magnitude and no adverse employment effect for women as a result of the minimum wage increasing while much of the analysis in the literature on earlier periods did find large or moderate adverse employment impacts (Sabia, 2008; Sabia et al., 2012; Partridge and Partridge, 1999). My results then suggest that the conclusions made by Card and Krueger (1994) and Hoffman (2016), that the minimum wage doesn't adversely affect employment, are still plausible in more recent years, even as technology has developed and made low-skill labor and capital more substitutable.

5.4. Critiques of my analysis

The analytical approach that I took has with it several aspects of it that should be critiqued, such as the unintuitive interpretation of the results of a probit regression model. A probit regression model was used to analyze the employment effects of the minimum wage increasing since I was using a micro approach. This type of approach isn't absent in the literature, estimating employment effects with individual level data, but the macro approaches that have been used give results that are easier to interpret (Pratomo, 2013; Dickens et al., 2015). In other words, the estimated changes in the probability of being employed that a probit model estimates as the result of an increase in the minimum wage are more difficult to interpret than the estimated impacts the minimum wage has on the employment rate of a specific demographic of individuals hypothesized to be affected by the minimum wage. Whether the minimum wage has a positive or negative relationship with employment can still be estimated with the micro approach that I used, but the magnitude of these effects are less intuitive to estimate than the estimates that a macro approach would have.

The use of a pooled panel data set being run through a standard OLS regression equation can also be seen as a shortcoming of my method of analysis. This is not to say that there is anything intrinsically wrong with the use of a pooled panel dataset and a standard OLS regression, but rather that a difference in difference analysis may have been better, such as that used by Card and Krueger (1994), Sabia et al. (2012), Dickens et al. (2015), and Hoffman (2016). A difference in difference analysis would have been looking at individual increases in the minimum wage and would have possibly been able to control for general trends and other characteristics not present in my regression equation. This is because a difference in difference analysis uses a counterfactual, no treatment group to separate out these differences in general trends and provide a more accurate estimate on the impact of the minimum wage increasing. These general trends that my methodological approach may not have controlled for could have biased my results. Although, this might not necessarily be true, since in preliminary regressions that I had ran a state's overall employment to population ratio instead of state dummy variables was used, meant to control for any employment trends, but the results of those models didn't differ from the results of the regressions I used in this paper[7]. Regressions of this form weren't used in conjunction with my final regression models, they were only run before my regression equations were refined, so I can't conclude that my results aren't biased due to unobserved general trends.

The applicability of my results towards making any policy recommendations are limited by two factors, the narrow geographic region I analyzed and the range of minimum wages observed in my analysis, specifically on the high end. The highest state minimum wage that was present in my dataset was $10, which was for Massachusetts in 2016. While this is a relatively high minimum wage, it is only two thirds of the $15 minimum that is often recommended to be the new minimum wage and is the minimum wage that New York state plans on implementing. The positive employment effects and mild effects on hours worked that I estimate may no longer hold at these higher minimum wages, that is, there may be a possible nonlinear relationship between the minimum wage and employment, or the minimum wage and hours worked, where after a certain point the positive or small effects may start to become negative and severe. It is possible that a threshold like this exists and that none of the minimum wages present in my analysis had passed it.

Since my analysis only looked at individuals for the North East of the United States, my results can't definitively be assumed to still hold for other parts of the United States, or other parts of the world. Other parts of the United States, such as the west coast or the southern states, may have different impacts from the minimum wage due to unobservable characteristics. So my results are limited in only being able to make policy recommendations for states in the North

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[7] The results of these preliminary regressions will be provide upon request. The employment to population ratio variable wasn't included in my regressions due to collinearity existing between it and the state dummy variables.

East excluding New York. My analysis could then in the future be expanded to also cover other regions of the United States, as to see if there are any regional differences in the employment effects of the minimum wage. Even more generally, my results can only be seen as being applicable to developed nations, such as the United States, and it cannot reasonably be assumed for there to be the same relationship within developing nations. There is little research on the effects of the minimum wage in developing nations, so in the future my analysis on the minimum wage could be extended to the effects in developing nations (Pratomo, 2013). When both the limitations in the range of minimum wages and the narrowness of the states that my observations came from are considered, the scenarios where my choice of data was appropriate becomes narrow. My data is only appropriate for making policy recommendations to states in the North East of the United States that haven't raised their minimum wage to $10 yet, while recommendations can't be made for other regions of the United States or other countries, developing or developed.

