Minimum Wage Policy and Community College Enrollment Patterns

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Abstract: In this paper, I study the effect of the minimum wage on community college enrollment using cross-border variation in state minimum wages. To address spatial correlation in local labor market conditions, I pair schools on either side of each state border based on geographic proximity using the Integrated Postsecondary Education Data System. Comparing paired schools, I find a substantial reduction in enrollment at community colleges in an area where there is a higher minimum wage. This effect is only observed among part-time students. This suggests that the minimum wage primarily affects students at the margin between work and postsecondary education.

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On January 1, 2018, 18 states, as well as numerous cities and counties, raised their minimum wage. How the minimum wage affects the labor market, and whether it is beneficial to those it aims to help remain important questions. Many economists have studied how the minimum wage affects employment and wages. However, exclusive focus on the labor market will not provide the full picture of how the economy responds to minimum wage increases, if school attendance also responds. Existing studies have examined how the minimum wage affects high school completion, but its impact on older individuals is not as well understood. When the minimum wage increases, individuals may choose to forgo the returns to education realized later in life in favor of additional work experience and the immediate increase in their earnings. On the other hand, slack labor market conditions after a minimum wage increase may lead to unemployment. In this case, college enrollment can increase an individual's human capital and, in turn, their labor market opportunities. It is therefore an empirical question how minimum wages affect postsecondary enrollment.

In this paper, I study how a change in the minimum wage policy at the state or federal level affects community college enrollment in the US between 1990 and 2010. Community colleges are public two-year institutions that offer a wide range of programs at a low cost to any individual with a high school degree or GED. These factors make community colleges a natural choice for postsecondary education among individuals who find enrollment at four-year institutions either too costly or incompatible with their intended career path. According to a report by National Student Clearinghouse Research Center on attainment rates of the students entering college in Fall 2010, however, the majority of community college students do not complete a degree or certificate. This suggests that many potential community college students are not heavily invested in pursuing education, and their enrollment decision may change based on the attractiveness and availability of alternatives such as full-time employment.

Understanding how the minimum wage affects enrollment is important because a minimum wage increase has the potential to reduce community college enrollment. As the existing evidence suggests that community college graduates earn higher wages, reduced enrollment increases the number of workers in the lower tail of the wage distribution. This unintended consequence of a minimum wage increase counteracts efforts to increase postsecondary enrollment and reduces the skill level of many workers. It also has the potential to work against recent efforts to provide free community college education for low income groups.

My identification strategy takes advantage of labor markets with multiple minimum wage setting authorities across administrative boundaries. In these cases, the effect of a minimum wage increase affecting one side of the boundary, but not the other, can be estimated by comparing the changes in the enrollment decisions of individuals facing a different minimum wage policy based on their state of residence. The identifying assumption is that these individuals subject to different minimum wages are otherwise exposed to the same set of shocks affecting the enrollment decision. To emulate this experiment, I pair colleges located near state borders by geographic distance and assess whether different minimum wage policies in neighboring states cause a divergence in the patterns of enrollments at two colleges in each pair.

This paper makes several contributions to the literature. First, it expands the literature on how the labor market factors affect community college enrollment patterns, taking a labor market relevant policy as the source of a quasi-experimental variation. As a state-level public policy, the minimum wage is less likely to be correlated with other local labor market conditions that may also determine the enrollment patterns. Second, this paper extends the literature studying the minimum wage's role in determining educational attainment. While there is some research looking at high school completion and teenagers' attachment to school, this is the first paper to focus on postsecondary institutions. Finally, the paper utilizes the geographic discontinuity in the implementation of minimum wage policies to generate credible comparison groups. This method allows me to account for shocks shared by two communities in a common labor market. While similar analytical methods have been used in other settings, this paper brings the method to a new setting where the time-varying characteristics of each locality may be important in determining the enrollment patterns.

1 How can the minimum wage affect the enrollment?

The state and federal minimum wages in the US have increased substantially during the last three decades. A minimum wage increase raises wages paid to the workers with the lowest skill level, and it is generally used as a way to ensure living wage for all workers. According to the relevant literature in economics, however, a change in the minimum wage policy affects not only wages but also other labor market characteristics, such as unemployment and work hours. Community college enrollment may respond differently to an increase in wages as it does to a reduction in employment. So it is impossible to hypothesize how enrollment shifts in response to a minimum wage increase without considering all of these primary effects separately.

The literature is in agreement that wage levels increase for workers in the bottom of the distribution when the minimum wage increases (Neumark, Schweitzer, and Wascher, 2004; Sabia, 2009; Allegretto, Dube, and Reich, 2011). Neumark, Schweitzer, and Wascher (2004) suggests that a minimum wage increase affects the wage rates of the individuals earning up to 150 percent of the minimum wage. While there are substantial benefits from community college education (Kane and Rouse, 1995 and 1999; Belfield and Bailey, 2011; Jepsen, Troske, and Coomes, 2014; Grosz, 2017;

Stevens, Kurlander, and Grosz, 2018), a minimum wage increase offers a non-negligible earnings increase and provides additional work experience.[2] This implies that the individuals considering enrollment at a community college may respond to a minimum wage increase with greater effort in the labor market.[3]

The employment effect of a minimum wage increase may reduce community college enrollment as well. The literature on this topic remains contentious. Some papers (Card and Krueger, 1994; Dube, Lester, and Reich, 2010; Addison, Blackburn, and Cotti, 2012) find no evidence of employment loss while others find a reduction in local employment levels (Neumark, Schweitzer, and Wascher, 2004; Sabia, 2009; Neumark, Salas, and Wascher, 2014; Meer and West, 2015; Lordan and Neumark, 2017; Jardim et al., 2017) or work hours (Sabia, 2009).[4] Although many community college students receive financial aid from federal need-based programs such as the Pell Grant, they are much less likely to receive work-study or state-funded scholarships compared to their peers at four-year institutions. This leaves approximately 80 percent of community college students with unmet needs after financial aid compared to 54 percent at the four-year institutions (Institute for College Access and Success, 2009). Individuals losing employment due to a minimum wage increase are subject to a substantial reduction in income, which renders community colleges less affordable for them.[5]

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[2] Kane and Rouse (1995) estimate between 4 and 7 percent increase in earnings from each year at a community college. Jepsen, Troske, and Coomes (2014) find a 20 percent increase in earnings from community college degree for men and a nearly 50 percent increase for women. Grosz (2017) and Stevens, Kurlander, and Grosz (2018) find substantial earnings increase from nursing program and career technical education at community colleges.
[3] Related to the findings here, wage compression in Sweden during the 1970s substantially reduced university enrollment rates, which shows that individuals respond to relative returns by the level of education (Edin and Holmlund, 1995).
[4] Aaronson et al. (2018) suggest that the employment loss is driven by the replacement of labor intensive workplace by capital intensive workplace over time.
[5] Brock and Richburg-Hayes (2006) find that randomly distributing scholarships to part-time community college students increase their likelihood of returning to school in subsequent semesters. Financial assistance appears to increase school attachment.

Community college enrollment can decrease even if the overall level of employment remains unchanged. This can occur if employers replace less-qualified workers, such as teenagers and high school dropouts, with more skilled workers. Neumark and Wascher (1995a, 1995b) suggest this may explain the lack of the employment effect in some studies. Relying on the unemployment effect of the minimum wage to explain the fluctuations in community college enrollments is therefore insufficient when there are compositional changes in the labor force. Additionally, the perceived threat of dismissal may encourage workers to reduce their investment in education to focus on work.

The discussion so far suggests that a minimum wage increase reduces enrollment, but these labor market channels between the minimum wage and community college enrollment may lead to an increase in enrollment as well. For example, individuals, who face higher hourly wages due to a minimum wage increase, can maintain their previous level of income even if they work less. They can invest these extra hours on education to obtain additional skills.

An increase in the local unemployment rate due to a minimum wage increase may encourage students to enroll at community colleges as well. Betts and MacFarland (1995) and Boffy-Ramirez (2017) show that college enrollment rates increase under slack labor market conditions. Ost, Pan, and Webber (2016) and Foote and Grosz (2017) find an increase in the college enrollment rate as a result of mass layoffs. Losing an opportunity to work may be especially salient among recent high school graduates or those displaced from their previous job. These individuals may opt to improve their labor market prospects by attending community colleges before looking for work.

Previous literature on the minimum wage's effect on educational attainment studied high school completion (Chaplin, Turner, and Pape, 2003) and teenagers' work and school enrollment decisions (Neumark and Wascher, 1995a, 1995b, and 2003). Although Baker (2005) included young adults in their early 20s, they did not limit their sample to individuals with high school degree and above. The findings of previous research may not carry over to the study of how the minimum wage affects postsecondary enrollment patterns, because high school students and community college students may react to a minimum wage increase differently as the findings of Neumark and Wascher (1995a and 1995b) imply. Consequently, empirical evidence focused on postsecondary enrollment is needed.

The literature suggests that there are reasons to predict both a positive and negative enrollment shock as a result of changing labor market conditions, and the direction of the effect remains uncertain without empirical evidence. The subsequent sections discuss the relationship between a minimum wage increase and community college enrollment patterns using a school-level dataset.

2 Data

2.1 School-level Variables

The paper relies on school-level observations in enrollment counts to identify the relationship between enrollment and the minimum wage. All school-level variables come from the Integrated Postsecondary Education Data System (IPEDS), an administrative dataset provided by the National Center for Education Statistics (NCES), a unit within the US Department of Education. The IPEDS contains the universe of postsecondary institutions in the US participating in any federal financial aid program, and the 21 years of the data from 1990 to 2010 are used in the analysis.

The data is restricted to two-year public institutions (community colleges) with positive full-time and part-time enrollments in the fall semester of 2010. Private two-year institutions are excluded for two reasons. First, the estimates can be biased if students at private institutions are more likely to live and study in different states. This is a concern because the main deterrent to this behavior at a community college is the difference in tuition paid by in-state and out-of-state students. The private institutions, on the other hand, generally charge a single tuition regardless of the student's residency. Second, school-level variables reported by private two-year institutions are often incomplete. For instance, the cost of attendance is missing in nearly half of the observations for private two-year institutions.

Community colleges are observed yearly in the IPEDS, and enrollment is measured in the fall semester. The schools also report in-district and out-of-state fees and tuitions, demographic composition of the student body, and geographic location.[6] In-district tuition applies to students residing within the community college district to which each college belongs. Out-of-district-in-state and in-district tuitions differ in many, but not all, colleges. In the analysis, in-district tuition is used as the relevant monetary cost of education for in-state students living near the school.

