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Minimum Wages and Race Disparities
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ABSTRACT

We provide a comprehensive analysis of the effects of minimum wages on blacks, and on the relative impacts on blacks vs. whites. We study not only teenagers – the focus of much of the minimum wage-employment literature – but also other low-skill groups. We focus on employment, which has been the prime concern with the minimum wage research literature. We find evidence that job loss effects from higher minimum wages are more evident for blacks, and in contrast not very detectable for whites. Moreover, the effects of minimum wages are often large enough to generate adverse effects on earnings (and relative earnings) of blacks. Given strong residential segregation by race in the United States, the race difference in the effects of minimum wages implies that any adverse impacts fall on areas with a high black population share. We explore additional evidence on whether minimum wage effects are also more adverse in black areas, regardless of individual race. We find weak evidence of this heterogeneity, although it does accentuate the concentration of the adverse effects of minimum wages in areas where the black population is concentrated.

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Introduction

The literature on the employment effects of minimum wages is vast. For example, a recent survey of U.S. evidence only was limited to studies published (or forthcoming) between 1992 and 2020, and imposed other criteria for inclusion, and still ended up covering 70 papers (Neumark and Shirley, 2022).[1] This literature amply documents that the strongest evidence of disemployment effects, and the larger effects, appear for the lowest-skilled groups – usually defined in terms of either age or education (see, e.g., Neumark and Shirley, 2022). Presumably the reason is that the minimum wage is more binding for these groups, and hence a larger share of workers among them ends up with marginal revenue product below the minimum wage, even after reallocation of inputs and other changes in firm operations that impact the productivity of labor or otherwise offset the higher cost of the minimum wage.[2] Yet this literature pays scant attention to the differential effects of minimum wages on employment of lower-skilled minority workers, even though minority groups also earn lower wages (as emphasized by Deere et al., 1995).[3]

[1] An earlier extensive survey of the minimum wage-employment literature emphasized (but did not limit to) U.S. studies, and covered over 100 papers (Neumark and Wascher, 2007).

[2] Manning (2021) and Schmitt (2015) discuss many of the other margins of adjustment to a higher minimum wage (although motivating their discussions of other margins based on inaccurate summaries of the research on employment effects as failing to detect job loss).

[3] There are scattered exceptions – by our count, four U.S. studies, only two of which have race differences as their focus and none of which contrast the evidence for lower-skilled minorities and non-minorities. Neumark and Wascher (2011) report separate estimates of the effects of minimum wages, the EITC, and their interaction on less-educated Black or Hispanic men, but their focus is not on employment effects per se. Cengiz et al. (2019) briefly explore employment effects via their "binned wage/missing jobs" approach, and for blacks and Hispanics combined find a very small and insignificant disemployment effect, although they do not restrict attention to lower-skilled blacks or Hispanics. Of the papers more directly focused on race differences in employment effects, Deere et al. (1995) study the effects of federal minimum wage increases in 1990 and 1991, identifying employment effects by comparing changes in employment for low- vs. high-wage groups. They report a higher fraction of low-wage workers among blacks than whites or Asians, for both women and men, and larger employment declines for black women and men. In regressions for teenagers and high school dropouts adjusting for cyclical changes, they report estimates for blacks, but not other races, thus not providing comparisons for lower-skilled blacks vs. other races. Wursten and Reich (2023) use the Cengiz et al. binned data approach with Current Population Survey (CPS) data, finding no employment effect for blacks but reductions for Hispanics, although they, too, do not restrict to lower-skilled minorities.

Whether the lower wages among minorities reflect actual lower skills, or "discounting" of minority workers' productivity à la Becker (1957), minimum wages should be more binding for minorities. Thus, the competitive model of the labor market should predict more adverse minimum wage effects on minorities.[4] With regard to minimum wage effects on blacks, Milton Friedman put this most succinctly and provocatively in a 1966 op-ed in *Newsweek*: "I am convinced that the minimum-wage law is the most anti-Negro law on our statute books."[5] Another hypothesis is that even if skills and wages are similar for blacks and whites, employers choose to reduce employment among blacks more than among whites – behavior that could also be interpreted as discrimination if skill differences do not motivate this response.

In contrast, advocates for higher minimum wages claim that they are a critical tool for closing gaps between blacks and whites (Derenoncourt et al., 2020). This argument focuses on wages, which ignores the potential job loss that, as argued above, could be worse for blacks. The research underlying this argument, based on 1960s expansions of the minimum wage (Derenoncourt and Montialoux, 2021), reports that wages for blacks were increased relative to wages for whites, without an accompanying decline in employment for blacks. On the other hand, studying the same 1960s expansions, Bailey et al. (2021) find similar earnings effects but offsetting

[4] Some recent research puts forward evidence of monopsony-like power in labor markets (e.g., Azar et al., 2022; Rinz, 2022), and a couple of papers argue that this framework applies to low-wage labor markets and hence minimum wage effects (Azar et al., forthcoming; Corella, 2020). This paper is not the place to adjudicate this evidence. However, we would suggest caution in adopting this view. First, the literature on how labor market power might mediate minimum wage effects on employment is in its infancy, and there is debate over whether concentration measures capture employer labor market power (Yeh et al., 2022). Second, most evidence is in fact consistent with the competitive model (Neumark and Shirley, 2022), so even if labor market power reduces or eliminates the adverse employment effects of minimum wages in some markets, this does not happen broadly, and minimum wages would still be more binding for minority workers.

[5] He also referenced the adverse effects of minimum wages on teenagers, referring to the lower skills of both teenagers and blacks. However, as we have pointed out, the same prediction would apply if blacks do not have lower skills, but their productivity is discounted as in the employer discrimination model. Myrdal (1944) also warned of the potential for more adverse employment effects of minimum wages on blacks.

disemployment effects that were larger for black men (compared to the overall modest effects).[6] Regardless, the employment effects debated in these two papers are from many decades back.

Given the strong possibility of more adverse employment effects for blacks, and the dearth of evidence, in this paper we provide a comprehensive analysis of the effects of minimum wages on blacks, and on the relative impacts on blacks vs. whites. We study not only teenagers – the focus of much of the minimum wage-employment literature – but also other low-skill groups. We focus on employment, which has been the prime concern with the minimum wage research literature. Moreover, employment effects are of first-order importance, as constraints on employment from a high minimum wage can potentially have both short-term adverse effects on earnings and longer-term adverse effects on human capital accumulation.[7]

We find a good deal of evidence that job loss effects from higher minimum wages are much more evident for blacks, and in contrast not very detectable for whites. We also estimate impacts of the minimum wage on estimated wages, as well as on earnings. The evidence from these analyses further reinforces the conclusion that there tend to be adverse effects of minimum wages on blacks, and more so on black men.

Given extreme residential segregation by race in the United States, the race difference in the effects of minimum wages imply that much of the adverse impact of the minimum wage falls on areas with a high black population share. We explore additional evidence on whether minimum wage effects are also more adverse in black areas, regardless of individual race. We find relatively little evidence of this heterogeneity, although it does accentuate the concentration of the adverse effects of minimum wages in areas where the black population is concentrated.

