2020

How Does an Increase in the Minimum Wage Affect High School Enrollment?

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May 2 2020

Abstract

In this paper, I explore how the probability of a student being in different combinations of enrolled/not enrolled and employed/unemployed/not in the labor force is affected by an increase in the minimum wage. I use binomial logistic regression, and experiment with both state and county level of observation and fixed effects. I also use year fixed effects. I find that when either the nominal or real minimum wage increases, the probability of a student being employed and enrolled increases, while the probability of being in any of the other groups decreases. However, these changes are not substantial. I determine that these results are relatively consistent for both boys and girls. My results are robust to a variety of specifications. The analyses of gender and real vs nominal wage are previously unexplored, and mark my main contributions to the existing literature.

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1 Introduction

Dropout rates and the factors that determine them have been an important topic in education discussions for decades. Although overall dropout rates have declined in recent years, there is still significant variation between different schools and within those schools. Understanding this heterogeneity and exploring its probable causes is thus important when analyzing education policy. The precise causes of a student dropping out of high school are unique to each individual. Dropout rates vary by gender, race, ethnicity, age, and grade (Stearns et al. 2006). However, many studies have attempted to generalize about common causes. The forces acting on a student can be separated into "push" and "pull" factors (Warren and Hamrock 2010). Push factors are anything that creates an unproductive or unhealthy atmosphere for the student. Pull factors are any outside incentive to leave school, essentially any component of a better offer. Intuitively, one of the most important pull factors is the outside wage - the opportunity cost of school. For most teenagers this is the minimum wage. While intuitively it makes sense that increases in the minimum wage makes students more likely to drop out, the opposite could also be true. Students earning a higher wage could work less without changing their income and thus spend more time on school. This assumes, however, that they have control over their hours worked and could increase or decrease to whatever their ideal is. In reality, the situation is much more complicated. Policies intended to increase high school enrollment are often created to reduce poverty, and similarly the minimum wage is often claimed as an instrument of reducing poverty. If the minimum wage decreases enrollment, what then is its effect on poverty? Is one more important than the other? Which is more helpful? Knowing whether or not we even have to ask these questions requires understanding whether the minimum wage and high school enrollment are truly in opposition to each other.

Researchers disagree on whether an increase in the minimum wage leads to higher or lower youth employment, and thus on how it affects enrollment or if it does at all. Consider the following six groups shown in Figure 1.

Figure 1: The six groups a student can be a part of

	In labor force		Not in labor force
	Employed	Unemployed	
Enrolled	(1)	(3)	(5)
Unenrolled	(2)	(4)	(6)

A theoretically logical story could be told for each move between groups (though some are more likely than others), and thus there is no clear answer or definitive prediction for the effects of a minimum wage. For example, after a minimum wage increase, employers may substitute away from high schoolers and towards more skilled or experienced workers, increasing unemployment. In addition, students may see the higher returns to labor and drop out of school to pursue these higher rewards, decreasing enrollment. If these happen at the same time, then the number of teens both unenrolled and unemployed (group 4) increases. However, it is also possible that students notice the decrease in available jobs and decide to go back to school, increasing enrollment. They may even leave the labor force entirely while doing so, increasing the number of students in group 5. However, it is also possible they become discouraged while not going back to school, increasing the number of students in group 6. Due to this theoretical ambiguity, empirical analysis is needed to determine overall effects.

In the following research, I explore how the probability of being in each of these groups is affected by an increase in the minimum wage, using panel data at the state and county level from 2009 to 2017. I use binomial logistic regression and a variety of specifications of the explanatory variables in order to determine the changes in probability. I find that for both a nominal or real wage increase, the probability of a student being employed and enrolled rises while the probability of being in any of the other groups falls. While these findings are statistically significant, they are not practically significant as the coefficients are small. These results are robust to a variety of specifications, including separate estimations by gender. The analyses of gender and real vs nominal wage are previously unexplored, and mark my main contributions to the existing literature.

2 Literature Review

There is substantial debate over how an increase in the minimum wage affects teen employment. Neumark and Wascher (2008) review 53 studies that use state level panel data, and summarize that almost all of them find statistically significant disemployment[1] effects, using panel data at the state level and state and year fixed effects. Partridge and Partridge (1998) find not only that a higher minimum wage decreases teen employment, but that there is a corresponding decrease in labor force participation (people in or looking for a job) as well. They thus claim that traditional estimates of employment that do not consider labor force participation underestimate the effects of an increase in the minimum wage. Couch and Wittenburg (2001) similarly claim traditional disemployment estimates are understated, citing the same reason. In order to account for this, I include labor force participation in my estimation.

Allegretto, Dube, and Reich (2011), on the other hand, argue that most disemployment effects are overstated. They claim the estimates are biased downwards by a lack of sufficient controls for counterfactual employment trends. They investigate common models in this body of literature and find that frequently, teen employment in states that increased their minimum wage was decreasing before the change took

[1] A reduction in hours worked or a decrease in employment.

place. They thus argue that there is an endogeneity problem or an issue of confusing correlation with causation in these studies. They replicate the results from these studies and show that additional controls for the general state of employment eliminates the significance of these estimates. Allegretto et al. thus finds no effect on teen employment from a minimum wage. However, Allegretto et al. include both state-specific year fixed effects and census-division specific year fixed effects, which are likely highly correlated and thus would reduce the variation in their analysis. This may be partially responsible for the low level of significance they find. There is thus still ambiguity about the expected direction of the coefficient for employment of teens after a minimum wage increase. Some research claims negative estimates are too strong, while other research finds they are too weak. An estimation strategy that combines elements of the two groups and accounts for complaints from both sides would be helpful in determining the true effect. I include both unemployment rates at my level of observation and labor force participation in my analysis in an attempt to reconcile these views.

There is even more uncertainty in how enrollment is affected by an increase in the minimum wage. Several studies look at enrollment and employment simultaneously. For example, Campolieti et al. (2005) use panel data in Canada to estimate the probability of being in one of the four combinations of enrolled/employed, as well as the transitional probabilities of moving between each group. These dependent variables are at the individual level, which allows them to estimate the transitional probabilities. Their independent variable is a minimum wage index at the province level, created by dividing the nominal minimum wage by the average wage. There is no federal minimum wage in Canada, which has the advantage of creating significant variation within the nation. They include both province and year fixed effects in their estimation. They find that in Canada between 1993 and 1999, an increase in the minimum wage index is associated with a decrease in the probability of teenagers being unenrolled and employed. As there are no statistically significant changes for any other variables, this doesn't tell us much about what happens. Do they leave work to go back to school, or are they still unenrolled but now also unemployed? Do they manage to juggle both after the change, becoming both enrolled and employed? Their results are ambiguous.

Regardless of the story this estimation tells, the results may not be directly related to the minimum wage. An increase in the minimum wage index is not necessarily an increase in the minimum wage. The minimum wage index would also increase if the minimum wage was constant but average adult wages decreased. Falling average wages could be a sign of something else going on in the economy that is not related to the minimum wage. This means that the causal effect claimed in the paper may be the result of some other force, overstating the impact of the minimum wage. They do not include any general economy variables (as Allegretto et al. suggest) that could control for this. Furthermore, "unemployed" is defined in this case as anyone not employed - there is no distinction between true unemployment (looking for a job) and being out of the labor force (not looking for a job), which Neumark et al. and Couch et al. claim is an important nuance. Finally, this situation may simply not be applicable to the United States due to the many differences in labor laws, school laws, and other regional characteristics.