2.2 Minimum Wage

The minimum wage that students see when they finalize their enrollment decision is necessary for capturing the relationship between a minimum wage increase and community college enrollment. While it is impossible to know when individuals make the decision in the data, community colleges set a strict deadline for dropping classes with a full refund. This date generally falls in August or September. To align the minimum wage with this date, the minimum wages measured on September 1 are used in the analysis. It is possible that most students make their

[6] Additional variables, such as revenues and expenses by source, are omitted from the analysis because they are missing for many schools before 1994 and between 2001 and 2002.

decision when the enrollment window opens. The relevant date, in this case, falls between May and July. This behavior, however, is unlikely to be an issue as using the minimum wages measured on June 1 yields similar results.[7] The data on the minimum wage is collected from various sources such as the websites of the state governments and the media.[8]

2.3 Additional Variables

Accounting for the population size is essential because enrollment patterns likely mirror the changes in the size of the population most likely to attend community colleges.[9] For the analysis, the data published by the Centers for Disease Control, containing yearly county-level population counts by age, gender, and race, is used. In particular, the share of Hispanic, Black, Asian, and Native Americans in each county as well as the gender composition control for demographic differences between counties. In addition, the logged population counts of those aged 15 to 29 are used to account for any changes in the number of individuals eligible to attend community colleges in each county. The restriction on age ensures that the variable is representative of the subset of the population most likely to attend community colleges.[10] These county-level population estimates are then assigned by geographic location to each school.

As changes to the minimum wage are mostly introduced at the state or federal level during this period, the relationship between minimum wages and enrollments may be confounded by various

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[7] The results are available on request.

[8] This dataset is verified by the historical minimum wage data made publicly available by Vaghul and Zipperer (2016) for consistency.

[9] Given the findings of Neumark and Nizalova (2007), population size is a bad control if minimum wage causes migration. Omitting population from the econometric specification, however, does not change the results. Therefore, the effect of migration as a channel between minimum wage and enrollment appears to be minimal.

[10] According to the College Board's Trends in Community Colleges Research Brief, those aged below 30 account for 72 percent of the students enrolled at community colleges in the US (Ma and Baum, 2016).

time-varying state-level characteristics. This is especially problematic if other policies affecting enrollment are introduced as the minimum wage is increased. This may occur if the party affiliation of elected officials is correlated with the willingness to raise the minimum wage. For example, a state with higher minimum wage may simultaneously increase funding for public education. In order to account for these state level variations that may affect the school enrollment rates, variables on a state's economy and political climate from the University of Kentucky Center for Poverty Research (the UKCPR) National Welfare Data are used. In particular, the variables of interest are the participation rates for AFDC and SNAP, poverty rate, and the share of Democrats in elected posts within each state such as state legislatures and governorship. In addition, the estimates for the median wage in each state obtained from the Federal Reserve Economic Data (FRED) are used to account for the difference in relative earnings across the states.

3 Empirical Strategy

For the empirical analysis, schools on either side of state boundaries are paired by geographic distance and pair-specific time-varying fixed effects are used to create a setting that resembles an experiment in which some individuals in a local labor market are treated with a higher minimum wage. Comparing schools in proximity is important because ignoring the spatial distribution of schools may introduce a bias if unobserved time-varying factors are spatially correlated. To see why this may be, consider the following example. Suppose there are many schools and two of the schools, *A* and *B*, are located within a common labor market. In year *t*, the schools *A* and *B* face the same minimum wage. In year *t+1*, two shocks occur: the minimum wage remains same for *A* while it increases for *B*, and a large factory closes, affecting both *A* and *B*. Comparing *A* and *B* yields unbiased estimators as the unobserved shock affects both schools, but a bias is introduced when *A* is compared to school *C* if *C* is not affected by the factory closure.

The pairing procedure matches each school to the closest out-of-state school in 2010. If the distance between a school and its match exceeds *X* kilometers, the pair is excluded from the sample. With this method, 849 pairs are constructed without imposing a restriction on the geographic proximity. Restricting the sample by the maximum distance within pair to 80, 100, and 120 kilometers (49.7, 62.1, and 74.6 miles) reduces the number of pairs to 149, 201, and 243 respectively.[11] This particular pairing scheme is chosen due to the concerns for heterogeneous population density affecting the estimates.[12] Common shocks within a pair may be more localized in urban centers compared to sparsely populated areas because urban centers tend to be more heterogeneous in their makeup of population and industries than suburban or rural communities of a similar land mass. This pairing method ensures that the distance within each pair is negatively correlated with the population density under the assumption that population density is correlated with the spatial concentration of community colleges.

The empirical model, which is referred to as the pair-by-year FE model, is defined as

$$\log(y_{ispt}) = \beta_0 + \beta_1 \log(mw_{st}) + \beta_2 \log(o_{it}) + \eta Z_{it} + \gamma X_{st} + \varphi_i + \varphi_{pt} + \varepsilon_{ispt}$$

where the outcome variable is the natural log of the enrollment at community college *i* located in state *s* and pair *p* on year *t*. The effect of the minimum wage on the outcome variable is captured by the coefficient on the natural log of the minimum wage ($\log(mw_{st})$).[13]

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[11] Figure A1 shows the number of schools in the sample relative to the restriction on the distance between schools in a pair.
[12] Alternative pairing strategies are explored in Section 4.
[13] Log-log model estimates the elasticities that are easier to interpret. Additionally, using unlogged enrollment as the outcome variable may produce noisier estimates because community colleges vary in size.

The natural log of the county-level population aged between 15 and 29, denoted $\log(o_{it})$, accounts for change in the number of potential community college students. The vector of school- and county-level characteristics (Z_{it}) contains the number of in-state and out-of-state community colleges within 120km radius from each school, in-district and out-of-state fees and tuition, the share of Hispanics, Blacks, Asians, and Native Americans in each county, and the gender composition of the county.[14] The number of colleges nearby accounts for other community colleges available to students. The tuition levels are important as changes in the cost of education is relevant in individuals' decision to enroll. Gender and race may correlate with unobservable determinants of enrollment. For example, Hispanics tend to be overrepresented in community colleges even when states with large number of both community colleges and Hispanics are excluded (Ma and Baum, 2016).

A vector of state-level characteristics (X_{st}) consists of the median income, poverty rate, the share of each state's population receiving AFDC and SNAP benefits, and the share of the Democrats in the state legislatures and governorship. The median income accounts for the affordability of community colleges, and other state level characteristics, as discussed earlier, account for the political and economic climate of the state that may affect enrollment.

The estimated enrollment effect of a minimum wage increase measures the average effect of the treatment accounting for the differential trends in enrollment across labor markets. The identification relies on the assumptions that the colleges in each pair draw students from a common labor market, students do not cross the treatment-control boundary to attend school or to work, and

[14] The number of in-state and out-of-state community colleges within 40 and 80km have been considered as well, but changing the radius in construction of the variable does not change the results.

the minimum wages are determined exogenously from time-varying unobserved factors that differ within each pair.

The assumption that the colleges in each pair draw students from a common labor market is likely to be valid as the pairs are formed based on the geographic distance.[15] If this assumption fails, however, the estimates become susceptible to bias induced by unobserved heterogeneous shocks to the local labor markets. While it is impossible to explicitly test the assumption, Section 4 tests whether the effect persists when the sample is restricted to the pairs with similar observable labor market characteristics and investigates the robustness of the results by implementing alternative pairing methods.

It is unlikely that students cross state borders to study when there are schools on both sides due to the difference in the tuition paid by in-state and out-of-state students.[16][17] It is, however, plausible that individuals cross a state boundary to work when the minimum wage differs in two neighboring states. If such behaviors are common, the individuals in the state without a minimum wage change can be directly exposed to a higher minimum wage in a neighboring state. This misalignment of treatment variable has the potential to attenuate the estimates. To assess whether the students are working and studying in different states, an additional sample of school pairs is generated where all schools located within a certain distance from the state borders are dropped. Under the assumption

[15] Another way to characterize a common labor market is to conduct the analysis within commuting zones. However, commuting zones containing multiple states are rare and the resulting analysis is based on a highly selected sample of schools. To address this issue an additional analysis of pairs with similar labor market characteristics is presented in section 4.4.

[16] The median difference between out-of-state tuition at a community college in a neighboring state and in-district tuition at a local community college was around 4,300 in 2010 $.

[17] According to Hillman and Weichman (2016), the median distance to school among the first year community college students was 8 miles whereas the same statistic was 18 miles for students at public four-year institutions and 46 miles for students at private nonprofit four-year institutions.

that workers are less likely to cross a state border to work if they live farther away from the border, this restriction excludes the workers most likely to live and work in different states.

Another issue with the paired sample is the over-representation of the schools paired with multiple schools. Take three schools, *A*, *B*, and *C*, for example. The school *A* is in state 1 while *B* and *C* are in state 2. If the closest school for both *B* and *C* is *A*, then the procedure generates two pairs, (*A*, *B*) and (*A*, *C*). The sample, as a result, would contain two observations of *A* and one observation of *B* and *C* each year. In order to test whether including multiple copies of one observation affects the results, the sample is further restricted by randomly eliminating duplicate observations. Applying the pair-by-year FE model on the sample of uniquely matched schools does not change the results.[18]

Keeping multiple copies of the same observation in the sample also induces a mechanical correlation across the pairs sharing one school. In order to account for this, groups of pairs (i.e. pair-groups), where each pair-group includes all connected schools within an area, are created.[19] The error terms are clustered at the pair-group level and, therefore, allowed to be correlated cross all observations within a same pair-group. Following the suggestions of Cameron, Gelbach, and Miller (2008), Carter, Schnepel, and Steigerwald (2017), and Lee and Steigerwald (2018), the critical values are obtained from the wild cluster bootstrap procedure to account for the possible over-rejection of the null hypothesis caused by the small number of heterogeneous clusters used in the analysis.

[18] See Section 4 for the results.

[19] In the above example, a pair-group will be comprised of the three schools, if *A*, *B*, and *C* are not paired with any other schools. If *A* is connected to *D* as well, then this pair-group would include *D*.

4 Results

4.1 Data Restrictions and Descriptive Statistics

The paper uses the data from 1990 to 2010. Omitting the observations collected prior to 1990 improves the data quality as some of the school-level variables are frequently missing in the 1980s. Including more recent observations made during the current decade complicates the analysis as the sub-state minimum wage laws have grown in popularity during the 2010s.[20] As new schools opening up after 1990 are allowed to enter the sample, the panel is not fully balanced. While the dataset contains 914 community colleges and 16,021 school-by-year observations for the years 1990 to 2010, the sample size varies by the criterion for pairing as unpaired schools are dropped from the sample. Figure 1 depicts the spatial distribution of the paired schools with the maximum pairwise distance of 100 kilometers (62.1 miles). The distribution reflects the population density of the US, and the schools remaining in the sample are concentrated in the Atlantic coast, the Midwest, and the South.