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[6] Bailey et al. suggest that the lack of employment impact in Derenoncourt and Montialoux depends on excluding from the model state-by-birth cohort effects and a GSP control, and using a reference week rather than annual employment measure (Table 2 and Appendix).

[7] Neumark and Nizalova (2007) find adverse effects of exposure to a higher minimum wage when young on later wages, employment, hours, and earnings. These effects appear to be stronger for blacks.

Data

We use American Community Survey (ACS) data from 2005-2019. To keep the race comparisons straightforward, we focus only on blacks and non-Hispanic whites and study those aged 16-65.[8] The ACS data are invaluable in studying the effects of minimum wages on low-skilled blacks because other data sets used to study the employment effects of minimum wages generally – mainly the CPS – are likely to have very low observation counts for these groups for many states.[9]

The smallest unit of disaggregation available in the publicly available ACS micro data is the Public Use Microdata Area (PUMA). Per the Census Bureau's definition, PUMA boundaries are defined using three main criteria: 1) each PUMA must have a population of 100,000 or more at the time of delineation, and this population threshold must be maintained throughout the decade; 2) PUMAs are formed only by aggregating whole census tracts or counties and must not cross state boundaries; and 3) the building blocks for PUMAs must be contiguous or share a common border.[10] The Census Bureau updates PUMA boundaries every 10 years based on new population data from the Decennial Census. The 2012 ACS data files were the first to include PUMAs defined using the 2010 Census data. ACS data files from 2005-2011, which we also include in our analysis,

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[8] For our wage analysis, we additionally drop unpaid family workers (0.28%) and the self-employed (8.4%). The ACS oversamples units in areas with smaller populations (https://usa.ipums.org/usa/chapter2/chapter2.shtml#ACS). All individual-level estimates (in all tables and figures) are weighted by ACS person weights.

[9] For example, Wursten and Reich (2023) note that for their binned estimator more than 50% of cells for blacks are empty. They also note that this likely leads to attenuation towards zero in estimated effects for blacks, which could partly account for their findings. It is not feasible to try to replicate the binned data approach using ACS data, because wages would have to be estimated from annual wage and salary information, as discussed in detail below.

It is possible that the small samples of blacks available in some states in the CPS have deterred a focus on race differences. And other datasets prominent in the minimum wage literature, like the QCEW and CPB, do not distinguish workers by race. The QWI does, however, and could potentially provide further evidence, although the QWI does not disaggregate by race and skill (age/education); see https://lehd.ces.census.gov/doc/QWI_101.pdf.

[10] Certain exceptions to these rules and further guidelines for creating PUMAs can be found here: https://www.census.gov/content/dam/Census/library/publications/2020/acs/acs_pums_handbook_2020_ch02.pdf.

use PUMAs defined after the 2000 Census. There are 2,072 PUMAs in our sample from 2005-11, and 2,351 PUMAs from 2012-19 (after the 2010 boundary changes).

We use state, city, and county level minimum wages for the years in our sample. We map these minimum wages to PUMAs for our PUMA-level analysis. To do so, we map cities within the boundaries of each PUMA and assign the highest binding annual average minimum wage within a PUMA's boundaries as the PUMA's minimum wage. The average was generated based on the number of months a sub-PUMA jurisdiction spent at each minimum wage level.

Figure 1 displays information on the minimum wages assigned to PUMAs. The top panel shows levels and the bottom panel changes. The figure shows box-and-whisker plots for each year. The rectangle extends from the 25th to the 75th percentile, the upper horizontal lines show the 75th percentile plus 1.5 times the interquartile range, and the lower horizontal lines show the 25th percentile minus this value.[11] The top panel also shows the federal minimum wage values. These figures clearly illustrate the extent to which states and localities have advanced minimum wages well beyond the federal level in recent years.[12]

Although wages are not central to our analysis, we are interested in estimating wages, to assess the extent to which the bindingness of the minimum wage may vary between blacks and whites. The ACS does not report hourly wages, so they have to be estimated from information on annual wage and salary income and total hours worked. We drop those reporting zero hours. However, these are either unemployed or not in the labor force the entire year. Weeks worked last

[11] The latter is often not shown because of bunching attributable to the federal minimum wage. Note that there are a few minimum wage declines owing to deflation for an indexed minimum wage (Colorado in 2010, https://staffscapes.com/colorado-s-minimum-wage-rate-for-2010/), and legislation (Iowa, in 2017, https://www.johnsoncountyiowa.gov/wage) and a court ruling (Kentucky, in 2016, https://nkytribune.com/2016/10/kentucky-supreme-court-invalidates-minimum-wage-measures-passed-by-lexington-louisville/) overturning local minimum wages. Note also that some PUMA definitions change in 2012, in which case the first percent change can be in 2013.
[12] Most of the variation is at the state level, so the state versions of these figures look similar.

year is a categorical variable with ranges 1-13, 14-26, 27-39, 40-47, 48-49 and 50-52 weeks. We use the midpoints of these ranges. Hours are reported as usual hours worked per week, reported as 1-99, and top-coded at 99. We thus estimate hourly wages as (wage and salary income/{weeks x usual weekly hours}). This approach generates a handful of extreme outliers, with some maximum values in the tens of thousands of dollars, as well as some very low values.[13]

We first inflate all income and wage data to 2019 dollar values using the Consumer Price Index from the U.S. Bureau of Labor Statistics.[14] Next, we identify two types of wage outliers. At the low end are those reporting zero annual income (308 out of more than 16 million). Even if they are over-reporting hours, such as by adding an extra zero, their estimated wage would still be zero, so we do not try to correct these (they will be eventually dropped based on truncation rules discussed shortly). There are also some very high values; for example, the 99th percentile is \$151. In many cases, these are associated with high annual incomes. For example, of those with hourly wages above the 99th percentile, 68.5% have annual wage and salary income above \$297,000 – the 99th percentile of population wage and salary income distribution. When estimated hourly wages are high and reported wage and salary income is high, there is no obvious problem. These people generally work 40-60 hours per week (Figure 2, Panel A). In other cases, though, those with wages above the 99th percentile and income below the 99th percentile have low reported/estimated hours per week; they have much more hours mass below 20 hours per week and even below 5 hours per week (Figure 2, Panel B). And this is even more apparent if we restrict income to a lower value, like income below the 90th percentile while wages are still above the 99th percentile (Figure 2, Panel C). Thus, it seems likely that in many of these cases hours are reported or coded with a missing

[13] There were 0.12% of observations with estimated wages < \$1, 0.02% with wages > \$1,000, and 0.0004% with wages > \$10,000.)