A further shortcoming of my analysis and results comes from not capturing the possible indirect effects of the minimum wage across states. Kalenkoski and Lacombe (2012) found results that indicate that not accounting for the effects that a neighboring state's minimum wage has on employment would underestimate the employment effects of the minimum wage. Since I didn't account for the indirect, cross state effects of the minimum wage, this may explain why I found only modest impacts of the minimum wage on employment. The indirect state effects weren't something that my econometric methodology could account for. To capture these indirect effects, I would have to use a more sophisticated econometric model that implements spatial econometric techniques. The analysis of mine on the minimum wage that will follow what is reported in this paper will attempt to capture these indirect effects.

5.5. Policy prescriptions

The results of my analysis would indicate that states in the North East of the United States that haven't raised their minimum wage to $10 or have kept their minimum wage at the federal minimum wage should consider raising their minimum wages. The impacts that my analysis estimates on employment as a result of a minimum wage increase are positive for young and low-educated women, and are larger than the magnitude of the estimated negative effect for men of this same demographic. The effect on hours worked are also small, resulting in a less than one-hour reduction for men of this demographic per week and an even smaller increase in the weekly hours worked for women. The full scope of what these results can suggest is that states who have relatively low minimum wages compared to other states in the North East of the United states should consider raising their minimum wage to that of their neighboring states. Since my results also suggest that the minimum wage is associated with large increases in wage/salary income, it is advisable to increase the minimum wage at least up to $10 for states in the North East, since the sum of all the statistically significant estimated employment effects is positive, and the only statistically significant adverse effect on hours worked is small in magnitude.

6. Conclusions

This study analyzed the minimum wage's impact on employment an hours worked through regression analysis that used data from 2010 to 2016 on individuals between the ages of 16 and 29 that lived in the United States' North East. The results of my analysis suggest that the minimum wage's employment effects aren't the same for men and women. My analysis estimates that men see a reduction in their hours worked as the minimum wage increases, while women see an increase. However, these respective reductions and additions are small in magnitude, less than half an hour per week for every $1 increase in the minimum wage, which might be better seen as the minimum wage having no effect on hours worked. The current year employment effect for the minimum wage is similar to its effect on hours worked, it adversely effects men while positively affecting women. These impacts are also small in magnitude and may also be better seen as indicating no current year employment effects, although they are statistically significant. Only women had a statistically significant lagged employment effect, which is positive and of economic significance. This lagged effect is greater in magnitude than both of the current year effects, and may suggest that the total employment effect for the minimum wage increasing is to positively impact employment, following from Partridge and

Partridge's (1999) summation of the minimum wage's lagged and current year effects to get the total effect.

Also through my regression analysis, I estimated that both men and women of my target demographic had their wage/salary income increase by the same amount when the minimum wage increased. This makes it unclear why these differences in employment effects by gender are present, since it would seem that both genders' wage is equally affected. The different effects by gender and the positive employment effects that women of this demographic, who have their wages increase as the minimum wage increases, experience is inconsistent with standard economic theory. This is because standard economic theory would suggest that both men and women in this demographic should experience negative employment effects since both of their wages are increased as the minimum wage increases.

Since this research only looked at the North East of the United States and the highest minimum wage for a state in my analysis was $10, the policy implications that can be drawn are small. This is because there may be heterogeneity in the minimum wage's employment effects by regions in the United States, such as the north west experiencing different effects. Heterogeneity by region seem plausible given Hoffman's (2016) findings that New York's minimum wage had no employment effect while other states' minimum wages had positive employment effects. Having the highest minimum wage in my analysis be $10 also limits policy implications since a non-linear relationship may exist, such as once the minimum wage increases past some threshold above $10, then the employment effects may change and become adverse. What these results do suggest is that New Hampshire, New Jersey, and Pennsylvania should all work towards raising their respective minimum wages to $10 given that they are in the North East, and my results suggest a positive total employment effect for this region.

In the future, I intend to expand my research to analyzing other regions of the United States to see if there are heterogeneous employment effects for the minimum wage increasing. Future research of mine will also explore if there is a non-linear relationship between the minimum wage and employment as to identify any limitations in how high the minimum wage should be set. To capture the full effect of the minimum wage, future research of mine will also incorporate analysis of the cross-state effects of the minimum wage. This follows from Kalenkoski and Lacombe's (2013) findings that suggest that not capturing the minimum wage's cross-state effects doesn't show all of the minimum wage's employment effects. All of these plans for future research should increase what policy prescriptions can be drawn from my research