Neumark and Wascher (1995) use a similar approach in their research on the United States. They also consider the probability of being in one of the four combinations of enrolled/employed, but find an increase in the proportion of students that are neither enrolled nor employed. This does not necessarily contradict Campolieti et al. - it is possible that the number of students unenrolled and employed decreases while the number of students unenrolled and unemployed increases, if students are unable to find work due to the higher minimum wages but don't return to school. However, this may also tell a different story - there were no significant decreases in other groups so we don't know with certainty where this increase came from. Neumark and Wascher use panel data at the state level to conduct their analysis, and again use a relative minimum wage. They attempt to control for potential labor trends that could skew this by including the "prime-age male unemployment rate", which may not be fully indicative of the actual unemployment rate. They exclude this control in an alternative specification, and there is no effect on the estimation. They also control for state-level variables that could affect enrollment, such as compulsory schooling laws and teacher salaries. The exclusion of these also does not significantly affect the coefficients. In general, several alternative specifications show that the results are robust to a variety of models. I follow a similar empirical strategy as Neumark and Wascher and Campolieti et al. in my analysis, considering the probability of being in a certain group. However, I use the minimum wage itself rather than an index.

In a different study entirely, Crofton, Anderson, and Rawe (2009) find that a higher minimum wage leads to higher dropout rates for Hispanic students, but find no significant effect for other groups. This study only looks at Maryland, however, so the results may not be externally valid. In addition, the authors collect their own data but do not give details of the process, so selection bias or other data collection errors are a concern and could bias estimates in either direction. More recent analysis using more reliable data would be helpful in determining the effects on the proportion of teens in these different groups. Furthermore, including labor force participation would provide a more nuanced estimate.

The minimum wage is not the only factor that determines whether or not students drop out. Push factors, forces that create an inhospitable academic environment, are also important. If things are worse in school, a higher minimum wage will be more tempting. Hence, push factors are important to consider when analyzing pull factors such as the minimum wage. There are three main models explaining push factors: the frustration self-esteem model (Finn 1989), the participation-identification model

(Finn 1989), and the social capital model (Stearns et al. 2007). These three models offer complementary rather than competing explanations, and all help explain the different factors that can push students out of school. The frustration self-esteem model describes how children who repeatedly do not do well in school begin to believe they will never be able to achieve success, discouraging them to the point of dropping out. There is evidence of this - Jimerson et al. (2002) showed that students who repeat a grade one or more times are significantly more likely to eventually drop out. These retained students may lose faith in their academic potential and decide they would be better off working. Similarly, the participation-identification model outlines how children who do not feel engaged with their education may lose interest and motivation until they leave school entirely. Mahoney et al. (1997) shows that the dropout rate among at-risk students was lower for students who had participated in extracurricular activities, which supports this. Finally, the social capital model (Stearns et al. 2007) conceptualizes academic relationships as a resource and argues that students with fewer connections are more likely to drop out. There are also push factors that don't fit neatly into these models. For example, higher graduation requirements can also cause students to drop out (Lillard et al. 2001; Warren et al. 2006), as fewer students will be able to meet a higher standard.

Different groups are affected heterogeneously by push factors. The most studied aspect of this is how students of different races are affected. It is well documented that dropout rates vary significantly by race (Crofton et al. 2009). Additionally, white and Latino retained students are more likely than Black retained students to drop out (Bankston and Zhou 2002; Pallas et al. 1990). Multiple studies find that white students are more likely to participate in extracurricular activities and benefit academically from this participation (Brown and Evans 2002; Davalos, Chavez, and Guardiola 1999; Eitle 2005; Eitle and Eitle 2002), which supports the participation-identification model. Finally, there are persistent differences with respect to academic social capital (Crosnoe, Johnson, and Elder 2004; Faircloth and Hamm 2005; McNeal 1999; Ream 2003; Valadez 2002; Yan and Lin 2005). For example, Latino students may not benefit as much from having teacher and parent based social capital (Ream 2003; Valadez 2002). Moreover, students of color face institutional racism as a push factor. All of this contributes to push factors and could influence the choice of whether to stay in school or not.

There is thus substantial debate over how an increase in the minimum wage affects high school enrollment. In order to understand more exactly what is happening, an analysis of more than just enrollment or dropout rates is needed. More specific estimates of effects can help uncover not just whether teens are leaving school but where they are going, and not just whether they are coming back but why. To this end, I will use the previously unexplored probability of being in one of the six previously defined groups (combinations of being in/not in the labor force, enrolled/unenrolled, and employed/unemployed) as my dependent variable. Since the minimum wage (and confounding variables) can vary at a substate level, I will be using counties as my unit of analysis to facilitate a finer analysis. I will also include controls that align with the participation-identification model, frustration self-esteem model, and social capital model, such as race and household characteristics. These strategies will allow me to contribute to the existing literature by examining the relationship between minimum wage and enrollment in a more detailed way on multiple levels.

3 Theory

3.1 Income and Substitution Effects

The simplest way to conceptualize the opposing effects of minimum wage on enrollment is by considering income and substitution effects. If the minimum wage increases, the opportunity cost of not working rises, so students may choose to work more hours. This is the substitution effect. However, if the minimum wage increases, they can work less and earn the same income, so they may choose to work fewer hours. This is the income effect. Either one may dominate, meaning that whether a student works more or fewer hours depends on the preferences of the individual student. If the income effect dominates, the number of hours spent on school increases. If the substitution effect dominates, then the number of hours spent on school decreases. If the change in the number of hours is significant enough, a student may switch from being enrolled to unenrolled and vice versa.

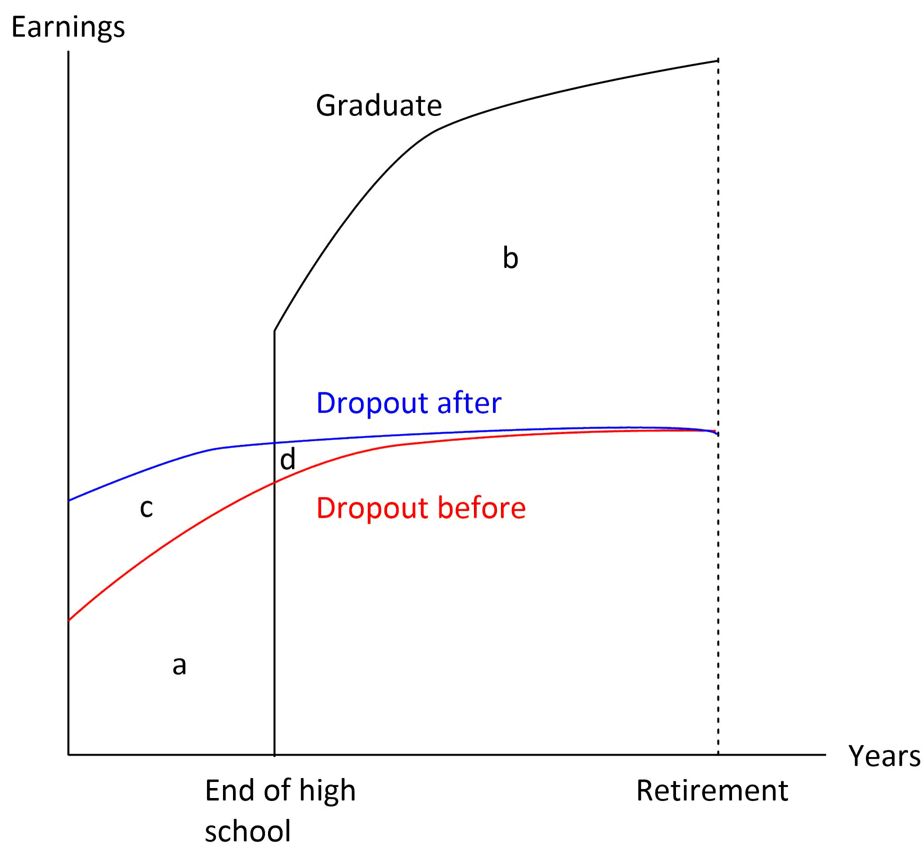
There are countless reasons why preferences would differ between students. Students who are struggling more financially, for example, might have a stronger substitution effect. It could also depend on whether the student prefers working or learning. Thus, increasing the minimum wage could either increase or decrease high school enrollment, depending on whether the income or substitution effect dominates overall for the students in question.