[14] The source for this is https://fred.stlouisfed.org/series/CPIAUCSL#0.

zero after the first digit. We thus added a zero to hours when hours were reported as a single digit and wages were above the 99th percentile. After doing this, we restrict wages to between ½ of the prevailing federal tipped minimum wage[15] and $130, in 2019 dollars. With these changes and restrictions imposed, the distribution of estimated hourly wages looks well-behaved (Figure 3).[16]

The main outcome on which we focus is employment in the reference week. We also present results for any employment in the past year (in appendix tables); the results are qualitatively similar. In addition, we present some analyses for wages, annual earnings, and annual hours.

Descriptive Evidence

There are race differences in skills that would make minimum wages more binding for blacks. As shown in Figures 4A and 4B, blacks are younger and less educated. However, our constructed/estimated hourly wage data indicate lower wages for blacks conditional on age and education. As an example, Figure 5A shows these hourly wage differences by year for black and white males with at most a high school degree, who are younger than 30 years of age. If we condition on working full-time (40 hours a week) and full-year (50-52 weeks a year), the gap is somewhat larger (Figure 5B). In contrast, however, hourly wages for black teens are higher than for white teens (Figure 5C).[17]

In our analysis, we estimate employment regressions for subsets of the population distinguished by education, age, etc. (as well as race). Wage differences by race within these groups could reflect unobserved skill differences (stemming, for example, from lower school quality for

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[15] The source for this is https://www.dol.gov/agencies/whd/state/minimum-wage/tipped/History.

[16] Nonetheless, as this discussion suggests, using the ACS data to estimate employment effects of minimum wages using a "wage bin" or a "fraction affected" approach would be ill-advised.

[17] Teenagers may be a quite heterogeneous group, ranging from high school dropouts to those who will eventually have very high education (for example, 59% of teenagers do not yet have a high school degree), and part-time as well as full-time workers. Moreover, these characteristics may differ by race. Thus, it is perhaps not surprising that the black wage shortfall we generally see does not appear for teenagers. We cannot observe future education in these data. However, if we condition on full-year, full-time workers there is somewhat more of an indication that wages are higher for white teenagers (Appendix Figure A1).

blacks) or discrimination, but either way they might predict stronger disemployment effects for blacks when minimum wages are more binding.

We next examine evidence on whether minimum wages are more binding for blacks. Figure 6A shows that, for all workers, the spike in the wage distribution at the minimum wages is much more pronounced for blacks. This is sometimes the case, although less markedly so, for subgroups defined by education, age, and gender, suggesting that the evidence in Figure 6A is not fully attributable to measurable differences between blacks and whites along these dimensions, although these differences clearly matter. For example, Figure 6B, for males with a high school degree or less, shows quite clearly a larger spike and more mass near the minimum for blacks than for whites. But in Figure 6C, for male high school dropouts only, the differences are much less pronounced – presumably because a larger share of blacks than whites, in Figure 6B, are high school dropouts. Similarly, Figure 6D is for high school dropouts under age 30; again, the race differences are less pronounced than in Figure 6B, because the age restriction accounts partly "controls" for blacks being younger. Consistent with Figure 4C, the distributions are not notably different for teens (Figure 6E). This descriptive evidence suggests that race differences in employment effects of minimum wages could be more pronounced when we condition on low education and relatively young age, but not necessarily teenagers. Even more clear from these figures, though, is the motivation for looking at less-educated and younger workers rather than all workers when studying the employment effects of minimum wages, because the minimum wage is binding for larger shares of these groups.

Employment Results

Baseline minimum wage-employment regressions

We first estimate some standard minimum wage-employment regressions, focusing on evidence of differential effects of minimum wages for different groups of workers, without yet distinguishing effects by race. We focus on those with a high school education or less, and under different age thresholds, because minimum wage effects for these groups can, on the one hand, do the most to boost incomes, but on the other hand can also have the most adverse labor demand effects. We also study combinations of low education/young age criteria, and in each case include estimates by gender as well. Our analysis is at the PUMA-level, wherein each observation is a PUMA-by-year-by-race cell.

The initial PUMA-level regressions are of the form:

$$Y = \alpha + \beta \cdot \ln(MW) + \gamma_B \cdot Black + X\delta + D_P \cdot \lambda + D_T \cdot \tau + \varepsilon \qquad (1)$$

Y is the mean employment rate, MW is the highest minimum wage prevailing in a PUMA, Black is a dummy variable for PUMA cell means for blacks, X is a vector of controls, including the proportion of males, average number of children, average age, and the proportion of people in each category of marital status and education, in each PUMA by year and race.[18] D_P and D_T are PUMA and year fixed effects. This regression is standard in the minimum wage-employment literature.

The results are reported in Table 1, for a large number of low-skilled groups. Note that we have not included any cyclical control. Although some minimum wage studies include an unemployment rate – sometimes calculated for a more-educated and/or older group assumed to be unaffected by the minimum wage – given that we are estimating minimum wage effects for a number of age and education groups beyond the common focus on teenagers, it seemed inappropriate to assume we know which group's unemployment rate is unaffected by the minimum

[18] Marital status has the following categories: married (spouse present), married (spouse absent), separated, divorced, widowed, and never married/single. Education has the following categories: no schooling, nursery school through grade 4, grade 5-8, grades 9-12 (without completion certificate), 12th grade completed (GED or regular high school diploma), some college experience, bachelor's degree, and master's degree or above. Ethnicity is not added as a control as it has little variation; only 2.6% of blacks report Hispanic ethnicity while the remaining 97.4% are non-Hispanics. For our analysis, we are only considering blacks and non-Hispanic whites, as noted earlier. All PUMA-level estimates (in all tables and figures) are weighted by the corresponding PUMA population in each year.

wage and hence a valid control. This issue is, a priori, less of a concern for our primary question of interest – differences in the effects of minimum wages on blacks vs. whites, although the business cycle may have different effects by race (e.g., Forsythe and Wu, 2021). Nonetheless, we estimated equation (1) for the same less-skilled subsamples we study in Table 1, but adding as a cyclical control the unemployment rate of prime-age, male, college-educated workers, and the results were not sensitive.

Turning to teens, the estimated effect of minimum wages on teen employment is negative but not significant, with an elasticity of −0.079. Broken out by gender, the results are not very different, although the point estimate and elasticity are a bit larger for male teens. The remaining rows move away from the usual focus on teenagers, with the model estimated for those with less education (high school at most, or less than high school), age (less than 25 or less than 30), and gender, and then the combinations of these.[19] None of the estimated minimum wage effects are significant at the 10% level. However, almost all of the estimates are negative: for teens (overall and by sex); for those under age 25 (overall and by sex); for high school dropouts (overall and by sex); and for all combinations of younger age and lower education (overall and by sex).

Differences in employment effects by race

We next turn to our primary analysis – estimation of differences in minimum wage-employment effects by race. We estimate equation (1) separately for each race:

$$Y = \alpha + \beta \cdot \ln(MW) + X\delta + D_P \cdot \lambda + D_T \cdot \tau + \varepsilon \qquad (2)$$

This is equivalent to estimating a fully interactive model with Black, where "Black" is a

[19] Note that these low-skill groups have some overlap – e.g., there are many teenagers in the groups defined based on age below 25 or 30 and education less than high school or at most a high school degree. (For example, 78% of those with less than a high school degree and under 30 are teens, but on the other hand 41% of teens have a high school degree or more education.) Our goal was to define low-skill groups based on age, based on education, and based on both (the strictest definitions), rather than to study small mutually exclusive groups.

dummy variable for PUMA cell means for blacks. We also estimate this interactive model so that we can easily calculate the significance of the race differences in estimated employment effects.