The left panel of Figure 2 plots each state's minimum wage, measured on September 1 of each year and inflation-adjusted to 2010 $, in light gray overlaid by the annual mean, minimum, and maximum in black and navy. The gray lines show substantial fluctuations in the state minimum wages between 1990 and 2010. The empirical strategy does not exploit all of the minimum wage differentials. Instead, it uses the minimum wage differentials in neighboring states sharing a border. The right panel of Figure 2 plots the mean and maximum of the within-pair minimum wage

[20] According to UC Berkeley Labor Center (http://laborcenter.berkeley.edu/minimum-wage-living-wage-resources/inventory-of-us-city-and-county-minimum-wage-ordinances/), some municipalities in the U.S. introduced local (city or county) minimum wages before 2010: San Francisco and Santa Fe in 2004 and Bernalillo county, which contains Albuquerque, in 2007. However, none of the cities are located near state boundaries. As the empirical strategy exploits the cross-border minimum wage differentials in schools located near the boundaries, the restriction on the within-pair distance eliminates the schools affected by these local minimum wage increases.

differentials in the sample of paired schools with the maximum distance within pair restricted to 100 kilometers. The figure demonstrates substantial within-pair differences in the real minimum wage between 1990 and 2010.

The descriptive statistics of the school-level variables are presented in Table 1. The first four columns list the means of the relevant school-level variables in the years 1995, 2000, 2005, and 2010 for the sample restricted by the maximum pairwise distance of 100 kilometers. Column 5 presents the means of the variables for all community colleges in 2010.

Consider the changes in school-level variables between 1995 and 2010 depicted in the first four columns. Enrollments have substantially increased between 1995 and 2010 from 4,866 students per school in 1995 to 6,785 students per school in 2010. As the number of students at each school increased, the proportion of students enrolled full-time rose from 41 to 46 percent. Roughly half of the schools in the sample are found in either small towns or rural settings and this ratio remains consistent over this time period. The tuition and fees experienced a steep increase for both in-district and out-of-state students. Also, it is worth noting that the tuition and fees charged to out-of-state students were on average between double and triple the tuition and fees charged to in-district students throughout this time period. Thus, attending a school from out of state may have been limited by the additional cost associated with doing so. Both the number of community colleges nearby and the state funding of the schools remained relatively constant.

A comparison between column 4 and column 5 reveals how the sample restriction affects the composition of the community colleges remaining in the sample. A statistically significant difference at the 5 percent level between the statistics presented in the two columns is denoted with boldface in column 5. Excluded schools are on average larger and more diverse as the significantly smaller share of students identifying as non-Hispanic white in column 5 suggests. In addition, the schools excluded from the paired sample are cheaper to attend and better funded on average. Most of these observable differences come from the omission of the schools in the West. In fact, excluding California from the sample eliminates most of the notable differences except for the financial disparity.

Table 2 presents the summary statistics for the state-level characteristics measured in 1995, 2000, 2005, and 2010. The state governorship moved from largely Republican to moderately Democratic, while the share of the Democrats in the state legislatures remained stable. The number of community colleges increased from 19.5 per state in 1995 to over 22 per state by 2005. This number, however, either plateaued or slightly decreased since 2005. This may be linked to a decline in public funds for community colleges during the Great Recession.

4.2 Main Results

Table 3 reports the estimated effect of the minimum wages on community college enrollments. Each cell of the table contains the estimated coefficient on the logged minimum wage from a distinct regression.[21] The three rows each correspond to the three outcome variables: the total, full-time, and part-time enrollments. The first three columns contain the estimates obtained using the pair-by-year FE model with the sample restricted by the maximum pairwise distance of 80, 100 and 120 kilometers (49.7, 62.1, and 74.6 miles respectively). Next three columns present the estimates obtained using year fixed effects instead of pair-by-year fixed effects with the sample of the paired schools. The difference in the estimates between column 1 and column 4 therefore reflects the bias arising in the presence of unobserved time-varying local characteristics.[22] Column 7 presents the

[21] The full set of estimated coefficients from column 2 is reported in Table A1.
[22] Comparison of columns 2 and 5 or 3 and 6 serves the same purpose.

estimates obtained using the empirical model with year fixed effects on the universe of schools regardless of their distance from the border. Thus, the differences between the estimates in column 7 and the previous columns reflect the bias caused by comparing schools regardless of their distance to the border. The sample is identical between column 7 and 8. In column 8, however, region-by-year fixed effects are included to capture any time-varying characteristics common within a region, where a region is defined as agglomeration of contiguous states created by the IPEDS.[23] Comparing column 7 and column 8 tests whether accounting for regional differences in trends can reduce the bias.

The estimates obtained using the pair-by-year FE model link a 10 percent increase in the minimum wage to a 4.4 to 5 percent decrease in the total enrollments. A 10 percent increase in the minimum wage reduces part-time enrollments by 5.2 to 6.1 percent while the effect on full-time enrollments is insignificant and close to zero. Although the difference in the estimated elasticities for full-time and part-time enrollments is not statistically significant, the comparison of the elasticities by enrollment intensity indicates that part-time enrollments drive the results. A possible explanation for the difference in the estimates may be that individuals less invested in education are more easily enticed by an outside option.

A comparison between the estimates obtained using pair-by-year fixed effects (columns 1-3) and the estimates obtained using year fixed effects (columns 4-6) shows a non-negligible disparity in the enrollment effect based on the model. While the difference is not statistically significant, the magnitude of the difference is sizable at around one standard error. As noted earlier, the two analyses differ only in inclusion of pair-by-year fixed effects that limits the comparison to within

[23] Table A2 lists the number of schools by region.

one pair. The difference between the estimates indicates that comparing schools located far away from one another may yield biased estimates.

Using the universe of schools in column 7 reduces the magnitude of the effect rendering the estimate insignificant with the total enrollment as the outcome variable. The relationship between the minimum wage and enrollment is positive among full-time students while the effect on part-time enrollments remains negative and significant. Including region-by-year fixed effects in column 8 produces estimates closer to those obtained in the analysis using communities near state borders. Unobserved regional differences in time-varying characteristics may be responsible for the loss of significance with the total enrollment as the outcome variable in column 7.

The magnitude of the estimates found in this paper is in line with the literature on the enrollment effect of labor market shocks. As one standard deviation change in the state minimum wage during this time period corresponds to around 6.1 percent, one standard deviation increase in the minimum wage reduces the total enrollments by 2.9 percent. By comparison, Betts and MacFarland (1995) find that one standard deviation increase in local unemployment among all adults increases community college enrollments by 3.2 percent, and Charles, Hurst and Notowidigdo (2017) link one standard deviation increase in housing demand to around a 10 percent reduction in community college enrollments.[24]

4.3 Heterogeneity

[24] Betts and MacFarland (1995) find enrollment responses to a 1 percent increase in unemployment. The estimates are scaled based on the average change in unemployment rate across all states between 1990 and 2000 for the comparison.

The effect of minimum wage increase may be heterogeneous across the demographic characteristics of student body such as previous college attendance, race, and gender.[25] The pair-by-year FE model with the log of enrollment in each category as the dependent variable is used to test for the heterogeneous enrollment response to a minimum wage increase. The first two columns of Table 4 compare enrollment responses by previous college experience. The enrollment of the individuals without any previous experience at a postsecondary institution falls by around 12 percent when the minimum wage increases by 10 percent. On the other hand, the effect size is close to zero and insignificant among the continuing students with previous college experience although the estimate remains negative with the total and part-time enrollments as the outcome variables.

In contrast, the effect is homogeneous across gender and race. While the size of the estimates appear to be larger among female students, the differences in the estimates are not statistically significant and the estimates remain negative and significant for both men and women. Among the four race categories, Asians and Hispanics appear to be more responsive to minimum wage increases relative to Blacks and non-Hispanic Whites. However, the elasticities remain negative among all races included. Importantly, the hypothesis that the enrollment responses are homogeneous across races cannot be rejected.

4.4 Robustness

Validity of comparing schools paired by proximity

[25] The IPEDS collects enrollment separately by previous college attendance, race, gender, age, and migration status. Age and migration status are not used as a source of heterogeneity because they are reported every two years before 2000, and many schools do not report the enrollments by age and migration status. Consequently, the paper focuses on the other margins for which reliable data exist.

The use of pair-by-year fixed effects in the analysis reduces the bias under the assumption that the difference in the enrollment response to localized time-varying shocks decreases in geographic proximity. This assumption may be violated if minimum wage policies are driven by local labor market conditions that are correlated at the state level. Under this alternative environment, using the pair-by-year fixed effect may not account for unobserved time-varying local labor market characteristics because the communities in different states do not face similar labor market shocks. As a result, a community college in a different state located nearby may not serve as a valid control for identification.

To assess whether restricting the sample by geographic proximity limits the bias, additional regressions are conducted with subsamples created based on whether two schools in a pair face similar labor market characteristics across the sample period. The county level public sector wage, location quotient of public sector employment, and public sector employment levels obtained from the Quarterly Census of Employment and Wages are used as the metric for creating the subsamples.[26] The public sector labor market characteristics are used because the metric must be relatively unaffected by minimum wage changes. A recent report on characteristics of the minimum wage workers published by the Bureau of Labor Statistics shows that the proportion of hourly paid workers receiving the minimum wage or less was 1.3 percent in the public sector whereas it was 3.5 percent in the private sector.[27]

The analysis is conducted in following steps. The differences in the public sector labor market characteristics are calculated for each pair and averaged for the years 1990 to 2010. The median of the difference is used to split the sample in two where the median of the difference is around half of

[26] The location quotient is the ratio between local concentration and national concentration in particular industry. For example, location quotient in public sector of 1 implies that public sector accounts for the same proportion of employment locally as it does nationally.
[27] Tables available at https://www.bls.gov/opub/reports/minimum-wage/2015/home.htm

one standard deviation in each of the variables. Then, the pair-by-year FE regression model is used to analyze the effect of the minimum wage on community college enrollments separately for the two subsamples. The estimates of the enrollment elasticities in each group as well as the difference in the estimates from the two regressions and the p-value of the difference are presented in Table 5. The table shows a sizable difference in the magnitude of the estimated enrollment elasticities between the subsamples although the differences are not statistically significant in most of the specifications. Comparing column 1 and column 2, it becomes immediately clear that the enrollment effect is significant in the sample of schools that are considered “similar” but not in the sample of schools that are considered “dissimilar” when the local wage levels in the public sector are used as the metric. This pattern holds for other public sector labor market characteristics as well although some of the samples of “dissimilar” schools are significantly affected by minimum wage increases. This divergence in the enrollment responses suggests that comparing dissimilar schools has an effect analogous to using year fixed effects instead of pair-by-year fixed effects, which indicates that the empirical strategy used in this paper does limit the comparison to the schools facing similar local labor market characteristics.