3.2 Human Capital Model

While income and substitution effects are helpful in understanding the choices facing students, this model says nothing about why students may choose one option or the other. It hinges on heterogeneous preferences, with no real explanation of how or why these preferences are different. The human capital model considers this more fully, as a two-period version of the income/substitution effects framework. The educational investment model is a part of the human capital model that pertains to educational attainment, traditionally modeling the differences between high school and college graduates. Figure 2 below shows the expected trajectory for high school graduates versus dropouts, before and after the minimum wage change.

This graph shows the possibility that while high school dropouts may have higher

Figure 2: High school graduates versus dropouts



earnings for a time while graduates accumulate costs, eventually graduates will surpass high school dropouts in earnings and make more overall. At the lower minimum wage, they have a cost a of staying in school and a benefit b. After the minimum wage increase, the costs of staying in school are higher: they now face a cost of $a + c$, but also an increased benefit $b + d$. This graph assumes a public school student whose only cost of school is their lost earnings, rather than a direct cost. It also assumes that the student who dropped out ends up at the same wage, as a higher starting wage will likely not last. This may not be the case - their trajectory may be constant, landing them at a higher end wage. However, the implications are the same regardless of which occurs.

Human capital accumulation can be modeled using net present value, the difference between the present value of benefits and the present value of costs, both direct and indirect. The present value is calculated by discounting future money. Almost everybody will have a positive discount rate - most people prefer instant gratification and the present value of income in the current moment declines the longer you have to wait for it. One possible explanation for differences in preferences is heterogeneity in discount rates - if two students value the future differently, they will plan for it differently. This could factor into the decision of whether or not to leave high school because of a higher minimum wage. If a student heavily discounts the future, preferring to maximize their current earnings, they may choose to leave school even though they will earn less overall. Somebody who discounts the future less may choose to wait, sacrificing current earnings for greater total earnings mostly received in the future. The human capital model thus predicts different responses based on discount rates for current versus future income.

3.3 Sorting and Signaling Model

Another model is the sorting and signaling model, which both competes with and is complementary to the human capital model, depending on the student. This model theorizes that although there is an inherent value to human capital accumulation, this may not be the primary goal of completing high school. Graduating sorts a student into a higher qualified group, and signals to employers that they should hire them. This model implies that when the minimum wage increases, if unemployment increases and thus there are fewer jobs available, teens will stay in school as a way to differentiate themselves and increase their probability of employment.

Thus, there are a variety of models that could be used to inform hypotheses about the response of teenagers to an increase in the minimum wage. An empirical framework is needed to explore this ambiguity further. Following the human capital model, different responses to a minimum wage increase could be attributed to heterogeneous discount rates. There is no one hypothesis generated by the human capital model. In contrast, the sorting and signaling model predicts that when the minimum wage increases, enrollment will increase and employment and/or participation in the labor force will decrease.

4 Empirical Strategy

The ideal way to explore the ambiguity in this question would be to randomly assign minimum wages to students and measure the effect on enrollment. Since this is neither practical nor ethical, an alternative is to study a city that has increased its minimum wage in comparison to a similar (ideally statistically identical) city that has not. The advantage of this method is a relatively reliable conclusion, as the difference between the treatment and control cities can be estimated before and after the wage change.

This quasi-experimental design has greater potential to determine the causal effects of the minimum wage on enrollment, allowing for more confident interpretation of coefficients. Numerous papers use this method to study how minimum wage increases affected employment in Seattle (Jardim et al. 2018; Reich et al. 2017; Jardim 2017), however these do not consider employment specifically of teens. This is because the data was taken from a dataset created from information used for unemployment insurance, which most teenagers do not have. Due to a lack of suitable data, an experimental approach was not feasible for this project. There was no data available for teen employment, as explained, or for enrollment either in areas that have recently had a significant minimum wage or reasonable control areas.

Instead, I use panel data for all 50 states from 2009-2017. I experiment with a variety of levels - county level data with county fixed effects, state level data with state fixed effects, and county level data with state fixed effects. These all have their own advantages and disadvantages. Using a county level gives me a finer unit of observation and more variation in enrollment and employment. In addition, the minimum wage occasionally varies at a substate level so there is additional variation there that a state level fails to account for. However, the majority of the variation in the minimum wage does occur at the state level, suggesting state fixed effects may be a better choice. A possible compromise would be to use county observations but state fixed effects. I run each of these specifications with year fixed effects in order to compare and contrast the results.

For each of these levels, I run multiple regressions modeling the probability of being in each of the six groups (each combination of enrolled/unenrolled and employed/unemployed/not in labor force). I use a binomial logistic regression, which takes the number of trials as the total number of students and the number of successes as the number of students in the designated group. This is helpful as the interpretation can be translated into the probability that an individual student will be in that specific group. In addition, it forces the probability to be between 0 and 1, which is good as it is impossible for the proportion of students in a group to be negative or greater than 1.

I will use both the real and nominal minimum wage as my independent variable, in separate specifications. I calculate the real wage using a regional consumer price index that varies by census level. This includes four sections: Northeast, Midwest, South, and West. This accounts for some of the regional differences in cost of living that the nominal minimum wage does not include.

I originally planned to use the seemingly unrelated regression strategy in my estimation, but could not in the end as it is impossible to run with a binomial logistic regression. This would have run separate regressions (in my case, one for each group) that are assumed to have correlated error terms (highly likely in my case). It then would have accounted for this correlation by specifying a covariance matrix for the error terms. I ran a specification with the dependent variable as a simple proportion of students in the group both with and without using seemingly unrelated regressions, and find no significant difference. Thus, I feel confident leaving it out of my final estimation strategy.

I also include various controls in my regression. When I use the state minimum wage and aggregate the response variable by state, I also use state-level controls. When I use the county minimum wage and the county response variable, I use county-level controls. I use the annual unemployment rate as a control, since it is likely that this will affect the decision for a student to drop out. If there is high unemployment in general, they may be less confident they can get a job once the minimum wage increases since that will further reduce jobs. As students make these decisions gradually and at different times, I use the annual average unemployment rate rather the rate in a particular month. I also control for the population of a county/state. This ensures that my results are not driven by changes in population. Additionally, I use race as a control because different racial groups may respond differently to minimum wage changes due to heterogeneous push factors [2]. Finally, I use the percentage of households receiving SNAP (Supplemental Nutrition Assistance Program, previously Food Stamps) benefits as a control. This is important to include, because it may make a large difference on an individual level. If a student receives SNAP benefits, they may be more likely to go to school and less likely to work as they have greater food security. As well, SNAP benefits may fall as the minimum wage increases, as the student or their family earns more and their benefits decrease as a result. Thus, ignoring this factor may bias the estimates of enrollment downwards. Including the state or county level rates accounts for some of this individual motivation. All of these control variables will improve my estimation by removing some of the omitted variable bias.

I will also be including time fixed effects, which should account for unobserved variables that are the same for every entity within a given year. These are national variables that change over time, such as frequently updated federal regulations. Year fixed effects will control for any macroeconomic condition that affects all counties.

Thus, each of my regressions will follow the basic form below, where P_{jit} is the probability of being in group j for an entity i and a year t, MW_{it} is the minimum wage in that county and year, α_i and β_t are the entity and year fixed effects (respectively), and X_{it} is a vector of controls.

$$log(\frac{P_{it}}{1-P_{it}}) = MW_{it} + \alpha_i + \beta_t + X_{it} + \epsilon_{it}$$

The entity will either be at the county level, state level, or a combination. The minimum wage will be either nominal or real. This creates a total of 6 models

[2] However, I do not have unemployment rates by race.