The race differences in estimated minimum wage effects, reported in Table 2, are striking. The estimated employment effects for whites are never statistically significant and they are small, although they are negative in most cases. However, the estimated employment effects for blacks are negative for *every* low-skill group we consider. Moreover, the estimated differences and the overall effects for blacks are statistically significant at the 1%, 5% or 10% level for many groups. For the overall effects for blacks ("Black empl. effect"), these include: teens (all, male and female); high school dropouts (all, male, and female); under 25, high school dropouts (all, male, and female); under 25, with at most a high school education (all, and male); under 30, high school dropouts (all, male, and female); and under 30, with at most a high school education (male).[20] In general, when we consider low education (high school dropouts), or combinations of low education (up to at most a high school education) and being young, there is clear evidence of adverse effects of minimum wages on black employment – and more so for males. This is also true for teens.

In addition, when we look at elasticities, the race differences are even more pronounced, because for every group we consider, the employment rate is lower for blacks. As an example, looking at those with at most a high school education, under 30, and male, the estimated minimum wage coefficient for whites is 0.002, vs. −0.048 for blacks. But because the employment rate is 0.334 for blacks and 0.527 for whites, the elasticity difference is much larger (0.004 for whites vs. −0.144 for blacks). In addition, there are some cases of quite large elasticities for low-skilled blacks: e.g., −0.244 for black teens; −0.365 for black high school dropouts under 30; −0.389 for black male high school dropouts under 30; and −0.480 for black male high school dropouts under

[20] The "daggers" in the second column report the statistical significance of the difference between the estimates for blacks and whites.

25. These are much larger disemployment elasticities than are typical of most of the research literature (Neumark and Shirley, 2022). Moreover, there is some hint that minimum wages may be more adverse for employment of black men compared to black women.[21,22]

Potential econometric biases

Recent econometric work has highlighted potential biases in panel data estimates when there are pre-trends or heterogeneous (dynamic) treatment effects (e.g., Callaway et al., 2024; Wooldridge, 2021). On a priori grounds, we are less concerned about these biases in this paper, because in large part we focus on relative effects of minimum wages on blacks and whites. These comparisons likely net out any common shocks/changes for the low-skill groups we study. Still, the overall effects for each group are also clearly of interest. As noted in regard to Table 2, the adverse effects of minimum wages for blacks are stronger when we focus on lower-skilled groups, such as both young and less-educated. The alignment of these differences with how we would predict minimum wage effects to vary with skill makes it less likely they are spurious.[23] Moreover, we do additional analyses that rule out meaningful biases.

First, we can define a subperiod after the last federal minimum wage increase (in 2009), when there are some never-treated PUMAs (those where the federal minimum wage continued to bind or there was no minimum wage change at the state or local level) that can be compared to

[21] Table 2 also reports the share of whites and blacks in each of the skill groups defined by age and education. Consistent with the descriptive information reported earlier (Figure 4), there is a larger proportion of blacks than whites in each of these lower-skill groups.

[22] Appendix Table A1 reports estimates paralleling Table 2, but defining employment as any weeks worked in the past year. These are qualitatively similar to the estimates in Table 2. Appendix Table A2 reports estimates for annual hours. These provide even stronger evidence than the employment effects, with negative and significant estimates for blacks in the majority of cases, and many elasticities exceeding −0.2 or −0.3.

[23] In addition, prior research (Cengiz et al., 2019; Dube et al., 2024) has argued that the shocks to employment in the 1980s and 1990s that predated later minimum wage increases are what leads to bias in estimated employment effects of minimum wages, and Dube et al. (2024) argue that starting analyses in 2000 avoids this problem. This question is not settled, but regardless, our data start in 2005, so if one were concerned about contamination from these earlier shocks, it would not raise questions about our findings.

ever-treated PUMAs (where the state or local minimum wage increased since 2009). We start this analysis in 2012, which puts a few years between the last federal minimum wage increase and the end of peak labor market effects of the Great Recession (the unemployment rate peaked in 2009), and the start of the period we consider. Moreover, new PUMA definitions were established in 2011.[24] We first estimate the models from Table 2 for this sub-period and show that the results are very similar – which is itself a useful robustness check. These results, discussed in more detail below, are reported in the first two columns of Table 3.

This analysis of the data from 2012 on, with a sizable number of never-treated areas, is useful because pre-treatment trends can be compared, and contrasts between treated and untreated areas can be made with less reliance on regarding previously treated areas as untreated (although we present a more formal analysis below). We can then examine trends in employment rates for blacks and whites for various low-skill subgroups. We focus on teens, high school dropouts, and high school dropouts less than either 25 or 30, as these are the groups with the strongest adverse effects for blacks in Table 2, and hence the ones we want to probe further to assess whether these estimates are likely causal. These results are reported in Figures 7 and 8. Figure 7 displays the trends in employment rates by race for the treated and never-treated PUMAs, for blacks and whites and for different skill groups. The figure also displays the number of local minimum wage increases (by PUMA) in each year, indicating a rising number of such increases once we get a few years past the 2012 start year. Figure 8 reports similar information but showing instead the differences between black and white employment rates. The latter are somewhat easier to interpret, since we ultimately are interested in how employment evolves differently for blacks and whites when the minimum wage increases.

[24] There are 1,000 never-treated PUMAs and 1,351 ever-treated PUMAs in this sub-period.

Our core result from the prior regression analyses is that minimum wage increases reduce employment of low-skilled blacks (overall, and relative to whites). Hence the concern would be an indication that black employment was declining in the ever-treated areas relative to never-treated areas before the minimum wage increases occurred. As shown in the figures, there is at most some indication of declines in the ever-treated areas in the first year but then, if anything we tend to see faster-growing black employment in the ever-treated areas in the early years (e.g., for high school dropouts overall and for high school dropouts under age 30). This evidence suggests that our panel data estimates should be reliable for this sub-period, and as noted above, these estimates yield similar results as the full-period estimates shown in Table 2.[25]

Moreover, Figure 8 provides a relatively simple depiction and understanding of the relationships between minimum wages and employment rates for blacks and for whites over this sub-period. In particular, black and white employment rates are evolving similarly in the ever-treated and never-treated PUMAs in the early part of this sub-period, with the race differences declining somewhat in most panels of the figure. In the latter part of this sub-period, however, the race differences decline in the never-treated PUMAs, likely in response to the tightening labor market from about 2016 (which also can be seen in many panels in Figure 7, where the never-treated line for blacks moves closer to that for whites).[26] But in the treated PUMAs this does not happen – as reflected in the flattening or downward slope of the black dashed lines, corresponding to the ever-treated states. This seems consistent with rising minimum wages in these states offsetting the greater advantageous effect of the tightening labor market for lower-skilled blacks

[25] We found similar trends in employment rates for additional combinations of low-skill groups not reported in Figures 7 and 8, such as those under 25, those with at most a high school education under age 30, and high school dropouts under age 25.