List of Tables

Table 1. Dependent Variable: *The Natural Log of Wage/Salary Income*

	New York Excluded
Minimum Wage_{-1}	0.106*** (0.017)
Minimum Wage_{-1}* Female	0.005 (0.017)
Age	0.252*** (0.018)
Age^2	-0.004*** (0.000)
Female	-0.090 (0.129)
Number of Own Children	0.011 (0.011)
Number of Own Children * Female	-0.034** (0.015)
Married	0.160*** (0.025)
Married * Female	-0.079** (0.039)
White	-0.001 (0.015)
Black	-0.002 (0.024)
Hispanic	0.013 (0.014)
Self-Employed	-0.143* (0.079)
Usual Hours Worked	0.040*** (0.001)
Weeks Worked 14-26	0.895*** (0.016)
Weeks Worked 27-39	1.278*** (0.016)
Weeks Worked 40-47	1.532*** (0.019)
Weeks Worked 48-49	1.632*** (0.032)
Weeks Worked 50-52	1.792*** (0.015)
Connecticut	-0.013 (0.023)
Maine	0.022 (0.027)
Massachusetts	-0.000 (0.019)
New Hampshire	0.087*** (0.021)
New Jersey	-0.005 (0.013)
Rhode Island	0.101*** (0.027)
Vermont	-0.004 (0.038)
Constant	2.178*** (0.222)
R^2	0.752
Adjusted R^2	0.752
N	25,946

Notes: Standard errors are in parentheses below the coefficients and made robust by STATA.
***** Signifies significance at the 1% level**
**** Signifies significance at the 5% level**
*** Signifies significance at the 10% level**

Table 2. Dependent Variable: *Usual Hours Worked*

	New York Excluded
Minimum Wage	-0.023 (0.024)
Minimum Wage * Female	-0.008 (0.030)
Minimum Wage_{-1}	-0.401*** (0.095)
Minimum Wage_{-1}* Female	0.413*** (0.099)
Age	1.321*** (0.132)
Age^2	-0.020*** (0.003)
Female	-4.480*** (0.769)
Number of Own Children	2.776*** (0.174)
Number of Own Children * Female	-4.225*** (0.181)
Married	3.057*** (0.270)
Worked Last Year	20.889*** (0.063)
Child Last Year	-1.024*** (0.259)
White	-0.491*** (0.079)
Black	-0.916*** (0.102)
Hispanic	1.314*** (0.080)
Self-Employed	0.421 (0.402)
In School	-5.916*** (0.131)
Connecticut	-0.589*** (0.138)
Maine	-0.076 (0.165)
Massachusetts	-0.989*** (0.111)
New Hampshire	0.696*** (0.154)
New Jersey	-0.037 (0.072)
Rhode Island	-0.685*** (0.027)
Vermont	-0.788*** (0.263)
Constant	-7.534*** (1.576)
R^2	0.680
Adjusted R^2	0.680
N	98,450

Notes: Standard errors are in parentheses below the coefficients and made robust by STATA.
***** Signifies significance at the 1% level**
**** Signifies significance at the 5% level**
*** Signifies significance at the 10% level**

Table 3. Dependent Variable: *Employed*

	New York Excluded **Probit model with marginal effects**
Minimum Wage	-0.004*** (0.001)
Minimum Wage * Female	0.007*** (0.002)
Minimum Wage_{-1}	0.001 (0.005)
Minimum Wage_{-1}* Female	0.025*** (0.009)
Age	0.208*** (0.006)
Age^2	-0.004*** (0.000)
Female	-0.178*** (0.039)
Number of Own Children	0.090*** (0.005)
Number of Own Children * Female	-0.080*** (0.009)
Child Last Year	-0.109*** (0.009)
Married	0.064*** (0.009)
White	0.061*** (0.004)
Black	-0.117*** (0.005)
Hispanic	-0.010** (0.004)
In School	-0.044*** (0.006)
Connecticut	-0.035*** (0.007)
Maine	-0.014* (0.008)
Massachusetts	0.005 (0.006)
New Hampshire	0.053*** (0.008)
New Jersey	-0.039*** (0.004)
Rhode Island	-0.027*** (0.087)
Vermont	0.018 (0.013)
Pseudo R^2	0.074
N	98,450

Notes: Standard errors are in parentheses below the coefficients
***** Signifies significance at the 1% level**
**** Signifies significance at the 5% level**
*** Signifies significance at the 10% level**

Table 4. Descriptive Statistics: Male

Variable	Mean or Proportion	Standard Deviation	Minimum	Maximum	Number of Observations
Age	18.589	3.545	16	29	54,074
Number of Children	0.077	0.426	0	7	54,074
Child Last Year	0	0.000	0	0	54,074
Worked Last Year	0.415	0.493	0	1	54,074
Married	0.028	0.165	0	1	54,074
White	0.733	0.442	0	1	54,074
Black	0.127	0.333	0	1	54,074
Hispanic	0.166	0.372	0	1	54,074
Self Employed	0.021	0.144	0	1	54,074
In School	0.742	0.437	0	1	54,074
Connecticut	0.099	0.299	0	1	54,074
Maine	0.031	0.173	0	1	54,074
Massachusetts	0.187	0.390	0	1	54,074
New Hampshire	0.033	0.180	0	1	54,074
New Jersey	0.243	0.429	0	1	54,074
Rhode Island	0.028	0.167	0	1	54,074
Vermont	0.015	0.123	0	1	54,074
Pennsylvania	0.359	0.479	0	1	54,074
Weeks Worked 0-13	0.746	0.435	0	1	54,074
Weeks Worked 14-26	0.059	0.236	0	1	54,074
Weeks Worked 27-39	0.040	0.198	0	1	54,074
Weeks Worked 40-47	0.023	0.150	0	1	54,074
Weeks Worked 48-49	0.006	0.082	0	1	54,074
Weeks Worked 50-52	0.123	0.329	0	1	54,074
Wage/Salary Income	3,408.206	10,330.76	0	431,000	54,074
Usual Hours Worked	10.527	16.051	0	99	54,074
Employed	0.263	0.440	0	1	54,074