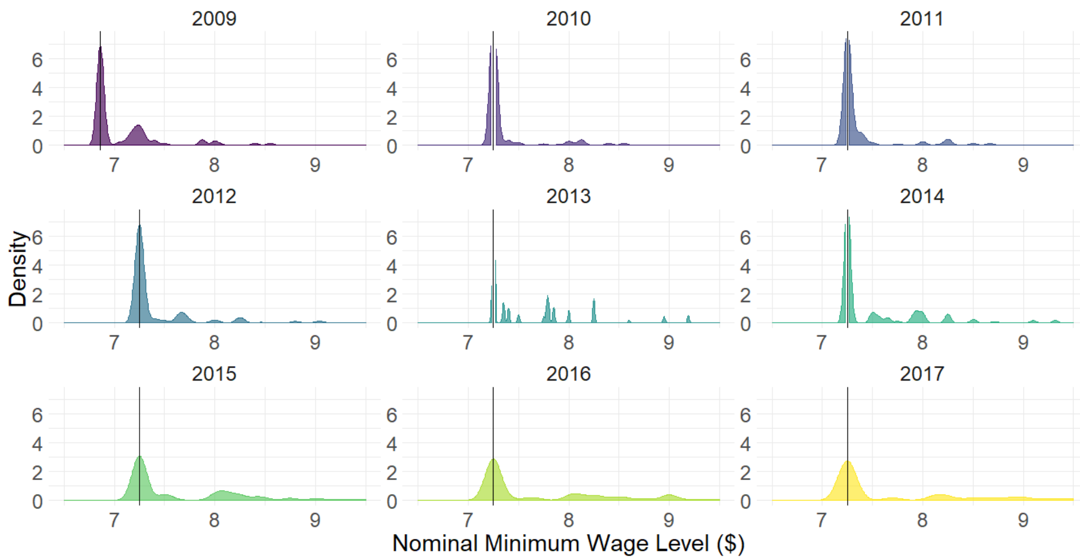
(one for each group) and 6 different specifications for each (entity and nominal/real combination).

5 Data Description

My data on the number of students in each group comes from the American Community Survey. This data is only available from 2009 to 2017 inclusive, which sets the years for my analysis. My data for the minimum wage at a sub-state levels comes from a 2016 paper by Vaghul and Zipperer, who compiled a list of all the sub-state minimum wages for each year. Their data is by city and by county - whichever the official level is. I transformed their data to be at only the county level by assigning the city minimum wage to the counties within that city, or to the county that contains the city. If both a city and the county containing it or multiple cities within a county had separate minimum wages, I choose the minimum wage that applies to the area with the highest population. Thus, the county wage would overrule the city wage. This will be a relatively accurate transformation, due to the spillover effects of minimum wage that reach beyond the official boundaries. I manually added the wage data for 2017, as their paper only goes up to 2016. In order to create a balanced panel, I remove counties who merge or split over the course of my time period. I also exclude Washington DC, as it is technically classified as an independent one-county state yet is within the borders of other counties and states. This creates overlap in the data, and DC is thus excluded. Finally, I do not include counties who have no students, or only male or only female students. This takes me from 3142 counties down to 3120.

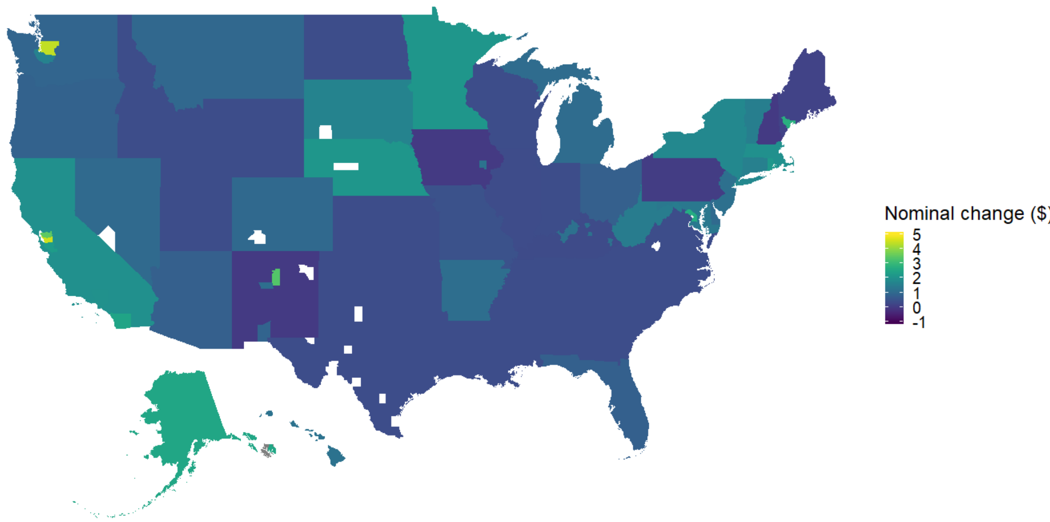
There are 107 distinct nominal minimum wages during the considered time period. The minimum nominal minimum wage during my time period is \$6.86, and the maximum nominal minimum wage is \$15. The mean is \$7.51. A density plot for each year is shown below in Figure 3; there are clear spikes at common minimum wages, especially the federal wage (represented by the vertical black line). As various localities increase their minimum wage above the federal level, the density curve flattens somewhat.

Figure 3: The density of minimum wages for each year



It is helpful to visualize the variation in the minimum wage at the county level. This is done below in Figure 4, where color represents the overall change in the nominal minimum wage between 2017 and 2009.

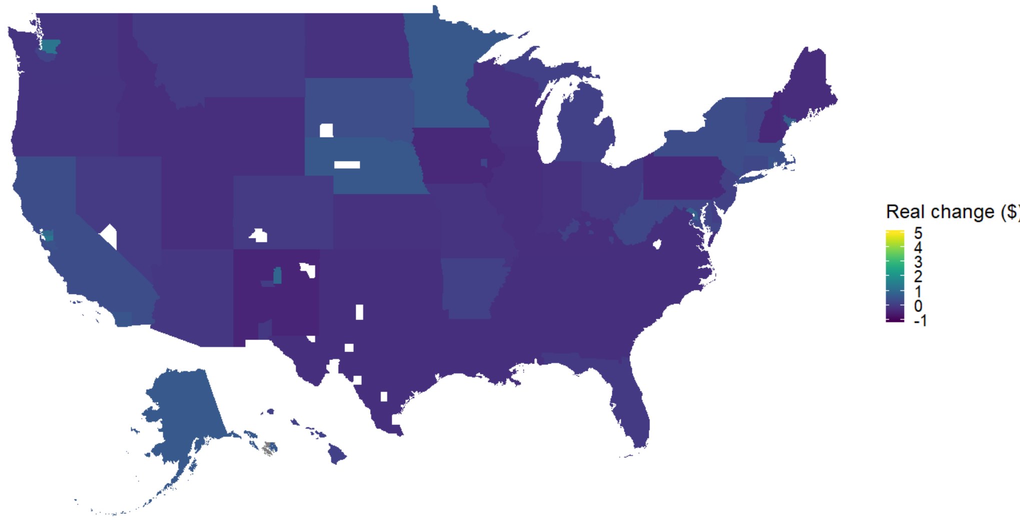
Figure 4: The change in nominal minimum wage by county



While much of the variation is on a state level (as expected), there is also a fair amount of county variation. In reality, the spillover effects of the county heterogeneity will be greater (as nearby counties may increase their wages to better compete), so this map understates the true variation in wage.

It is also helpful to visualize the real minimum wage, shown below in Figure 5.

Figure 5: The change in real minimum wage by county



There is less change in the real minimum wage over time. The majority of counties actually experience a small decrease in the real minimum wage. Much of the variation that exists is once again on a state level.