Pre-trend in enrollment patterns

The identifying assumption can be violated if the treatment is determined by unobserved time-varying factors affecting the enrollment patterns. One way to test for the violation is to estimate the difference in the enrollment patterns prior to minimum wage increases. Presence of a differential trend in enrollment may be indicative of time-varying unobservables that differently affect enrollment at two schools in each pair.

The repeated increases in the minimum wage faced by most states between 1990 and 2010 complicate the identification of the trends. The lack of single treatment causes an overlap between lead and lag periods, and the estimates obtained using the event study framework become highly confounded. Adding to the complication, the phase-in period often built into the implementation of new minimum wages renders the lag effects of the minimum wage unidentifiable. Given these limitations, I define the treatment period as the first in-sample divergence in the minimum wages within each pair, restrict the sample to the observations made in the treatment period and four pre-treatment periods, and apply the event study framework without estimating the effects in lag.

Specifically, the interactions between the change in the minimum wage on the treatment period and the time-to-treatment indicators capture the enrollment effect separately for the treatment period and four pre-treatment periods. It must be noted that pair-by-year fixed effects cannot be included due to multicollinearity. Instead, pair fixed effects and year fixed effects account for common characteristics within each pair as well as yearly fluctuations at the national level. Additionally, school fixed effects are omitted in order to identify the effect for all five periods. This means that the enrollments need to be centered by its pre-treatment average in order to identify the effect of the change. The specification is given as

$$\log(y_{ispt}) = \alpha + \sum_{j=0}^{4} \beta_j \log\left(\frac{mw_{s,\tau}}{mw_{s,\tau-1}}\right) I_{t=\tau-j} + \theta \log(o_{it}) + \eta Z_{it} + \gamma X_{st} + \varphi_p + \varphi_t + \varepsilon_{ispt}$$

where τ denotes the treatment period, j indicates the length of the lead, $I_{t=\tau-j}$ is the time-to-treatment indicator, and β_j captures the effect of a minimum wage change j years in the future. The outcome variable, $\log(y_{ispt})$, is now the natural log of enrollment of school i at time t minus the average enrollment of school i in years τ*-4* to τ*-1*.

The results are presented graphically where the estimates are plotted with ninety percent confidence intervals.[28] According to Figures 3 and 4, the enrollment response is close to zero during the pre-treatment period for both full-time and part-time enrollments although the effect of a minimum wage increase has a positive and significant effect on full-time enrollment three years prior to the treatment period. This can occur if the states with higher returns to lower postsecondary education choose to increase their minimum wage in order to close the gap between the wage floor and the median wage. Nonetheless, the significant effect is likely to be spurious as the effect sizes of full-time enrollment response is small and close to zero across the five years. With the part-time enrollments as the outcome variable, the estimates are negative yet insignificant during the pre-treatment period. On the treatment period, the enrollment effect of the minimum wage becomes significant with a break from the trend.

Additional robustness checks

This subsection briefly discusses additional robustness checks on alternate specifications and sample restrictions. A more detailed discussion can be found in Section 1 of the appendix.

The results reported in Table 3 will be attenuated if some individuals studying in a state without a minimum wage increase are treated because they work in a neighboring state with a minimum wage increase. As individuals living close to state boundaries are most likely affected by this, I exclude schools near state boundaries to test for the bias. The estimated enrollment effects are generally larger when schools located within 10 and 15 kilometers (6.2 and 9.3 miles) of the state boundary are excluded from the sample; the Table 3 results may understate the treatment effect.

[28] Table A4 presents the estimates in a table form.

Opening or closing of a community college may bias the results if a minimum wage increase occurs at the same time. However, the data shows that minimum wage increases and the number of proximate community colleges are uncorrelated. The estimates are therefore unlikely to be driven by changes in the number of local community colleges.

Finally, alternative pairing methods (matching schools based on neighborhood characteristics and geographic proximity or excluding schools paired with multiple schools) all render similar results. The results are similarly not driven by particular region or major events such as the Great Recession.

4.5 Back-of-the-envelope Welfare Calculation

Is the finding that individuals choose to reduce their investment in education when the minimum wage rises reasonable? On one hand, stayers, who continue education, have the potential to earn large returns once they complete their education. On the other hand, leavers, who choose to work full-time, lose out on the potential returns to education but receive wage income and work experience. Therefore, it is unclear how an individual's decision to forgo education in favor of work affects their lifetime earnings.

One way to address this is to quantitatively evaluate how forgoing education affects an individual's expected lifetime earnings. My back-of-the-envelope calculation estimates the net lifetime earnings by combining the projected income stream for each level of education and the probability of reaching that level of education. The projected income streams are estimated by fitting a cubic parabola on the 2000 US Census Public Use Microdata Sample (PUMS) separated by educational attainment.[29] The likelihood of obtaining a degree among community college students comes from Shapiro et al (2016).[30] The earnings are discounted at the rate of 5 percent per year, part-time students are expected to work half-time while in school, and I assume full-time employment when not in college. The expected lifetime earnings are calculated with and without a minimum wage increase at age 18. I approximate the fact that the minimum wage impacts only young less educated workers by assuming that all workers without a college degree between age 18 and 22 receive the minimum wage.

Based on these estimates, the average full-time student who leaves college reduces the net present value of their expected lifetime earnings by $57,239 before a 10 percent increase in the minimum wage, and $53,957 afterwards. As one might have expected, forgoing education is costly for full-time students. As a result, leaving school after a minimum wage increase is beneficial only for a few full-time students with low potential returns to education. In contrast, the average part-time student who leaves college reduces the net present value of their expected lifetime earnings by $831 before a 10 percent increase in the minimum wage, and only $81 afterwards. These numbers clearly show that the returns to education are much smaller for part-time students, and many of them are near the threshold between net gain and loss from continuing their education. This means that more part-time students are likely to cross this threshold and change their enrollment status after a minimum wage change compared to full-time students.[31]

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[29] The returns to education and experience are estimated by fitting a cubic parabola on each education group aged 18 to 65 with appropriate age adjustments for each level of education. The four levels of education are high school diploma, some college (less than 2 years), associate's degree, and bachelor's degree.

[30] Shapiro et al (2016) reports the attainment rates of students starting their community college education in fall 2010. Full-time community college students obtain an associate's degree with 28.5 percent and a bachelor's degree with 26 percent probability. Part-time students obtain an associate's degree with 17.6 percent and a bachelor's degree with 2.8 percent probability.

[31] Alternatively causal evidence can be used to estimate the net lifetime earnings. Kane and Rouse (1995) estimate 7-13, 26-36, and 52-66 percent for some college, associate's degree and bachelor's degree respectively. More recent results by Jepsen, Troske, and Coomes (2014) suggest 22-54 percent increase in earnings from associate's degree, and Oreopoulos and Petronijevic (2013) suggest 7-15 percent increase in earnings per year of education. When the

4.6 Potential Mechanisms

The analysis shows that an increase in the minimum wage reduces community college enrollment under the economic conditions prevailing in the US between 1990 and 2010. However, it remains unclear which factors drive this effect. As the primary effects of a minimum wage increase are changes in labor market characteristics such as wages and employment levels, the enrollment effect may be induced by these fluctuations in the labor market. It is possible, as argued above, that the effect is driven by the substitution between enrollment and employment among those at the margin of entering into the postsecondary education system. Another possibility is that the reduction in employment opportunities in the states with higher minimum wages leads to outmigration and, subsequently, a reduction in enrollment.

Dube, Lester, and Reich (2010), who use a similar empirical strategy based on minimum wage differences across border counties, find that the minimum wage does not significantly reduce employment. In absence of the employment effect, it is unlikely that outmigration drives the enrollment loss. But how is the increase in employment among the individuals at the margin of postsecondary education consistent with the lack of employment effect? One possibility is that employers choose to shift the skill distribution of their employees as shown in Neumark and Wascher (1995a, 1995b). As the minimum wage increases, employers replace existing workers with more qualified workers. As Neumark and Wascher (1995a and 1995b) suggest, displaced workers no longer work or study while employed workers choose to forgo education. Furthermore,

estimates of Kane and Rouse (1995) are used to generate the net lifetime earnings, forgoing college leads to $38,430 and $34,736 loss for full-time students before and after a 10 percent minimum wage increase and $7,077 and $6,173 loss for part-time students before and after a 10 percent minimum wage increase. While the loss for part-time students is no longer close to zero, it is still much smaller than the loss full-time students face.

the previous literature on the labor market's role in the community college enrollment patterns suggests that unemployment causes the enrollment to go up, contrary to the findings of this paper.

The heterogeneity in the enrollment effect between part-time and full-time students is in line with the hypothesis that the enrollment loss is driven by the wage increase under the assumption that enrollment intensity is indicative of attachment to education. The back-of-the-envelope calculation supports this as full-time students lose more from forgoing community college education compared to part-time students. If the enrollment loss occurs via alternative channels such as outmigration or a shift in enrollment to other types of institutions, the effect would be observable in full-time enrollment as well. This, however, is not the case.[32]

Further investigation of the potential mechanisms related to the labor market using the IPEDS is not feasible as the data does not disclose whether students concurrently work and, more crucially, does not provide information on activities that the individuals who choose not to enroll engage in. To remedy this issue, an additional dataset is used to test whether an individual's current and past employment spells affect their decision to enroll after a change in the minimum wage. A fall in school attendance among the individuals employed both before and after a minimum wage change indicates that they choose to focus on their current job in response to higher earnings. On the other hand, a reduction in school attendance among the individuals who have become unemployed after a change in the minimum wage implies that the income loss renders college enrollment unaffordable. Importantly, different responses to a minimum wage increase based on

[32] Under the assumption that four-year college students are more invested in education than community college students, the enrollment effect of minimum wage must be smaller for four-year college students, similar to full-time community college students. The analysis of four-year college enrollment patterns utilizing the paired sample approach finds no statistically significant change in enrollment (both full-time and part-time) at four-year colleges as a result of a minimum wage increase. The results are presented in Table A5.

individuals' employment history show that enrollment decisions are likely driven by the changes in the labor market conditions.