[26] This improvement in minorities outcomes during a tight labor market has been described in Okun (1973), validated in, e.g., Hoynes (2000) and Jefferson (2008), and updated and analyzed further in Aaronson et al. (2019).

that would otherwise have occurred.

In addition, we implement the two-stage difference-in-differences method of Gardner et al. (2024). Unlike some recent methods developed to address potential biases in two-way fixed effects estimates, this method can be implemented when there is continuous treatment (as well as other complications). The basic idea is to estimate area and period fixed effects for any untreated observations available (which can be subset of observations for treated observations, and excludes always treated observations). Under a parallel trends assumption, these are unbiased for the full sample. One can then residualize, and estimate "2nd-stage" regressions on residuals, leading to unbiased estimates (with the correct standard errors recovered from GMM).[27]

The estimates are reported in the "2S-DID" columns of Table 3, for the same 2012-19 period for which we have never-treated PUMAs and PUMAs treated after the first year (with one or the other required for inclusion in the sample for which this method can be implemented). The conclusions are generally very similar. The standard errors are a bit larger, as we would expect. But we still obtain a consistent pattern of negative estimated employment effects for blacks for every age and education group, with a number of them statistically significant, although the estimates are a shade smaller in absolute value and a few of the estimates become insignificant.[28]

[27] Gardner et al. also show that this estimator performs better than other estimators when used on simulated data where the assumptions that make two-way fixed effects unbiased are not violated.

[28] Other recent papers in the new difference-in-differences literature have sometimes examined evidence on minimum wage effects, but by necessity using a discrete treatment (e.g., Callaway and Sant'Anna, 2021; Clemens and Strain, 2021, who use three dummy variables for different types of minimum wage increases – indexed, non-indexed large, and non-indexed small; and Hampton and Totty, 2023). Given that the Gardner et al. method can use continuous variation, there is no reason to discard such variation. Nonetheless, we look at event-study evidence, treating the first minimum wage increase in our sample period as the treatment. There was no evidence of violation of parallel trends; pre-treatment estimates going back up to three years are close to zero and statistically insignificant (results available from authors upon request, but for examples, see Appendix Figure A2). Interestingly, as these estimates indicate, and as we further document in estimates corresponding to Table 3 for this discrete definition of minimum wage treatment (Appendix Table A3), the estimated employment effects on blacks using this discrete definition are not distinguishable from zero. This suggest considerable caution in drawing substantive empirical conclusions from the application of methods that require defining what is actual continuous treatment as discrete treatment – at least in the minimum wage context.

Exploring Some Explanations of the Stronger Employment Effects of Minimum Wages on Blacks

We have documented considerably stronger effects of minimum wages in reducing employment of black low-skilled workers than white low-skilled workers. Indeed, while we find significant negative employment effects for blacks, with quite large elasticities, we find no statistically significant effects for whites (and correspondingly the elasticities are much closer to zero, although generally negative). In this section, we explore some evidence on why. To be clear, though, the main focus of this paper is on whether minimum wage effects differ by race; more definitive evidence on why the race differences we find exist await more and different kinds of research.

One explanation for the race difference is that minimum wages could be more binding for blacks. It is true that blacks are younger and less educated than whites (Figure 4), and overall minimum wages are more binding for blacks. But recall that our regressions condition on young ages, low education, or both, and the spikes in the wage distribution for lower education and age groups were not that much more pronounced for blacks – although they were to some extent (Figure 6). The latter – i.e., wages lower for blacks even conditional on these observable skill measures – can occur because of lower unmeasured components of skill owing to early skill gaps (e.g., Carneiro et al., 2005), school quality differences (see, e.g., the evidence and other studies reviewed in Hanushek and Rivkin, 2009), or other pre-market factors (Neal and Johnson, 1996). Wages for blacks can also be lower conditional on age and education because these variables do not capture actual labor market or job tenure (nor do other variables in the ACS). Lower employment rates and higher unemployment rates for blacks would likely imply that their actual labor market experience is lower for the same potential experience, and that job tenure is also lower. Wages can also be lower for observationally similar blacks because of discrimination that results in lower wages for blacks.[29]

In addition, even if skills and wages are similar, when employers choose to cut back employment in response to a higher minimum wage increase, the job loss could fall mainly on blacks. This is another form of discrimination, if there is no observed or unobserved skill difference that could justify such decisions. However, given that employment adjustment to the minimum wage may come about mainly via slower hiring (e.g., Liu et al., 2016; Portugal and Cardoso, 2006), hiring discrimination may be the culprit.[30,31]

We assess whether minimum wages are more binding for blacks in two ways. First, we contrast the bindingness of the minimum wage for the different groups we study with the estimated employment elasticities. Second, and related, we compare estimated employment effects to estimated wage effects.

Figure 9 plots – for many of the groups we study in Table 2, again focusing on the groups for which we found the strongest adverse effects for blacks – the proportion below 110% of the

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[29] There is a good deal of evidence of discrimination in hiring against blacks and other minority groups (Neumark, 2018). In search models (e.g., Black, 1995), hiring discrimination against a group by some employers will lower market wages for that group.

[30] If the minimum wage has caused employers to adjust labor and other inputs so that many workers' marginal revenue products are equal to the minimum wage (consistent with spikes in the wage distribution at the minimum wage), then there is no cost to employers to discriminate against a particular group in reducing employment. (For an early version of this argument, see Stratton, 1993.) One still might expect some mitigation of discrimination from the threat of lawsuits. But research on the employment effects of the minimum wage suggests that higher minimum wages reduce employment via lower hiring. U.S. discrimination law might do little to prevent hiring discrimination that reduces black employment, both because damages are low (as workers get hired sometime later) and it hard to identify a class for a class action lawsuit (Bloch, 1994).

[31] Yet another explanation is that the lower-skilled or younger blacks and whites that we study work in different industries with different elasticities of labor demand. However, the industry distributions are very similar across blacks and whites. For example, for teens, high school dropouts, and high school dropouts under age 30, respectively, the correlations between NAICS two-digit industry employment shares for blacks and whites are 0.98, 0.99, and 0.99. Furthermore, both blacks and whites (in each of these sub-groups) have the highest representation in the two industries – Retail and Food & Accommodation – which have been the primary focus of industry-specific studies examining the negative impacts of minimum wage increases (e.g., Kim and Taylor, 1995; Dube et al., 2010; Jha et al., forthcoming). We thus think industry composition plays little role.

minimum wage, and the estimated employment elasticities for blacks and whites.[32] Differences in the shares below 110% of the minimum wage for blacks and whites are not apparent. To reiterate, though, these comparisons of bindingness can reflect a number of factors and not simply wage differences (or lack thereof) between otherwise identical blacks and whites.[33] Figure 9 also displays the estimated employment elasticities. As we saw in the earlier tables, the employment effects are considerably more adverse for blacks. The figure emphasizes that these differences in employment effects emerge even though the bindingness of the minimum wage is very similar for blacks and whites. This is apparent, for example, for: high school dropouts (all), for teenagers (all, male, and female), and for and high school dropouts under 30 (all, male). For some groups like high school dropouts (female) and high school dropouts under 30 (female), the employment elasticities are more adverse for blacks even though the minimum wage is more binding for whites. Thus, this evidence does not suggest that the more adverse effects of minimum wages for black employment are attributable to minimum wages being more binding for blacks.