Let us now consider general enrollment and employment trends over time. First, Figure 6 below shows national enrollment compared to the total number of people aged 16-19. There is a slight increase (about 2 percent) in the proportion of students who are enrolled.

A similar story can be told for employment of teens 16-19 years old over this time period. Figure 7 below shows the national employment compared to the total student population, and although there is a slight decrease, once again the magnitude of the fall in proportion is small, about 6 percent. This fall is likely due to the Great Recession.

Figure 6: Proportion of teens 16-19 years who are enrolled

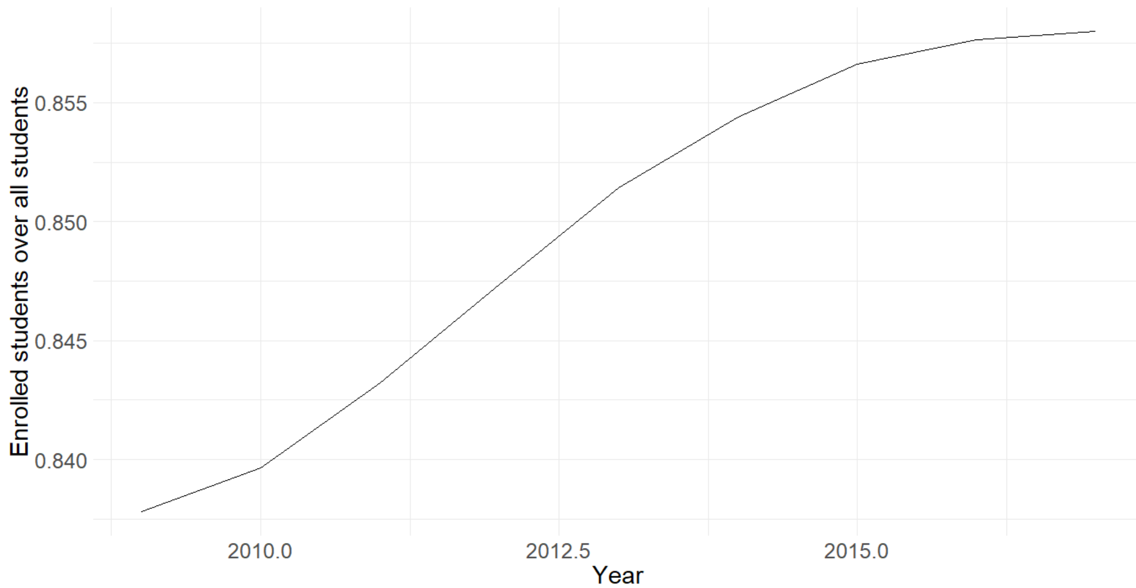
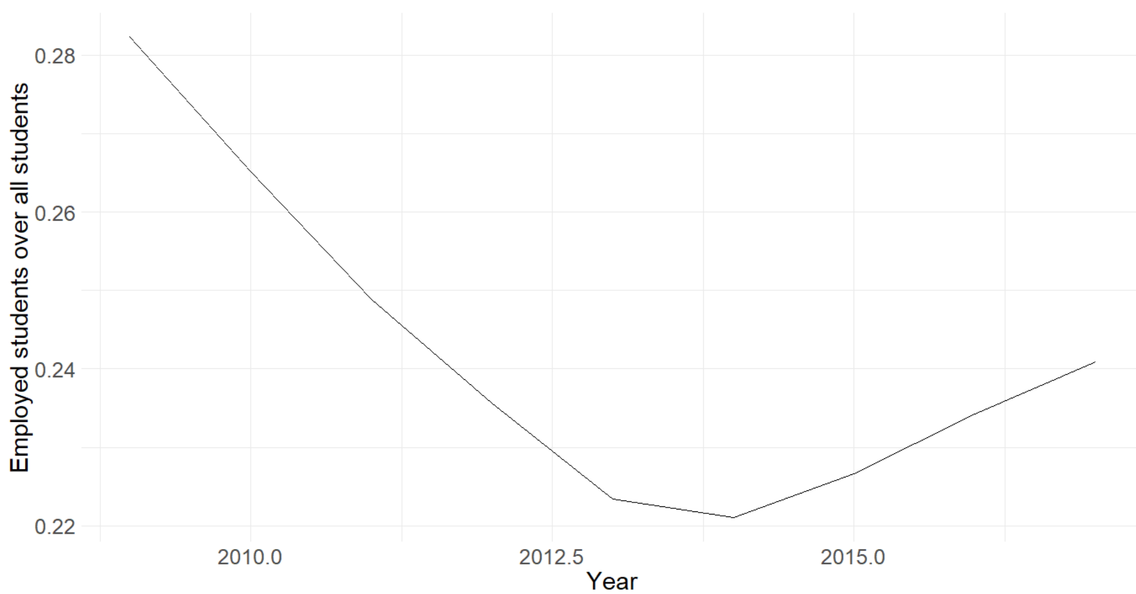
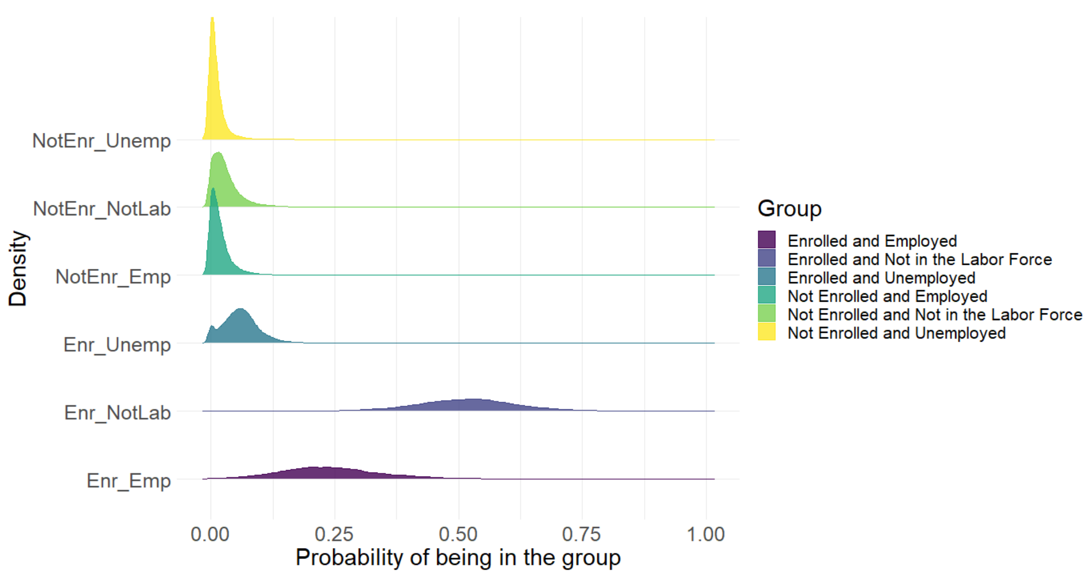


Figure 7: Proportion of teens 16-19 years who are employed



If we look now at the probability of being in each separate group (all combinations of enrolled/unenrolled and employed/unemployed/not in the labor force), we see that the minimum is 0 and the maximum is 1. This is true for males, females, and the aggregation of both. This means that for each of these distinctions, there is at least one county somewhere that has no students in one group and at least one that has all students in one group. If we consider instead the actual levels (number of students in each group) rather than probabilities, the minimum is 0 (as explained before) and the maximum is 203,556. The mean number of students in a group is 421 for males and 408 for females. The density of the probability of being in each group is shown below in Figure 8.