In order to conduct this analysis, the Public Use Microdata Sample (PUMS) of the American Community Survey (ACS), a repeated cross-sectional survey of the US population conducted each year by the Census Bureau, is used. The ACS contains information on each individual's current employment status, work experience within the previous 52 weeks, current school attendance, and the location of their residence. The sample is restricted to the individuals living in the Public Use Microdata Areas (PUMAs) where the community colleges in the paired sample used in the main analysis are located. The individuals are grouped by their current and past work experience, and the analysis tests whether the effect of the minimum wage on school attendance differs by employment history.

The main finding of this analysis is that the negative correlation between the minimum wage and school attendance is observed among individuals consistently employed for at least 50 weeks prior to the survey but not in any other group. This indicates that the reduction in enrollment due to a minimum wage increase may be driven by the individuals with a stable employment spell deciding to reduce their investment in education as their wages rise. The analysis rules out the loss of income as a channel because the negative elasticity should be observed among the newly unemployed if the affordability of education is driving the results. These results, however, must be interpreted with caution as it is not possible to discern the type of school that a respondent is attending. The empirical method and results of this analysis are described in a greater detail in the appendix.

Another factor that may explain the enrollment effect is an exodus of students from public to private institutions (trade schools). Students may choose to enroll at a trade school instead of a community college if they consider the two types of institutions to be substitutes and trade schools become more attractive after a minimum wage change. The heterogeneity in the enrollment response based on the availability of a trade school nearby indicates whether the movement of students from community colleges to trade schools explain the enrollment loss. The analysis is conducted using a DID specification defined as

$$\log(y_{ispt}) = \beta_0 + \beta_1 \log(mw_{st}) + \beta_2 access_{ispt} + \beta_3 \log(mw_{st}) \times access_{ispt} + \beta_4 \log(o_{it}) + \eta Z_{it} + \gamma X_{st} + \varphi_i + \varphi_{pt} + \varepsilon_{ispt}$$

where all subscripts and notation are unchanged from the pair-by-year FE model. The new variable, *access*, is an indicator taking the value of one if a community college has at least one trade school within a 30km (18.6 mi) radius.[33]

If trade schools drain students away from community colleges when the minimum wages rise, enrollment at community colleges with an access to trade schools must fall more sharply relative to enrollment at community colleges without the access. In the regression above, the coefficient on the interaction term captures this difference in enrollment response. According to Table 6, the difference in enrollment response by the accessibility of a trade school is insignificant and close to zero, which indicates that the analysis does not provide evidence supporting the hypothesis that trade schools play a significant role in determining the effect of the minimum wage on community college enrollment.

6 Conclusion

[33] Changing the radius to 20km does not affect the results.

This paper studies how the minimum wage affects community college enrollment patterns, where the effect is ex-ante unclear based on the previous findings of the literature. Utilizing the cross-border minimum wage differentials between neighboring states, I find that a higher minimum wage reduces community college enrollment. Specifically, the analysis of the community college enrollment patterns in the US between 1990 and 2010 suggests that a community college subject to a 10 percent higher minimum wage loses 5 to 6 percent of part-time students relative to a community college facing a lower minimum wage located nearby. This divergence in the enrollment is likely due to the increase in returns to work and the resultant reduction in net returns to education. As the effect is mainly observed among part-time students, a higher minimum wage appears to be most salient among the students at the margin between work and education. This intuition is corroborated by an analysis of the students enrolled at four-year universities, where the paper fails to find an analogous effect. The paper is able to rule out potential confounders such as trade schools, school openings and closures, and unobserved trends in enrollment. Finally, the paper uses the ACS to find suggestive evidence that the enrollment loss may be driven by the potential students at community colleges choosing to focus on work instead of education.

The findings of this paper suggest that an increase in the minimum wage has a substantial effect on the enrollment at the lower postsecondary level. Specifically, minimum wage increases have the potential to cause a downward shift in the educational attainment of the local workforce in the short to medium run. However, it is possible that this trend reverses itself in long run as individuals who initially have left community colleges return to obtain education after their experience in the labor market better informs the individuals their ability. Future research in this topic may consider the effect of a minimum wage increase in the distribution of educational attainment in long run and its consequences on the local economy. If the technology advances eliminate jobs requiring less education and specialization, this downward shift in educational attainment may be suboptimal.

The minimum wage nonetheless remains an important policy used to guarantee a living wage for the workers near the bottom of the wage distribution. Because of this, the results shown here do not necessarily imply that an increase in the minimum wage has a negative overall welfare effect. The back-of-the-envelope calculation, in particular, suggests that part-time students may gain from reducing their enrollment. The results, however, do imply that caution is needed in part of the policymakers to consider the potential negative consequences of increasing the minimum wage.

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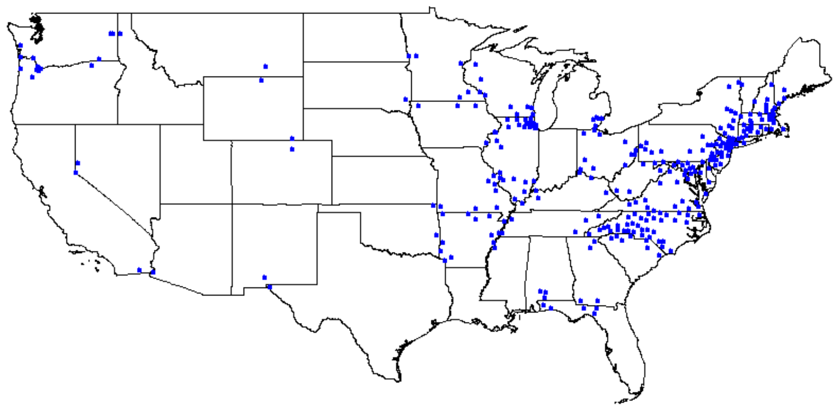

Figure 1: Distribution of schools in pairs restricted by <100km distance

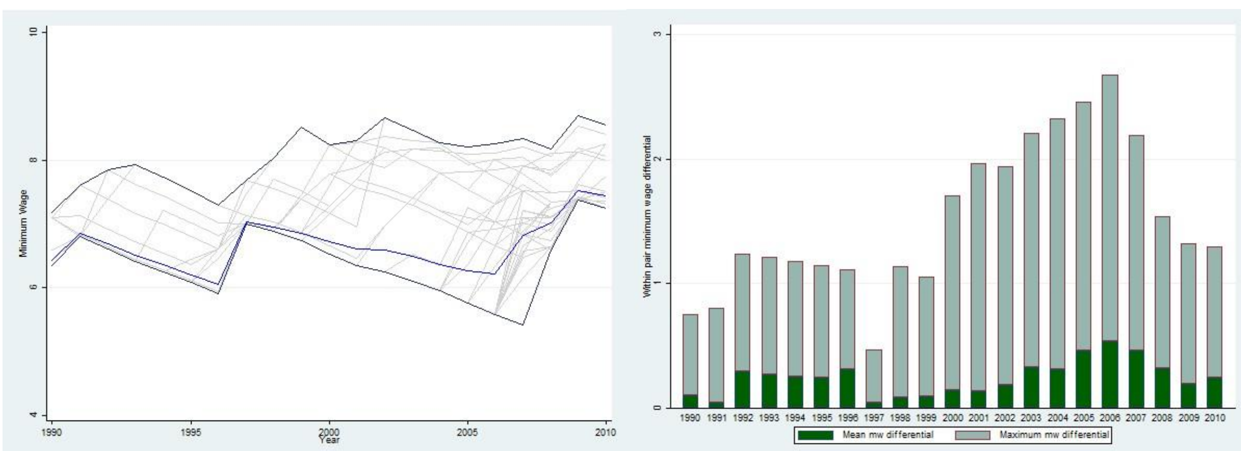

Figure 2: Left: Mean of minimum wage in blue; Right: Mean and maximum of within pair minimum wage differential