We can get a somewhat different perspective from comparing wage and employment elasticities. The wage elasticities are estimated using the same regression as in equation (2), although for log wages. The results are presented in Figure 10, which plots the estimated wage elasticities and employment elasticities for each group. These figures provide a way to display more of these estimates compactly. There are a number of observations to take away from the figure. First, in all cases, the estimated wage elasticities are (mostly) positive (and range up to about 0.3). This is to be expected, although one might expect less precise estimates relative to results using

[32] Appendix Figure A3 includes the remaining groups covered in Table 2.
[33] We also note that minimum wages appear to be a bit more binding for females, as indicated by the slightly higher blue bars for them – in contrast to what we might have expected for blacks relative to whites. This may be because employment effects are more adverse for blacks but not for women, so that more women with lower wages are still working after minimum wage increases.

measured hourly wages like in the CPS; nonetheless, the point estimates are in the same range.[34]

Second, in every panel, groups with higher wage elasticities also have larger negative employment elasticities. This is clear from the plotted estimates, as well as the simple bivariate regression lines fitted to these points. This finding boosts the credibility of our employment estimates, in the sense that, within race, groups for whom wages are pushed up more by the minimum wage (for workers remaining employed) also experience larger job losses. However, recall that the estimated employed effects for whites were small – which is made clear in the figure by keeping the vertical axis the same for blacks and whites and noting that the white employment elasticities are much closer to zero.

Returning to our main inquiry, the third observation is that the wage elasticities are not larger for blacks than for whites, but rather are on average a bit lower (see the note to Figure 10). This is consistent with what Figure 9 showed – that minimum wages are not much more binding for blacks than for whites once we condition on education and/or age.

Fourth, for similar wage elasticities, the employment elasticities for blacks are considerably larger (in absolute value). This is of course related to the evidence from Figure 9, but here we can see that black employment declines following minimum wage increases are much larger than those experienced by whites despite similar or smaller effects on wages. Moreover, wage elasticities are estimated from the employed only, so if blacks experience more job loss, there may be more selection of low-wage blacks than of low-wage whites out of the samples used for the wage estimates. This would imply that wage elasticities for blacks could be biased upward, implying that the higher wage vs. fewer jobs tradeoff is even worse for blacks.[35]

[34] For example, looking at the less-educated or teenagers, Neumark and Wascher (2011) report estimates in the range of about 0.15 to 0.3. The measurement error of relevance here is in the dependent variable, which should just lead to imprecision in estimating the effect of the minimum wage, not bias (assuming the measurement error is classical).

[35] The same would apply to Figure 9. On the other hand, there is a potentially offsetting source of bias. As noted earlier

Together, we interpret this evidence as indicating that the stronger adverse employment effects of minimum wages for blacks are not necessarily explained by lower skills of blacks, or lower wages (even unrelated to skills). These are likely part of the story, given that minimum wages are generally a bit more binding for them. However, the evidence on wage effects does not establish that blacks' wages would be pushed up more – although this may be obscured by selection out of employment of lower-wage blacks in response to a higher minimum wage. It is possible that an additional factor is that employers simply choose to reduce employment of blacks more when reducing overall employment in response to minimum wage increases, whether through hiring or separations.

Earnings Effects

Our estimated employment and wage elasticities provide information on the "wage elasticity" of employment stemming from variation in the minimum wage. This parameter is of interest because the larger it is (in absolute value, assuming the employment effect is negative), the less likely that a higher minimum wage raises earnings of the affected groups.[36] For whites, the wage elasticities are largely in the 0.05 to 0.15 range, and the employment elasticities smaller (in absolute value), implying employment-wage elasticities that can be quite close to zero, in which case higher minimum wages would increase earnings for white workers. For blacks, in contrast, in

(and shown in Appendix Table A2), a higher minimum wage reduces hours for blacks. Given that we construct wages by dividing annual earnings by midpoints of weeks worked ranges, hours reductions for blacks are sometimes not captured by the midpoints we use (unless the range changes), implying downward bias in wages measured for blacks following minimum wage increases (although if the decline puts a person in a lower range but is smaller than the midpoint difference, the opposite could occur).

[36] Freeman (1996) interprets the elasticity of employment with respect to the minimum wage as the elasticity of demand for minimum wage workers. He notes: "[I]f the elasticity of demand for minimum wage workers exceeds one [*in absolute value*], the minimum wage will reduce rather than increase the share of earnings going to the low-paid" (p. 641, italicized text added). Unless one is looking only at workers paid the minimum wage, the wage elasticity with respect to the minimum wage is well below one (a common value in many studies is around 0.15-0.3, as noted earlier). Thus, to estimate the elasticity of demand for minimum wage workers and draw inferences about the effects of the minimum wage on earnings of minimum wage workers, one has to divide the employment elasticity by the wage elasticity.

most cases the employment elasticity is larger in absolute value. In that case, black workers' earnings are likely to decline in response to higher minimum wages (even more so if the wage elasticities for blacks are biased upwards).

Rather than speculate based on estimated employment and wage elasticities (and ignore potential effects on hours), in Table 4 we directly estimate effects on earnings (including zeros, so bias from selection into the sample with wages is now irrelevant). The results are striking. For most definitions of low-skilled workers, the estimated earnings effects for whites are positive, and they are significant in some cases: for < 25 (overall and females); less than high school (females); and those with at most a high school education (female). In sharp contrast, the estimated effects for blacks are much more likely to be negative, and significant in many cases (for five groups at the 10% significance level or less): for high school dropouts under 25 (overall, and males); for high school dropouts under 30 (overall, and males); and for those with at most a high school education under age 25 (males). In addition, there are other sizable negative effects for blacks that are not significantly different from zero but are significantly different from the effects for whites (e.g., for teenagers). Moreover, some of the negative elasticities are sizable, ranging to as much as −0.51, with the estimated adverse impacts sometimes considerably larger for black men. The conclusion appears to be that young and less-educated black men, in particular, are harmed by higher minimum wages.

Table 5 presents estimates from the same two-stage difference-in-differences method used in Table 3 (again, for 2012-19). The results are quite robust, and in some cases stronger. The results in the first two columns also indicate that the results are robust to the shorter sample period – with even more evidence of adverse effects on blacks, again more so for black males.

Spatial Implications and Analysis

Implications of residential racial segregation.