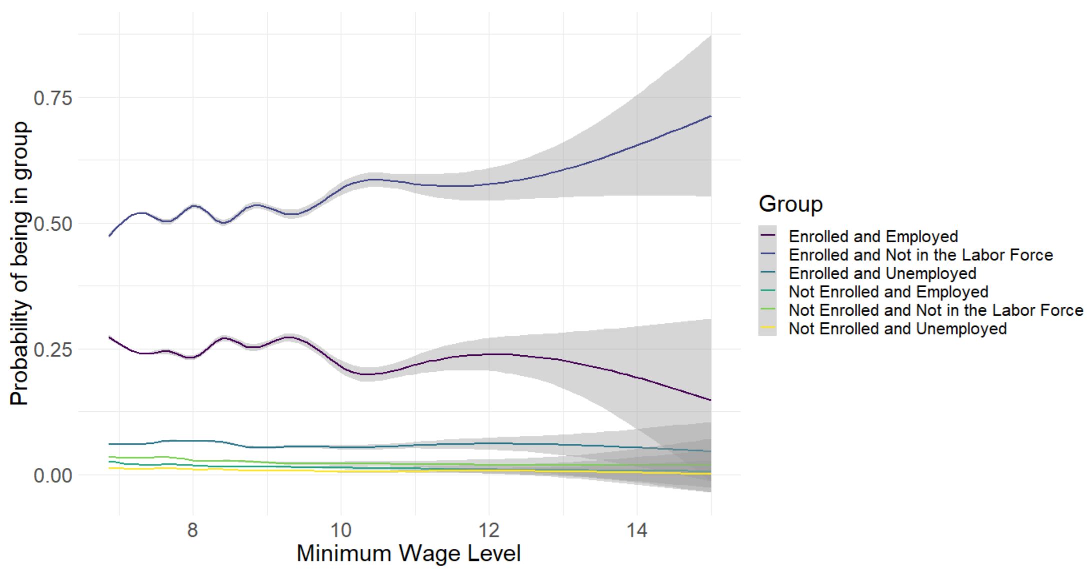
Figure 8: Density of the probability of being in each group, aggregated



We can see from this that being both enrolled and employed or enrolled and not in the labor force are the most common groups, while being not enrolled and unemployed or not enrolled and employed are the least common, and that students are generally enrolled.

We can also see this below in Figure 9 of the probability of being in each group as the minimum wage changes. The lines represent the smoothed conditional mean, while the gray outline shows the confidence interval. This plot appears to show that the probability of being enrolled and not in the labor force increases to a small extent with the minimum wage, while the probability of being enrolled and employed decreases to a small extent. We may thus expect this to be reflected in the coefficients of the estimate. However, the proportions are relatively stable, suggesting that any significant coefficients will likely be small.

Figure 9: Probability versus minimum wage



6 Results

As outlined in my empirical strategy, I ran 6 specifications of each group model; a total of 36 regressions. I used binomial logistic regression, which means that each of the coefficients represented the average increase in the log odds of being in that group when the minimum wage increases by one dollar. The transformation between probability and odds is a monotonic transformation, meaning as the odds increase the probability increases and vice versa. Thus, we can interpret the sign and significance of our coefficients relatively simply as the extensive change in probabilities (whether they increase or decrease, but not by how much).

The results are shown in Tables 1 and 2 at the end of the paper for each of the six specifications (real and nominal wage for each of county observations with state fixed effects, state observations with state fixed effects, and county observations with county fixed effects). Table 1 shows the raw coefficients, while Table 2 shows the exponentiated coefficients. Coefficients for the controls in each specification are not listed. Out of 36 total, 32 coefficients are significant at the 1% level, one is significant at just the 5% level, and three are not significant.

The results are mostly robust to the different choices of county vs state observations/fixed effects. For each specification, the coefficients on enrolled and employed, enrolled and unemployed, enrolled and not in the labor force, and unenrolled and unemployed have the same sign. However, the coefficient on unenrolled and employed is equally split between positive and negative, with no clear pattern. The coefficient on unenrolled and not in the labor force is positive for the first five specifications, but is negative when county fixed effects are used with the real minimum wage.

The choice of nominal or real minimum wage does not seem to affect the sign of the coefficient - there are only two differences out of all 18 pairs of results. However, the coefficient for the nominal wage is almost always smaller than the coefficient for the real wage.

The coefficient on enrolled and employed is positive across all specifications. Similarly, the coefficients on enrolled and unemployed/not in the labor force and the coefficient on unenrolled and unemployed are all negative across specifications. As noted previously, the coefficient on unenrolled and employed and the coefficient on unenrolled and not in the labor force are both sensitive to the specification.

These results imply a situation where some teens who were previously not working but enrolled are willing and able to find a job after the minimum wage increase. Similarly, some students who were not working and out of school are able to both get a job and go back to school when the minimum wage becomes higher.

In addition, the state fixed effects specifications suggest the number of teens who are neither in the labor force nor in school rises, while the county fixed effects specifications suggest that this number falls. A positive coefficient weakens the earlier optimistic interpretation, implying that some of the students who were previously enrolled and unemployed/not in the labor force or unenrolled and unemployed became totally disillusioned. Maybe they dropped out of school to pursue a full-time job and then became so discouraged by continued unemployment that they stopped looking without returning to school. A negative coefficient implies the opposite, that teens are moving from this group to another. Perhaps now it is more worthwhile for them to work a formal job rather than supporting their family with informal labor, such as providing childcare for a sibling. County fixed effects account for all variables that are the same within a county over time. As state fixed effects are mostly a subset of this group (something that is the same within a state over time is the same within a county over time), the county fixed effects results are more reliable.

The coefficient on unenrolled and employed also differs depending on the specification. A positive coefficient may mean that students are dropping out of school to pursue greater employment and are succeeding in their endeavor. It may also mean that students who were previously unenrolled but not working now have a job. A negative coefficient implies the opposite: students who were not in school but working are either now in school, no longer working, or both. The coefficient is negative when county fixed effects are used, or when the nominal minimum wage is used for county observations with state fixed effects. As before, we lean towards the county fixed effects coefficient as there is less omitted variable bias.

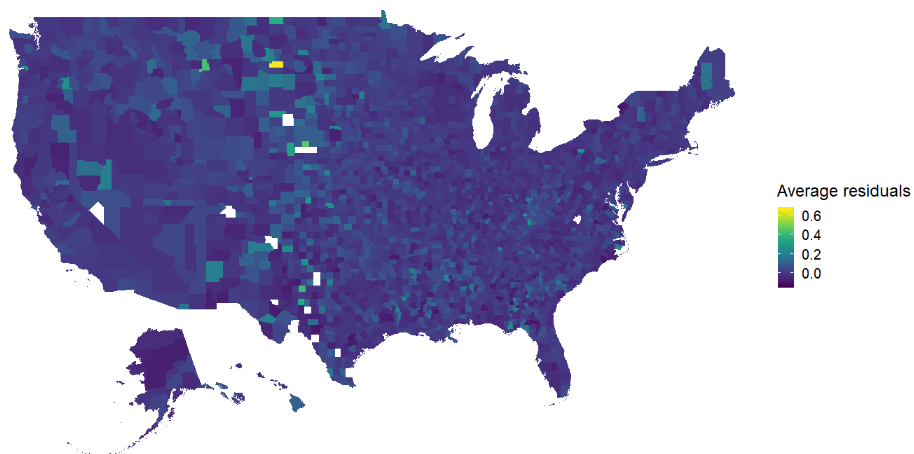
All of these results together tells a fairly positive story. The coefficient on every group except enrolled and employed is negative, and the coefficient on enrolled and employed is positive. Thus, while of course some students will switch between any two given groups, overall students are both working more and going to school more. Students who are enrolled and unemployed or not in the labor force may be getting a job while staying in school. Students who are unenrolled and employed may return to school, as they can now work fewer hours with the same income and thus have more time for school. Students who are unenrolled and not working also return to school, perhaps because they now wish to increase their human capital and/or signal to employers that they are more qualified in hopes of getting a higher-paying job later. On the surface, these results may encourage increasing the minimum wage as the number of students in potentially the most desirable group increases. However, there is no restriction that the total change must be 0, and thus overall employment may fall and enrollment may fall if the negative coefficients outweigh the positive.