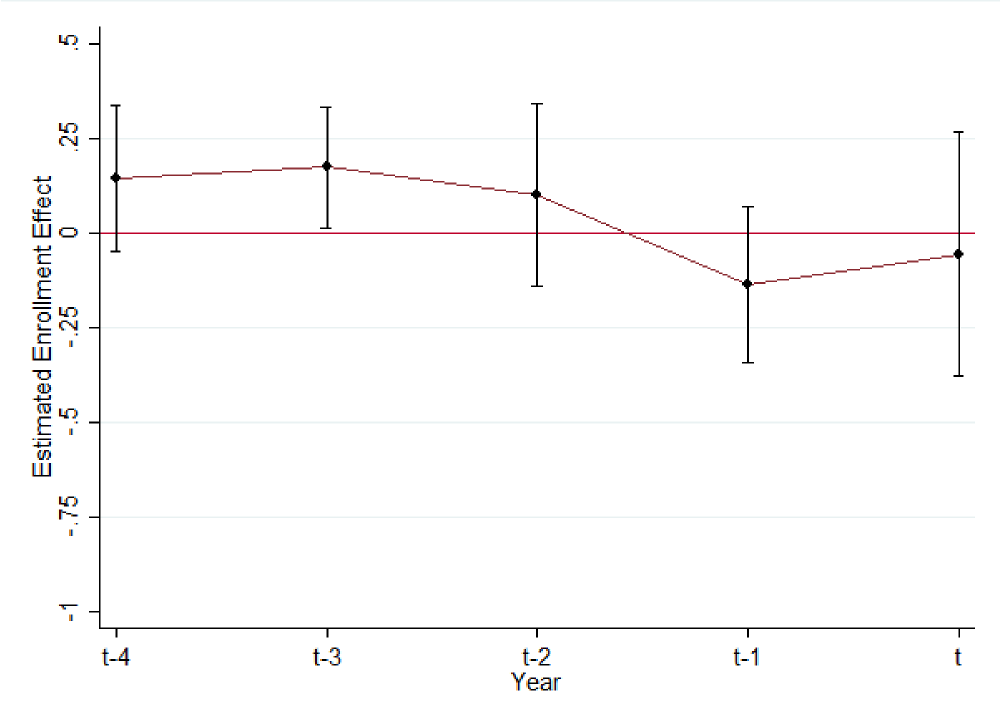

Figure 3: Event study: Full-time enrollment response to minimum wage

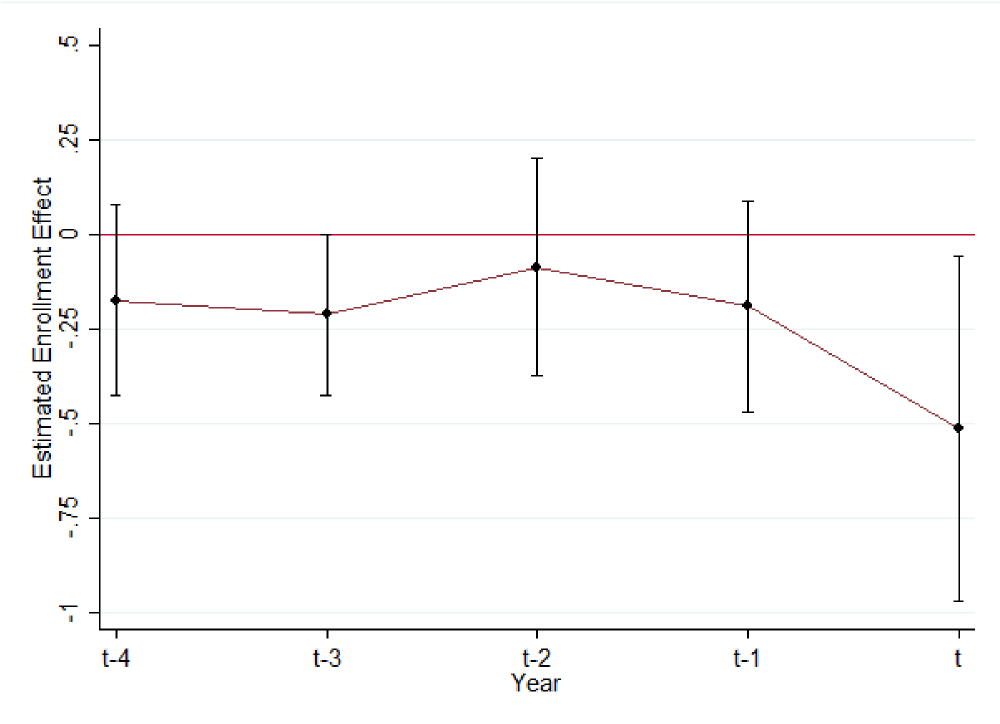

Figure 4: Event study: Part-time enrollment response to minimum wage

Table 1: Summary Statistic - School Characteristics

	School-Pair Sample				All Schools
Year	1995	2000	2005	2010	2010
Enrollments:					
Enrollment	4866.5	4832.5	5667.6	6785.7	**7744.6**
Full-Time/Total	0.410	0.413	0.434	0.464	0.450
First-time Enrollment	884.7	915.9	1031.8	1232.5	**1322.4**
Full-Time/Total First-time	0.630	0.616	0.661	0.698	**0.660**
Female/Total	0.603	0.595	0.606	0.585	0.572
Race:					
Asian	0.019	0.022	0.023	0.021	0.033
Black	0.119	0.141	0.144	0.152	0.144
Hispanic	0.053	0.054	0.065	0.083	0.122
Non-Hispanic White	0.759	0.718	0.697	0.655	**0.591**
Locale:					
Urban	0.276	0.268	0.272	0.259	0.302
Suburban	0.249	0.243	0.231	0.233	0.171
Rural	0.476	0.490	0.496	0.507	0.528
Finances:					
In-district Fees & Tuition	2192.5	2236.7	2696.7	3109.9	**2634.4**
Out-of-state Fees & Tuition	6625.4	6704.7	7191.8	7596.3	**6526.1**
# of in-state CCs within 120km	7.880	8.004	7.881	7.737	**9.539**
# of all CCs within 120km	14.769	14.879	14.795	14.626	**12.265**
State Funding(in Millions of $)	12.619	14.353	14.394	15.048	**16.212**
Observations	225	239	268	270	891

Note: Data from the IPEDS over years 1990 to 2010. Standard deviation in parentheses. All monetary variables are in terms of 2010 $.

Table 2: Summary Statistics - State Characteristics

Year	1995	2000	2005	2010
Minimum Wage	6.149	6.713	6.192	7.455
Poverty Rate	0.128	0.109	0.120	0.141
Democratic Governor	0.333	0.333	0.512	0.595
Proportion D in House	0.503	0.534	0.507	0.567
Proportion D in Senate	0.569	0.525	0.506	0.550
Number of CCs	19.500	20.575	22.439	21.333
Observations	39	39	41	42

Note: Data from the IPEDS, UKCPR National Welfare Data, and minimum wage data from various sources over years 1990 to 2010. Standard deviation in parentheses. All monetary variables are in terms of 2010 $.

Table 3: Minimum Wage Elasticity of Enrollment

Sample restriction	80km	100km	120km	80km	100km	120km	All Schools	All Schools
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:								
Log(Total Enrollment)	-0.449**	-0.469***	-0.494***	-0.304**	-0.303**	-0.289**	-0.088	-0.292**
	(0.191)	(0.172)	(0.173)	(0.119)	(0.114)	(0.109)	(0.089)	(0.112)
Log(F/T Enrollment)	-0.193	-0.215	-0.238	-0.137	-0.105	-0.080	0.108	-0.129
	(0.149)	(0.144)	(0.149)	(0.086)	(0.084)	(0.085)	(0.083)	(0.119)
Log(P/T Enrollment)	-0.526**	-0.566**	-0.601**	-0.323*	-0.336*	-0.317*	-0.237*	-0.440***
	(0.256)	(0.253)	(0.254)	(0.170)	(0.169)	(0.165)	(0.130)	(0.147)
School FE	✓	✓	✓	✓	✓	✓	✓	✓
Pair × Year FE	✓	✓	✓					
Year FE				✓	✓	✓	✓	
Region × Year FE								✓
Number of schools	220	284	333	220	284	333	914	914
Obs.	6052	8112	9686	6052	8112	9686	16021	16021

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (number of in-state community colleges within 120km radius, number of out-of-state community colleges within 120km radius, fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, and gender and racial composition of each county. Columns 1-3 include school and pair-by-year fixed effects. Columns 4-7 include school and year fixed effects. Column 8 includes school and region-by-year fixed effects. Standard errors in parentheses are clustered at the cluster-group level in columns 1-6 and at the state level in columns 7 and 8. The critical values are generated by wild bootstrap procedure.

Table 4: Heterogeneity Analysis

	College Exp.		Gender		Race			
	First time	Continuing	Female	Male	Asian	Black	Hispanic	White
Dependent variable:								
Log(Total Enrollment)	-1.168***	-0.138	-0.610***	-0.431**	-0.740**	-0.223	-0.718*	-0.475**
	(0.280)	(0.280)	(0.206)	(0.183)	(0.301)	(0.296)	(0.407)	(0.213)
Log(F/T Enrollment)	-0.606**	0.055	-0.298*	-0.150	-0.401	-0.029	-0.446	-0.158
	(0.265)	(0.230)	(0.141)	(0.170)	(0.302)	(0.325)	(0.464)	(0.165)
Log(P/T Enrollment)	-1.682***	-0.228	-0.622**	-0.502*	-0.839*	-0.412	-0.737	-0.545*
	(0.421)	(0.302)	(0.276)	(0.257)	(0.402)	(0.397)	(0.447)	(0.281)
Number of schools	284	284	284	284	284	284	284	284
Obs.	8112	8112	8112	8112	8112	8112	8112	8112

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (number of in-state community colleges within 120km radius, number of out-of-state community colleges within 120km radius, fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, gender and racial composition of each county, school fixed effects, and pair-by-year fixed effects. Standard errors in parentheses are clustered at the cluster-group level, and the critical values are generated using the wild bootstrap procedure.

Table 5: Subsamples by similarity in labor market characteristics in the public sector

Subsampled by:	Weekly Wage			Location Quotient			Employment Levels		
Similarity:	Similar	Dissimilar	Difference	Similar	Dissimilar	Difference	Similar	Dissimilar	Difference
Dependent Variable:									
Log(Total Enroll)	-0.609***	-0.245	0.364	-0.600***	-0.385*	0.215	-0.561***	-0.308	0.253
	(0.180)	(0.253)	*p=0.242*	(0.202)	(0.190)	*p=0.438*	(0.191)	(0.216)	*p=0.380*
Log(F/T Enroll)	-0.449*	0.074	0.523*	-0.259	-0.163	0.096	-0.215	-0.077	0.138
	(0.190)	(0.214)	*p=0.068*	(0.186)	(0.172)	*p=0.705*	(0.162)	(0.212)	*p=0.604*
Log(P/T Enroll)	-0.631**	-0.389	0.242	-0.903**	-0.370	0.533	-0.687**	-0.444	0.243
	(0.317)	(0.297)	*p=0.578*	(0.292)	(0.272)	*p=0.182*	(0.315)	(0.278)	*p=0.563*
Number of schools	163	156		158	163		165	152	
Obs.	4092	4020		4056	4056		4082	4030	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (number of in-state community colleges within 120km radius, number of out-of-state community colleges within 120km radius, fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, gender and racial composition of each county, school fixed effects, and pair-by-year fixed effects. Subsamples are created at the pair level by measuring the Euclidean distance in weekly wages, location quotient, and employment levels of each county's public sector labor force, and dividing the sample at the median of the distance. The pairs with the distance smaller than the median are considered "similar." Standard errors in parentheses are clustered at the cluster-group level, and the critical values are generated using the wild bootstrap procedure.

Table 6: Access to trade schools

Maximum distance	100km					
Dependent Variable:	Log(Total Enrollment)		Log(F/T Enroll.)		Log(P/T Enroll.)	
Log(MW)	-0.469***	-0.568**	-0.215	-0.197	-0.566**	-0.722**
	(0.172)	(0.213)	(0.144)	(0.143)	(0.253)	(0.319)
Access		-0.278		0.064		-0.433
		(0.221)		(0.252)		(0.352)
Log(MW)×Access		0.141		-0.027		0.220
		(0.113)		(0.130)		(0.180)
Number of schools	284	284	284	284	284	284
Obs.	8112	8112	8112	8112	8112	8112

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (number of in-state community colleges within 120km radius, number of out-of-state community colleges within 120km radius, fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, gender and racial composition of each county, school fixed effects, and pair-by-year fixed effects. Standard errors in parentheses are clustered at the cluster-group level, and the critical values are generated using the wild bootstrap procedure.