Table 5. Descriptive Statistics: Female

Variable	Mean or Proportion	Standard Deviation	Minimum	Maximum	Number of Observations
Age	18.159	3.282	16	29	44,376
Number of Children	0.179	0.644	0	8	44,376
Child Last Year	0.036	0.188	0	1	44,376
Worked Last Year	0.414	0.414	0	1	44,376
Married	0.040	0.196	0	1	44,376
White	0.758	0.427	0	1	44,376
Black	0.106	0.308	0	1	44,376
Hispanic	0.150	0.357	0	1	44,376
Self Employed	0.015	0.122	0	1	44,376
In School	0.800	0.399	0	1	44,376
Connecticut	0.099	0.299	0	1	44,376
Maine	0.032	0.176	0	1	44,376
Massachusetts	0.187	0.390	0	1	44,376
New Hampshire	0.034	0.181	0	1	44,376
New Jersey	0.245	0.430	0	1	44,376
Rhode Island	0.028	0.166	0	1	44,376
Vermont	0.016	0.126	0	1	44,376
Pennsylvania	0.356	0.478	0	1	44,376
Weeks Worked 0-13	0.753	0.430	0	1	44,376
Weeks Worked 14-26	0.067	0.250	0	1	44,376
Weeks Worked 27-39	0.046	0.211	0	1	44,376
Weeks Worked 40-47	0.025	0.159	0	1	44,376
Weeks Worked 48-49	0.006	0.078	0	1	44,376
Weeks Worked 50-52	0.099	0.299	0	1	44,376
Wage/Salary Income	2,048.528	6,474.605	0	406,000	44,376
Usual Hours Worked	8.076	12.512	0	99	44,376
Employed	0.281	0.449	0	1	44,376

Table 6. Heteroscedasticity Tests (Parks Tests)

$\boldsymbol{H_O}$: *The sizing variable's coefficient isn't statistically significant from zero; errors are homoscedastic*

$\boldsymbol{H_a}$: *The sizing variable's coefficient is statistically significant from zero; errors are hetroroscedastic*

Dependent Variable: Ln($errors^2$)

	Errors from the model for hours worked	**Errors from the model for employment**	**Errors from the model for Wage/salary income**
Ln(*Total Income*)	0.045*** (0.005)	-0.082*** (0.006)	1.401*** (0.012)
Constant	2.995*** (0.045)	-2.279*** (0.051)	1.870*** (0.100)
R^2	0.000	0.002	0.147
Adjusted R^2	0.000	0.002	0.147
N	75,548	75,548	75,548

Notes: Standard errors are in parentheses below the coefficients
***** Signifies significance at the 1% level**
**** Signifies significance at the 5% level**
*** Signifies significance at the 10% level**

Table 7. Estimated VIFs, Testing for Multicollinearity

Variable	Usual Hours Worked	Employed	Wage/Salary Income
Age	3.02	2.98	2.33
Female	1.04	1.04	1.08
Number of Children	1.68	1.68	1.56
Child Last Year	1.14	1.13	-
Worked Last Year	1.10	-	-
Married	1.44	1.44	1.46
White	1.89	1.88	1.73
Black	1.81	1.80	1.52
Hispanic	1.26	1.24	1.42
Self Employed	1.04	-	1.06
In School	2.67	2.66	-
Connecticut	1.13	1.26	1.25
Maine	1.06	1.06	1.06
Massachusetts	1.21	1.37	1.39
New Hampshire	1.08	1.08	1.10
New Jersey	1.38	1.38	1.39
Rhode Island	1.06	1.06	1.06
Vermont	1.05	1.05	1.05
Weeks Worked 14-26	-	-	1.38
Weeks Worked 27-39	-	-	1.35
Weeks Worked 40-47	-	-	1.24
Weeks Worked 48-49	-	-	1.07
Weeks Worked 50-52	-	-	1.98
Usual Hours Worked	-	-	1.83
Minimum Wage	1.27	1.29	1.32

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