These results are fairly robust to the different specifications, but are somewhat sensitive to changes in controls. For example, removing the control for population frequently makes the coefficient for enrolled and employed negative rather than positive. In a similar way, removing other controls one at a time will occasionally flip the sign of a coefficient in one of the specifications. The magnitude of coefficients will also change, sometimes as much as 30 standard errors from the original coefficient. As the coefficients and their standard errors are very small, this is not a huge practical change in the coefficient, but is still statistically substantial.

My process is fairly effective at predicting the proportion of students in each group.

I calculated the predicted probability of being in each group in each county and year, and then subtracted the actual proportion of students in that group in the county. I then found the average of these residuals for each county, with each group residual weighted by the total number of students in each group. The results are plotted in Figure 10 below. For the majority of counties, the average residuals are fairly low, and there is limited geographic variation apart from a few obvious outliers. These outliers have very few students arranged in a way that the model does not predict. Of course, the residuals vary by group model and specification - this is an example map with an overall view. A complete view would involve 36 different maps, one for each regression. However, they are relatively similar and this map provides a good approximation to evaluate the model with.

Figure 10: Average residuals by county



What do these numbers mean in a more practical sense? As noted before, the coefficients reported in Table 1 can be interpreted as the expected change in log odds from a one dollar increase in the minimum wage. The exponentiated coefficients in Table 2, e^{coef}, represents the expected change in the odds ratio from a one dollar increase in the minimum wage. For example, if the coefficient on minimum wage were 0.693, then the expected change in the odds ratio would be $e^{0.693}$, or approximately 2. This represents a doubling of the odds (which does not mean it is twice as likely to happen). The largest coefficient is -0.179, which corresponds to a $e^{-0.179} = 0.836$ change in the odds ratio, or a reduction of the odds ratio to about 83% of its previous value. Similarly, the coefficient of 0.145 corresponds to a change in the odds ratio by a factor of about 1.16. A coefficient of approximately zero would represent no change in the odds ratio, as $e^0 = 1$. As many of the coefficients in these results lie along these lines, there is no practical interpretation for much of the results. Although there may be a statistically significant change, there is no substantial change.

We can also convert these coefficients to probabilities for given values of each variable. As an example, let us take the median county by teen population size, which is Stephens County (Georgia) in 2016. Using specification 6, county fixed effects and the real minimum wage, the predicted probability of a student being both enrolled and employed is 0.208. If we now keep all other variables constant (at their actual level for Stephens County in 2016), but increase the real minimum wage by 1 dollar, then the new predicted probability is 0.229. This is a change of 0.021. Thus, in the median county, an increase in the real minimum wage of 1 dollar would theoretically increase the probability of a teen being enrolled and employed by 2.1%. As there are 1404 teens in 2011, this corresponds to roughly 30 teens. The predicted number of teens who are enrolled and unemployed decreases by about 4, the predicted number of teens who are enrolled and not in the labor force decreases by about 26, and the predicted number of teens in other groups decreases by less than 1. If we use instead an observation with a number of teens almost exactly equal to the mean number of teens, (Nacogdoches County, Texas in 2016) then the predicted change in the number of teens in each group is about 96 for enrolled/employed, -19 for enrolled/unemployed, -95 for enrolled/not in labor force, -2 for not enrolled/employed, 0 for not enrolled/unemployed, and -2 for not enrolled/not in labor force. For both the mean and median county by population of teens, the changes are not very practically significant. For many counties, there is no change at all in the number of students in each group. Even for Los Angeles County in 2011, the observation with the most teenagers, there is a change of less than 1 for the group of students that are unenrolled and unemployed, and the changes for unenrolled/employed and unenrolled/not in the labor force are both less than 2. Thus, although these results are statistically significant, they are not practically significant for the majority of counties at the level of common minimum wage increases, which are often less than a dollar (especially in real terms).

7 Gender Considerations

So far, only aggregate groups of students have been considered. It is possible, however, that boys and girls have different responses to an increase in the minimum wage. This is previously unexplored, so I expand my research to consider this possibility. In this section, I explore the theory and then repeat my empirical analysis separately for boys and girls in order to compare them.

Considering the role of gender in the human capital model, it is possible that women may discount the future more. For example, women may anticipate shorter, more disrupted work lives than men (Rosburg 2010). Discontinuous workers of this kind experience lower returns on investment (Rosburg 2010), which could discourage women from investing as much. There are other reasons women may choose to invest less in their human capital. Women with lower expected future labor force participation may choose lower-skill jobs (Rosburg 2010). Societal discrimination can also cause differences: students facing discrimination will have less incentive to invest in their human capital and may be more likely to drop out (Rosburg 2010). However, it is also possible that women value human capital investment more, on average. This would be reflected in higher dropout rates for boys than girls, which is in fact what we see (ChildTrends). If women discount the future more, they may be more likely to drop out when the minimum wage increases. If women value human capital investment more, they may be less likely to drop out when the minimum wage increases.

Using the sorting/signaling model instead, it is possible that women will be less likely to sort themselves into the higher category. If, as before, they perceive greater barriers to employment than their male counterparts they may not try as hard to get a job. However, they may also be more motivated to reach a higher standard because of these obstacles and thus stay in school more than boys. Finally, there may be family-level variables that cause girls to drop out of school - higher expectations for taking care of siblings or unsupported adolescent parenting, for example. Thus, the predictions for the differences between girls and boys are ambiguous - the theory doesn't point to one clear direction or even that there will be a difference.

We can see from the plots below that the latter is likely. There is no obvious difference between the two relationships that we might expect to see reflected in the estimations.

When the regressions are run, we see that this is mostly the case. The results are shown in Tables 3 and 4 for boys and Tables 5 and 6 for girls. There is no substantial difference in how the minimum wage affects boys and girls when it comes to the probability of being in one of these six groups. In fact, with the exception of the last two groups (unenrolled and either unemployed or not in the labor force), each regression has the same implication as those in the aggregate results. The sign and significance of the coefficients is the same, again with the exceptions of the last two groups. The coefficients are not persistently larger for either group compared the the other.

For the aggregate group of students and only males, the coefficient on being unenrolled and unemployed is always negative. For females, however, it is always positive and