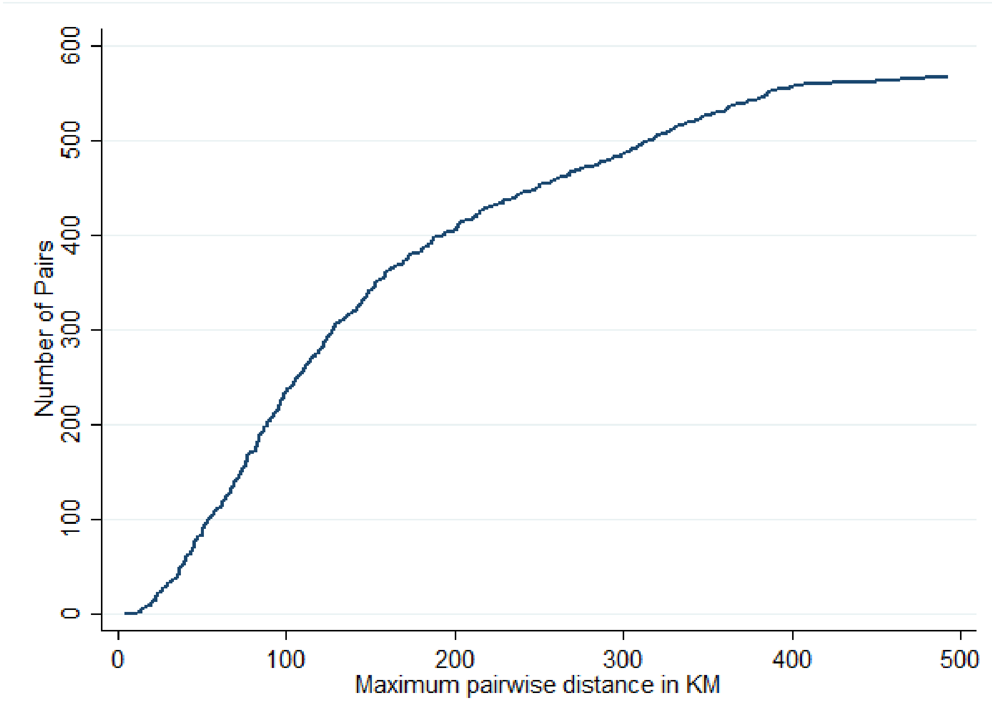

Figure A1: Number of pairs by pairwise distance

Table A1: School-Pairs - 100km

Maximum distance	100km		
Dependent Variable	Log(Enrollment)	Log(F/T Enroll.)	Log(P/T Enroll.)
Log(MW)	-0.469***	-0.215	-0.566**
	(0.172)	(0.144)	(0.253)
Log(o)	0.561*	0.304	0.859
	(0.335)	(0.215)	(0.564)
School Characteristics			
In-state CCs within 120km	-0.000	0.023	-0.008
	(0.019)	(0.016)	(0.029)
Out-of-state CCs in 120km	0.058**	0.052**	0.078*
	(0.026)	(0.023)	(0.040)
In-district fees	0.020	0.052**	-0.009
	(0.018)	(0.021)	(0.025)
Out-of-state fees	0.007	0.004	0.015
	(0.007)	(0.006)	(0.010)
State Characteristics			
AFDC	1.429	5.186***	-1.178
	(1.473)	(1.921)	(2.060)
SNAP	-2.775**	-2.885**	-2.844
	(1.257)	(1.145)	(2.029)
Poverty Rate	0.030	-0.775**	0.354
	(0.450)	(0.346)	(0.803)
Log(Median Income)	-0.215	-0.163	-0.260
	(0.143)	(0.153)	(0.219)
Democrat House	0.030	-0.128	0.160
	(0.171)	(0.143)	(0.306)
Democrat Senate	-0.076	0.100	-0.297
	(0.146)	(0.117)	(0.237)
Democrat Gov	0.005	-0.022	0.027
	(0.016)	(0.015)	(0.031)
County Characteristics			
P(Hispanic)	1.980*	0.655	3.052
	(1.110)	(0.939)	(1.627)
P(Black)	-1.302*	-0.174	-1.641*
	(0.738)	(0.837)	(0.926)
P(Asian)	-2.810	1.340	-5.051**
	(1.810)	(1.736)	(2.260)
P(Native)	-2.738	-2.901	1.922
	(3.893)	(7.417)	(4.323)
P(Female)	4.765	6.917*	3.755
	(2.948)	(3.654)	(3.240)
Number of schools	284	284	284
Obs.	8112	8112	8112

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (number of in-state community colleges within 120km radius, number of out-of-state community colleges within 120km radius, fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, gender and racial composition of each county, school fixed effects, and pair-by-year fixed effects. Standard errors in parentheses are clustered at the cluster-group level.

Table A2: Number of schools (100km paired sample) by IPEDS region

Region	# of schools
CT, ME, MA, NH, RI, VT	34
DE, MD, NJ, NY, PA	69
IL, MI, OH, WI	36
IA, KS, MN, MO, ND	19
AL, AR, FL, GA, KY, LA, NC, SC, TN, VA, WV	99
AZ, NM, OK, TX	6
CO, ID, MT, WY	5
CA, NV, OR, WA	16
Total	284

Note: The data comes from the Integrated Postsecondary Education Data System (IPEDS). States without any schools in the sample are excluded.

Table A3: Main Results with Different Controls

Maximum distance	100km				
	(1)	(2)	(3)	(4)	(5)
Dependent variable:					
Log(Total Enrollment)	-0.664***	-0.511***	-0.478***	-0.472***	-0.469**
	(0.222)	(0.173)	(0.175)	(0.169)	(0.172)
Log(F/T Enrollment)	-0.468**	-0.301**	-0.303**	-0.325**	-0.215
	(0.179)	(0.137)	(0.141)	(0.145)	(0.144)
Log(P/T Enrollment)	-0.745***	-0.582*	-0.535**	-0.490*	-0.566**
	(0.285)	(0.236)	(0.234)	(0.249)	(0.253)
Population	✓	✓	✓	✓	✓
School-Level Covariates		✓	✓	✓	✓
County-Level Demography			✓	✓	✓
Politics (State)				✓	✓
Economy (State)					✓
Number of schools	284	284	284	284	284
Obs.	8112	8112	8112	8112	8112

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (number of in-state community colleges within 120km radius, number of out-of-state community colleges within 120km radius, fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, gender and racial composition of each county, school fixed effects, and pair-by-year fixed effects. Standard errors in parentheses are clustered at the cluster-group level.

Table A4: Event Study

Maximum distance	100km		
Dependent Variable	Log(Enrollment)	Log(F/T Enroll.)	Log(P/T Enroll.)
Treatment (τ)	-0.249	-0.056	-0.514*
	(0.108)	(0.193)	(0.272)
$\tau - 1$	-0.108	-0.138	-0.190
	(0.096)	(0.123)	(0.165)
$\tau - 2$	0.020	0.101	-0.088
	(0.141)	(0.145)	(0.171)
$\tau - 3$	-0.041	0.173*	-0.212
	(0.092)	(0.095)	(0.126)
$\tau - 4$	-0.023	0.146	-0.174
	(0.104)	(0.114)	(0.150)
Number of schools	166	166	166
Obs.	1190	1190	1190

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (number of in-state community colleges within 120km radius, number of out-of-state community colleges within 120km radius, fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, gender and racial composition of each county, school fixed effects, and pair-by-year fixed effects. Standard errors in parentheses are clustered at the cluster-group level.

Table A5: Paired four-year institutions

Maximum distance within pair	80km	100km	120km
Dependent variable:			
Log(Total Enrollment)	0.162	0.155	0.161
	(0.141)	(0.138)	(0.138)
Log(F/T Enrollment)	-0.013	0.011	0.022
	(0.118)	(0.116)	(0.116)
Log(P/T Enrollment)	0.262	0.236	0.254
	(0.290)	(0.273)	(0.259)
Number of schools	639	752	824
Obs.	20926	24950	27674

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, gender and racial composition of each county, school fixed effects, and pair-by-year fixed effects. Standard errors in parentheses are clustered at the cluster-group level, and the critical values are generated using the wild bootstrap procedure.

Appendix

1 Additional robustness checks

Spillover of minimum wage policy

As discussed in Section 3, misalignment between the place of work and residence has the potential to attenuate the estimates reported in Tables 3 and 4. Under the assumption that the likelihood of cross-border commuting decreases in the distance from the border, omitting the schools closest to the border from the sample reduces the number of individuals studying and working in different states. Creating a sample of schools in the “donut-shaped” area around the boundary produces estimates more robust to the attenuation bias. To test, the main specification is applied to the sample excluding the schools closest to the state borders. It must be noted, however, that this restriction has the potential to exacerbate the bias from the spatially correlated time-varying local characteristics because schools in each pair are located farther away from one another on average. The paired schools are therefore more likely to be exposed to different set of unobservables.

The results are presented in Table B1. Under the restriction that schools must be at least 15 kilometers (9.3 miles) away from the borders and paired with a school in another state located within a 100 kilometer (62.1 mile) radius, a 10-percent increase in the minimum wage reduces the total and part-time enrollments by 5.2 and 7.7 percent respectively. Although the estimates fluctuate slightly based on the sample restriction, they remain negative and significant across all columns. The greater magnitude observed in three of the estimates relative to the main results for the total enrollments and in all four estimates for the part-time enrollments suggests that the cross-border commuting has the potential to attenuate the estimates.

Opening and closing of community colleges

Although it is unlikely that the opening or closing of a community college affects the results as community colleges rarely open or close, there may be concerns of correlation between the changes in the number of community colleges in the vicinity causing a bias in the estimates. To investigate, additional regressions test whether an increase in the minimum wage is correlated with the number of in-state schools within the *X* kilometer radius of each school in the sample. The econometric specification follows the pair-by-year FE model, and the estimate captures the effect of a minimum wage change on the number of schools on either side of the policy discontinuity.

The results are presented in Table B2. Each column contains the estimates obtained with a different radius used to generate the outcome variable. The estimates remain insignificant and close to zero. Column 3 implies that when the minimum wage increases by 10 percent on one side of the border, the number of schools within 120 kilometers (74.6 miles) of the community college directly affected by a change in the minimum wage rises insignificantly by 0.065. As a 10 percent increase is a sizable change in the minimum wage, the correlation between the minimum wage and the number of in-state schools appears to be small and irrelevant in the identification of the relationship between the minimum wage and community college enrollment patterns.

Sample restrictions and pairing methods

Table B3 presents the estimates obtained from the additional analyses testing the robustness of the main results with a focus on the sample selection. In column 1, an alternative pairing method is used to ensure that the schools in each pair are located in similar communities in addition to being in proximity. Specifically, each school is assigned to three levels of urbanicity based on its urban-centric locale code and a pair is formed only if the locale codes of the schools match.[34] In column 2, whether the results are driven by the over-representation of the schools with more than one match is tested by randomly eliminating the copies of duplicate observations until each school appears in the sample once a year.[35] In columns 3 and 4, the school-level covariates are excluded to make sure that the results are not driven by the selection of schools consistently reporting these characteristics. In column 4, the panel is fully balanced by restricting the sample to the schools with twenty-one years of observations. In column 5, the schools in the New England are excluded to test whether the estimates are robust to omitting the region with the highest school density.[36] In column 6, the observations made during the Great Recession are omitted to ensure that the effect is not driven by concurrence of high unemployment rates and minimum wage hikes during this time period. Across all columns of Table 8, the elasticities remain negative and significant with the total and part-time enrollment as outcome variables showing that the main results are robust to various alterations of the paired sample.