There is extensive residential racial segregation in the United States (e.g., Iceland and Weinberg, 2002; Logan, 2013). Figure 11 shows information on this segregation at the PUMA level, in our data. We plot the share of the population that is black in PUMAs in each decile (and at some other percentiles) of the share black at the PUMA level.[37] A horizontal line would indicate that the share black is the same everywhere. The relationship is not only steep, but convex, indicating sharp segregation of blacks by PUMA, with, for example, the share black increasing from 42.33% to 91.45 % from the 90th to the 99th percentiles.

Given the residential concentration of blacks, the more adverse effects of minimum wages on black than on white employment imply that job loss from minimum wages will be sharply concentrated in black areas. In particular, combining the evidence on employment effects from Table 2 with the pattern of segregation in Figure 11, the very low share black in the first six or seven deciles of the share black implies that in most PUMAs, the overall effects of minimum wages will be minimal, whereas the overall effects would be quite strong in the higher deciles where the share black is much higher because of the nonlinear nature of residential segregation.

The much larger implied employment effect in areas with a high share black is illustrated, by way of example, in Table 6, where we use the estimates from Table 2 to do a simple simulation of the effects of a higher minimum wage. Specifically, we consider the effects of an increase from the federal minimum wage of $7.25 prevailing in 2019 (the end of our sample period) to the California minimum wage in that year of $12. We present estimates for teenagers, male teenagers, and high school dropouts under 30. Using the estimates from Table 2, the estimated elasticity varies across PUMAs (and the percent black) because the employment rate is different at different

[37] The first point in the graph corresponds to the 1st percentile and the last point corresponds to the 99th percentile of share black at the PUMA level. All deciles are computed as the weighted percentile of share black across PUMAs, where the weights correspond to the PUMA population in each year.

percentiles. Given the strong non-linearity in segregation (Figure 11), we show results at the 10th, 90th, and 95th percentiles.

For teenagers, the white population share at the 10th percentile is nearly one, (100%, 0.985), while the black population share is 0.512 at the 90th percentile and 0.660 and the 95th percentile. As shown in the third and fourth rows, employment rates of blacks are a good deal lower than employment rates of whites (and employment rates of both groups are lower in areas with a higher share black). In this case, the difference between the white employment rate in white areas (at the 10th percentile of the share black) and the black employment rate in black areas (at the 95th percentile of the share black is 0.205 (0.403 – 0.198), and the difference in the weighted employment rate between these areas is a bit smaller (0.171), but not by much. The minimum wage employment elasticities are larger in absolute value for blacks. As a result, the average employment elasticity (weighting by population shares) is small in white areas (−0.052), and much larger (−0.203) in black areas. As a result, as shown in the final row of the table, the large minimum wage increase considered would only lower the employment rate of teens in areas at the 10th percentile of the share black by less 1.3 percentage points. In contrast, the effect in areas at the 95th percentile of the share black would be a decline of 2.8 percentage points. The results for male teens are similar.

Going through the same calculations for high school dropouts under age 30, the difference is more dramatic. In this case, the large minimum wage increase considered would lower the employment rate of high school dropouts under 30 in areas at the 10th percentile of the share black by only 0.5 percentage point. In contrast, the effect in areas at the 95th percentile of the share black would be a decline of 3.5 percentage points.

These are simple simulations based on the estimates. But they suggest that some of the larger minimum wage differences that now exist in the United States could account for a sizable share of the lower employment rate of less-skilled workers in areas with a high black population share. Consider high school dropouts under age 30. The simulation implies that minimum wages lower the employment rate of blacks in heavily black areas by 3.0 percentage points relative to largely white areas. This is about 20% of the weighted difference in employment rates between PUMAs at the 10^{th} and 95^{th} percentiles of the share black (15.4 percentage points). The difference in impacts in areas with a high share black arises because the adverse employment effects of higher minimum wages fall mainly on blacks.

The estimates covering more groups are shown in Figure 12. Here, we graph the percentage of the variation explained that exactly parallels the calculation from the last row of Table 6 described just above – the percentage of the weighted difference in employment rates between areas with a high share white and a high share black that could potentially be accounted for by large minimum wage differences. For example, looking at the bars for high school dropouts under age 30, the height of the red bar is the same figure of just under 20% cited above. The red bars, which compare the 95^{th} and 10^{th} percentiles, are always higher than the blue bars, which is a function only of the higher share black interacting with the larger estimate of job loss for blacks. And these bars are, except for teens, in excess of 10% and near or above 20% for the different groups involving high school dropouts.

Variation in effects with share black in PUMA

We next take this one step further, asking whether race differences in employment effects of minimum wages also arise because of differences in employment effects by location, given the residential segregation of blacks from whites. That is, we ask whether the more adverse effects of minimum wages on blacks are attributable to more adverse effects on black individuals, or more adverse effects on neighborhoods with large black populations.

Residential racial segregation could matter for the employment effects of minimum wages on blacks vs. whites. Blacks tend to live in poorer neighborhoods with a higher concentration of low-skilled and younger workers, and a higher share of blacks as compared to whites, as shown in Figure 13A. These differences of course partly reflect underlying individual-level differences between blacks and whites (consistent with the earlier observation that blacks are, on average, younger and less educated than whites). Figure 13B instead shows differences based on the share black, indicating that in areas where blacks are concentrated, families are poorer, and workers are typically lower skilled and younger. Again, this pattern may simply reflect the fact that such areas have a higher share of blacks, who themselves tend to have these characteristics.

In contrast to Figures 13A and 13B, Figure 13C indicates that there are neighborhood characteristics in terms of skill and poverty that are independent of the race of the individuals who live there. In particular, the figure shows average characteristics of those in PUMAs at the 10th and 90th percentile of share black, by race. We see that both blacks and whites are less educated and younger in areas with a higher share of blacks. In addition, whites who live in areas with a high share black are more likely to be poor or extremely poor. This suggests that predominantly black neighborhoods differ from predominantly white neighborhoods not only because of the characteristics and composition of black workers, but also because of differences between whites living in the different areas.

The lower skills of workers in black areas can imply sharper disemployment effects of minimum wages in those areas in part independent of individual race, and the higher poverty (and extreme poverty) rate may be associated with fewer job opportunities in the first place, different kinds of businesses in the area, etc. However, the relationship of these differences to whether disemployment effects will be larger in areas with larger concentrations of blacks is subtle. Our regressions condition on skill, so even though blacks live in areas where workers are on average less skilled, the regression effects need not differ by area. On the other hand, to the extent that minimum wage effects are more adverse for the less-skilled, on average minimum wage effects would be stronger for blacks because of their position in the skill distribution.