Figure 11: Trends of probability versus minimum wage, for males

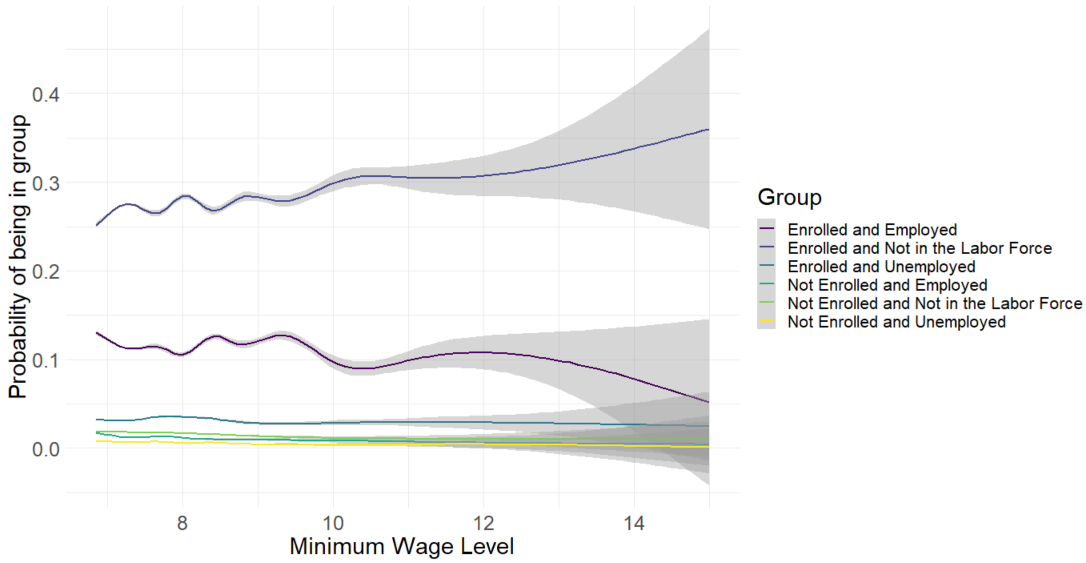
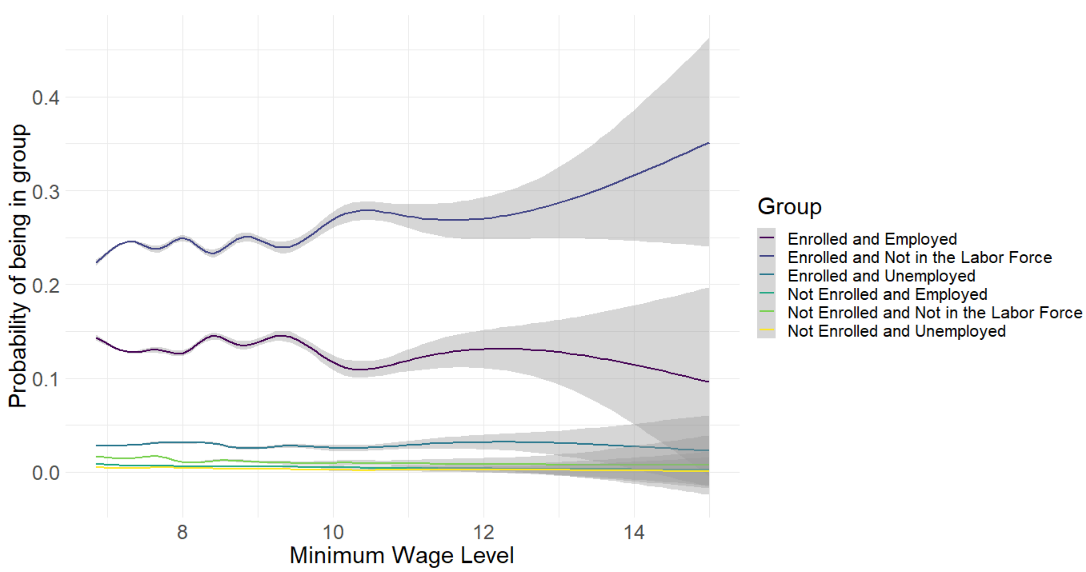


Figure 12: Trends of probability versus minimum wage, for females



is not significant for one of the specifications. This implies that girls are more likely to switch into the unenrolled/unemployed category than boys are. This could be due to labor market discrimination - perhaps it is harder for high school girls to get a job if employers are now being more selective due to higher wages. For the group of students who are unenrolled and not in the labor force, the coefficients for only females mostly align with the aggregate coefficients. The coefficients for males, however, do not. Their state level specifications have negative coefficients rather than positive, and one of them is not significant. This implies that boys are somewhat less likely than girls to switch into this category. This makes sense, as girls often have more demands on their time for informal labor such as childcare (not counted as being in the labor force by the American Community Survey).

8 Conclusion

My results on the effect of a minimum wage increase on the probability of being in one of six enrollment/employment groups are somewhat ambiguous, as there is no certain interpretation (switches between groups are implied by overall results, and may not be accurate) and my results vary by specification. Overall, however, I find statistically significant results that are not practically substantial. Some of my results support the previous literature, while others appear to contradict common findings.

For the specifications with county fixed effects and the specification with county observations, state fixed effects, and the nominal minimum wage I find that the probability of being unenrolled and employed decreases, as Campolieti et al. do. However, all other specifications show an increase in this probability. As I trust the county fixed effects specifications above the others, my findings adhere to those of Campolieti et al. In direct opposition to Neumark and Wascher, I find that the probability of being unenrolled and unemployed decreases unambiguously for males and for the aggregated groups. My results for females differ for some of the specifications, matching their results. The main findings of the two papers most similar to mine deal only with the groups where I find ambiguous results, and as such it is hard to determine whether my results confirm or contradict theirs. Although sign and significance are ambiguous, in any case the coefficients are not practically significant either way. The change of positive to negative generally comes down to whether a group gains a few students or loses a couple. This does unambiguously contrast with these papers, who find more substantial results. In addition, I also find statistically significant changes in the probability of being in other groups, which they do not.

There are multiple explanations for these differences, which coordinate rather than compete with each other. Most glaringly is the fact that neither of these papers uses the actual minimum wage. Instead, they use an index that is scaled by the average wage during a given year. As discussed in the literature review, this may skew their results in either direction. At any rate, their independent variable is fairly different than mine, which could easily create differences in results. When my minimum wage increases (both real and nominal), it is possible that their minimum wage also increases. If the average wage falls as a result (for example because of disemployment effects), or if the minimum wage was increased precisely as a result of falling average wages, then their index may increase more than the actual minimum wage. If, however, the average wage rises when the minimum wage rises (obviously possible, as many people are now earning more), then their index may increase less than the actual minimum wage. This may vary by region, causing very different variation in the minimum wage than I use, for both real and nominal. Furthermore, both of the papers are from a while ago and one of them is from another country. It is entirely possible that their results simply are not externally valid to the context I explore in my research. Similarly, none of the earlier papers consider the same six groups that I do. I find that the inclusion of labor force participation was helpful, as the direction of results for unemployed vs not in the labor force was occasionally different. Not including this nuance would pull your estimate in two directions, potentially erasing any significance. This is another possible reason for the differing results I find.

In addition, the inclusion of gender is previously unexplored. I run my analysis separately for boys, girls, and the aggregate in order to compare relationships. My findings do not vary substantially by gender - boys and girls react similarly to a change in the minimum wage.

My research has limitations that must be discussed. Most glaringly, there is omitted variable bias present. The factors that cause a student to be in one of these groups are, as we saw in the literature, hugely varied and dependent on each individual. Many of them are outside the student's control, and most of them are unobservable characteristics such as internal motivation. As I use only county level data, my analysis cannot account for these important factors. They may affect my estimation if they are correlated with the overall response to the minimum wage. In addition, I do not know who transferred groups, which would be instrumental in drawing conclusions about the effect of a minimum wage. Individual level data would be ideal for this topic, while I only have aggregate numbers with no idea about who makes them up. Another limitation is that my state and year fixed effects cannot account for important variables such as local labor laws that may in fact prohibit many students from entering the group they would otherwise like to be in, or misreport their status if they are working under the table. Moreover, misreporting is a serious concern in any case, as my data for the dependent variable comes solely from surveys, which are likely to be inaccurate in some way.

Overall, however, my findings reasonably fill a gap in the literature. I show that the effects on enrollment and employment of teenagers is similar for real and nominal increases. I explore the gender aspect and find that there is no clear difference. My findings about the changes in the probability of being in each group contribute to the understanding of how students react to a change in the minimum wage in a variety of relevant ways, most significantly that students do move into the group that is both enrolled and employed, but the change is not substantial. Potential future work could involve accounting for the correlation between the errors of the group models, which may further inform the conclusions of this research.

Acknowledgements

A huge thanks to my advisor Professor Sarah West, who put an incredible amount of time and energy into working on this project with me. I also want to thank my official readers Provost Karine Moe and Professor Lisa Lendway, who guided me along the way and dedicated their talents to this project as well. Finally, I'd like to thank the members of Macalester Economics Honors Seminar 2020 and Professor Amy Damon for all the tough love, feedback, and support!

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