2 Employment and school enrollment patterns

Minimum wage clearly affects community college enrollment patterns according to the main results. In addition, the paper finds that trade schools are unlikely to be credible alternatives for community college students leaving school when minimum wage rises. Therefore, the factors related to the labor market are likely drivers of the observed enrollment loss. Potentially, there are

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[34] NCES uses urban-centric locale categories to define the urbanicity of surrounding area for each school. The categorization is based on the size of the population in the metropolitan area and location of each locale relative to the closest urban center. There are twelve sub-categories that can be consolidated into four: city, suburb, town, and rural. In this analysis, town is merged with rural for simplicity.

[35] Alternatively, it is possible to downweigh each pair by inverse of frequency with which a school is included. Such downweighting does not change the results.

[36] Excluding other divisions or regions does not cause a significant change in the estimates. The results are available on request.

many channels through which labor market changes induced by an increase in minimum wage can influence an individual's decision to enroll. Of the potential channels, I focus on two channels most directly related to employment and wages: (1) the substitution effect from rising opportunity costs of education incentivizes potential students to focus on work and (2) the loss of employment opportunities reduces affordability of education.

The IPEDS lacks two necessary pieces of information for this analysis. First, the IPEDS does not include any data on individuals who choose not to enroll. Second, the IPEDS does not contain information on employment status of students. A further analysis studying the choice between employment and education, then, requires individual-level datasets with work and education histories.

An ideal dataset for this analysis is a panel of individuals with sub-state local identifiers with information on employment and school attendance. If such a dataset is available, the channels can be studied by dividing the sample into groups characterized by their work history and estimating the effect of a minimum wage change on school enrollment patterns of each group. If individuals with a continuous employment history exhibit a reduction in enrollment as the minimum wage rises, an implication is that the negative relationship between minimum wage and community college enrollment is driven by workers responding to higher wages by reducing their investment in education. On the other hand, if individuals who became recently unemployed choose to leave school, the reduction in enrollment may be driven by affordability of postsecondary education.

While the ideal dataset does not exist, the American Community Survey (ACS) serves as a close alternative. The ACS is an annual cross-sectional sample of the U.S. population. The strength of the ACS comes from size of the sample and richness of sub-state geographic identifiers. In this analysis, the Public Use Microdata Areas (PUMAs) are used to link the individuals in the ACS to community colleges in the sample of paired community colleges. Then, the sample is restricted to individuals living in these PUMAs aged less than 40 with educational attainment between high school diploma and a diploma or certificate from a two-year institution. The restricted sample contains potential community college students living in the PUMAs where community colleges appearing in the main sample are located.

As the dataset contains observations from a different cross-section each year, it is not possible to link individuals across time. However, the ACS contains information on the individual's employment status within last 12 months. Using this information, individuals are grouped into four categories based on their employment histories. The consistently employed are currently employed and employed at least 50 weeks last year; the recently employed are currently employed and employed less than 50 weeks last year; the recently unemployed are currently unemployed and employed at least 1 week last year; the consistently unemployed are currently unemployed and unemployed last year.

To test which of the groups exhibit reduction in school attendance, I construct an econometric model of the following form:

$$school_{imt} = \beta_0 + \beta_1 \log(mw_{mt}) + \beta_2 CU_{imt} + \beta_3 RU_{imt} + \beta_4 RE_{imt} + \beta_5 \log(mw_{mt}) \times CU_{imt} + \beta_6 \log(mw_{mt}) \times RU_{imt} + \beta_7 \log(mw_{mt}) \times RE_{imt} + \gamma X_{mt} + \varphi_t + \varphi_m + \varepsilon_{imt}$$

where the outcome variable $school_{imt}$ is an indicator taking a value of one if an individual *i* living in PUMA *m* on year *t* is currently enrolled at school. The employment history indicators are denoted CU, RU, and RE for the consistently unemployed, recently unemployed, and recently employed respectively. The left-out category is the consistently employed. The regression includes the state-level covariates from the main regression as well as PUMA and year fixed effects. Estimates are unbiased under the assumptions that the sample from each PUMA remains representative of the population and the minimum wages and composition of population in each PUMA are exogenously determined. Clearly this second condition is unlikely to be satisfied, and the estimated coefficients do not necessarily represent a causal relationship. It must be noted that the exact date of survey for each individual is unavailable. Any estimate therefore must be interpreted as the local average effect of an increase in the minimum wages sometime within last 24 months.

The results are presented in Table B4. A 10 percent increase in minimum wage is associated with 0.34 percentage point decrease in the probability of attending school among the consistently employed individuals. More importantly, the individuals with a consistent history of employment are much more likely to respond to a minimum wage increase by reducing school attendance relative to the individuals in other groups. If the restricted sample in the ACS represents the individuals most likely to attend community colleges in the paired school sample, the results in Table B4 suggests that a reduction in enrollment observed in the main analysis may be driven by individuals with a stable spell of employment before and after a minimum wage change.

In addition, I analyze whether the attendance effect of minimum wage increase depends on current employment status using the same dataset. According to Table B5, the only group for which I observe a reduction in school attendance is part-time workers. Full-time workers do not respond to a minimum wage change at all, and those without employment appear to increase school attendance.

Table B1: Schools near state boundaries excluded

Distance to border	At least 15km away		At least 10km away	
Maximum distance within pair	100km	120km	100km	120km
Dependent Variable:				
Log(Total Enrollment)	-0.516***	-0.462***	-0.544***	-0.520***
	(0.149)	(0.159)	(0.150)	(0.150)
Log(F/T Enrollment)	-0.183	-0.256	-0.213	-0.282*
	(0.143)	(0.143)	(0.145)	(0.148)
Log(P/T Enrollment)	-0.774***	-0.652***	-0.754***	-0.672***
	(0.205)	(0.213)	(0.188)	(0.185)
Number of schools	113	147	183	223
Obs.	3136	4234	5270	6618

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (number of in-state community colleges within 120km radius, number of out-of-state community colleges within 120km radius, fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, gender and racial composition of each county, school fixed effects, and pair-by-year fixed effects. Standard errors in parentheses are clustered at the cluster-group level, and the critical values are generated using the wild bootstrap procedure.

Table B2: School openings and closures

Dependent Variable:	Number of schools		
Radius	40km	80km	120km
Log(MW)	-0.004	0.239	0.648
	(0.121)	(0.434)	(0.456)
Number of schools	284	284	284
Obs.	8112	8112	8112

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (number of in-state community colleges within 120km radius, number of out-of-state community colleges within 120km radius, fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, gender and racial composition of each county, school fixed effects, and pair-by-year fixed effects. Standard errors in parentheses are clustered at the cluster-group level.

Table B3: Robustness checks

Maximum distance	100km					
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:						
Log(Total Enrollment)	-0.502***	-0.454**	-0.518**	-0.589***	-0.331**	-0.411**
	(0.170)	(0.184)	(0.189)	(0.200)	(0.153)	(0.174)
Log(F/T Enrollment)	-0.093	-0.115	-0.294*	-0.315*	-0.265	-0.134
	(0.123)	(0.196)	(0.152)	(0.162)	(0.156)	(0.146)
Log(P/T Enrollment)	-0.743***	-0.618**	-0.592**	-0.635**	-0.454*	-0.526*
	(0.224)	(0.258)	(0.259)	(0.262)	(0.260)	(0.258)
Locale Match	✓					
Unique Matches		✓				
No School-Level Covariates			✓	✓		
Fully Balanced				✓		
Northeast Omitted					✓	
Great Recession Omitted						✓
Number of schools	217	172	290	242	240	284
Obs.	5996	3372	8412	7476	6760	6872

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the IPEDS, the Census Bureau population estimates, and the UKCPR National Welfare Data from 1990 to 2010. Minimum wage is collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of population receiving AFDC and SNAP, poverty rate, log of the median income, an indicator for a Democratic governor, and the proportion of the seats held by Democrats in the state house and senate), school level characteristics (number of in-state community colleges within 120km radius, number of out-of-state community colleges within 120km radius, fees and tuition paid by in-district full-time students, and fees and tuition paid by out-of-state full-time students), estimated population of each county's residents aged 15 to 29, gender and racial composition of each county, school fixed effects, and pair-by-year fixed effects. Standard errors in parentheses are clustered at the cluster-group level.

Table B4: ACS - Employment History

Dependent Variable:	P(School Enrollment)
Log(MW)	-0.036*
	(0.020)
CU	-0.053
	(0.049)
RU	-0.036
	(0.068)
RE	-0.150**
	(0.056)
CU×Log(MW)	0.056**
	(0.025)
RU×Log(MW)	0.073**
	(0.035)
RE×Log(MW)	0.106***
	(0.029)
Mean of Dependent Variable among the Omitted Group	0.163
PUMAs	261
Obs.	347119

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The main sample comes from the American Community Survey over the years 2005 to 2011. The sample is restricted to the community-college-eligible residents of PUMAs with community colleges in the paired sample who have continuously lived in their state of residence for at least 12 months at the time of the survey. Covariates are constructed using the UKCPR National Welfare Data. Minimum wages are collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of AFDC and SNAP recipients, poverty rate, an indicator for a Democratic governor, and the proportion of Democrats in state house and senate), demographic controls (gender, age, age squared), year fixed effects, and PUMA fixed effects. Standard errors in parentheses are clustered at the state level, and the critical values are generated using the wild bootstrap procedure.

Table B5: ACS - Current Employment

Dependent Variable:	P(School Enrollment)
Log(MW)	-0.044*
	(0.025)
Log(MW) × Fulltime	0.050*
	(0.025)
Log(MW) × Unemployed	0.101***
	(0.034)
Fulltime	-0.278***
	(0.048)
Unemployed	-0.289***
	(0.066)
PUMAs	261
Obs.	347119

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The main sample comes from the American Community Survey over the years 2005 to 2011. The sample is restricted to community college eligible residents of PUMAs with community colleges in the paired sample who have continuously lived in their state of residence for at least 12 months at the time of the survey. Covariates are constructed using the UKCPR National Welfare Data. Minimum wages are collected by the author and crosschecked with other publications. All specifications include state level characteristics (proportion of AFDC and SNAP recipients, poverty rate, an indicator for a Democratic governor, and the proportion of Democrats in state house and senate), demographic controls (gender, age, age squared), year fixed effects, and PUMA fixed effects. Standard errors in parentheses are clustered at the state level, and the critical values are generated using the wild bootstrap procedure.