Effects can vary across neighborhoods even if workers are similar across neighborhoods, owing, for example, to the businesses or industries present in different neighborhoods (which may vary in sensitivity to minimum wages or present more or fewer product substitutes),[38] or differences in job density (including jobs available for minorities).[39]

Effects can also differ across neighborhoods if there is differential selection of black and white workers into neighborhoods depending on their racial mix, with unmeasured skill differences that could influence minimum wage impacts. In this case, differential effects on, say, black workers in more black vs. more white areas might reflect worker differences rather than neighborhood differences per se; nonetheless, the evidence would still tell us whether, e.g., effects on blacks are more adverse in black neighborhoods.[40,41]

More generally, there are numerous motivations for analyzing differences in minimum wage effects across areas. First, previous studies have repeatedly shown that poverty, and especially poverty among minorities, is spatially concentrated at a neighborhood or city level.[42]

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[38] See, e.g., Moore and Diez Roux (2006) for evidence on differences in the distributions of different types of food stores across white and black neighborhoods.

[39] See, e.g., evidence on differences in "spatial mismatch" and "racial mismatch" across neighborhoods (Hellerstein et al., 2008).

[40] We cannot necessarily distinguish between individual and neighborhood effects by, e.g., comparing effects for black vs. white workers in black vs. white areas, because the selection can be similar across races.

[41] There could also be variation in labor market competition across neighborhoods. See Jha et al. (forthcoming) for differences in concentration in the restaurant sector between more rural and urban areas. Recent research has highlighted possible impacts of higher labor market concentration in mitigating the negative effects of minimum wages on employment (Azar et al., forthcoming; Corella, 2020). However, we examined data from the National Establishment Time Series (NETS), computing PUMA-level HHIs at both the firm and establishment level for a couple of specific low-wage sectors (retail, and food and accommodations), and for a broader set of low-wage sectors (Arts, Entertainment, and Recreation; Administrative and Support and Waste Management; and Other Services except Public Administration). As shown in Appendix Table A4, there is not a clear relationship between the share black and concentration.

[42] For a sample of research documenting the concentration of disadvantaged minorities into neighborhoods and the effects on the residents living there, see: Federal Reserve System and Brookings Institution (2008); Small and Newman (2001); Morenoff and Sampson (1997); Cutler and Glaeser (1997); and Collins and Margo (2001).

Second, Thompson (2009) shows that effects of minimum wages are particularly concentrated in sub-state areas (counties, in this case) with high concentrations of workers that are relatively low-skilled. The concentration of poor and minority workers in the same areas, coupled with Thompson's findings, suggest minimum wage effects could be more adverse for blacks in black areas,[43] which would be relevant given that other types of policy efforts are devoted to *improving* outcomes for blacks in lower-income areas (e.g., Austin, 2011; Neumark, 2018a). Third, given geographic segregation by race, adverse minimum wage effects on minorities or the poor might be expected to spill over onto other minorities – specifically those in the same neighborhood. This can happen if reduced employment lowers incomes that support other businesses in the same location. Or it may happen because labor market networks have a strong local and racial component (Hellerstein et al., 2011 and 2014), so that fewer jobs for some lowers job finding for others of the same race.

For this analysis, because we are trying to disentangle the effect of an individual's race from the share black in the PUMA, we estimate the model at the individual level. We use a pooled interactive model, augmented to allow the effects of minimum wages to vary not only with race but with the racial composition of the area (%Black):

$$\begin{aligned} Y = {} & \alpha + \beta\cdot\ln(MW) + \beta_B\cdot\ln(MW)\cdot Black + \beta_{\%B}\cdot\ln(MW)\cdot\%Black + \gamma_B\cdot Black + \gamma_{\%B}\cdot\%Black \\ & + X\delta + X\cdot Black\cdot\delta_B + X\cdot\%Black\cdot\delta_{\%B} + D_P\lambda + D_P\cdot Black\cdot\lambda_B + D_P\cdot\%Black\cdot\lambda_{\%B} \\ & + D_T\cdot\tau + D_T\cdot Black\cdot\tau_B + D_T\cdot\%Black\cdot\tau_{\%B} + \varepsilon \end{aligned} \tag{3}$$

The model includes a full set of interactions with %Black, including the fixed year and PUMA effects, to ensure that we isolate the effects of variation in %Black on the effect of the

[43] We could also in principle estimate minimum wage effects in poor vs. non-poor areas. We refrain from doing so because poverty can be affected by the minimum wage (although the evidence on this is not strong; see Burkhauser et al., 2023).

minimum wage, rather than other omitted interactions of control variables with %Black.[44] Given that we now have to evaluate the effects of minimum wages (for blacks and whites) at different values of %Black, we report results for somewhat fewer low-skilled groups. In particular, we report them for the groups for which we found the clearest evidence of race differences in the employment effects of minimum wages in Table 2, and omit additional results for similar groups. We show results for teens, high school dropouts, high school dropouts under age 25, and high school dropouts under age 30.[45]

In Table 7, we first report the estimated minimum-wage employment effect for whites, followed by the interactions with Black and %Black. Comparing the former to Table 2, the estimated employment effects for blacks are generally similar. In contrast, in *no* specification is the estimated effect of the minimum wage x %Black interaction statistically significant, and the sign of this estimated effect varies.

Table 7 also reports the implied estimated minimum wage effects at the 10th, 50th, and 90th percentiles of the share black (with this share always estimated for the entire population), along with the average white and black employment rates, the estimated elasticities, and the difference between the white and black elasticities. In general, the variation in black employment elasticities is consistent with the most adverse employment effects for blacks in the areas with the highest share black in the population. The only exceptions are female teens and female high school dropouts under age 25, for whom the black employment elasticity is largest negative at the 50th percentile of

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[44] If we omit %Black x PUMA and %Black x year, we do not get as clear evidence of a black interaction, implying that minimum wages are tending to be increased in areas with high %Black and rising black employment (but within these areas, the results imply that higher minimum wages reduce black employment).
[45] As noted just above, we also found some evidence of stronger disemployment effects of minimum wages for blacks for other low-skill groups. However, our interest in this section is in variation in effects across the share black in an area, and since we do not find strong evidence of variation in effects, limiting the groups for which we report the evidence gives a fairly complete picture.

the share black, and is smaller in absolute value at the extremes (the 10^{th} and the 90^{th} percentiles). Still, recall that the estimated coefficients underlying these differences ($\beta_{\%B}$) are never statistically significant.

To provide richer information on how minimum wage effects vary with the share black, Figures 14A-C show the estimates graphically for three groups (by way of illustration): teens, male teens, and high school dropouts under age 30. These figures do not reveal any qualitatively different results than those reported in Table 7 (restricted to the 10^{th}, 50^{th}, and 90^{th} percentiles), but the visual display helps show that there is some evidence of somewhat larger adverse employment effects for blacks in areas with a high share black (for male teens and high school dropouts under 30, in Panels B and C). These figures reinforce the conclusion that while there are differences in the estimated effects of minimum wages on employment of blacks and whites, there is little evidence of differences in minimum wage effects for either blacks or whites across areas with varying share black that could underlie the differences based on an individual's race.

Finally, in Table 8, we illustrate the evidence a different way, going back to the simulation used in Table 6, but now comparing results with the heterogeneous minimum wage effects. We report the results in a slightly different way. First, Panel A simply reports the population shares and employment rates (the information from the top five rows of Table 6, although the estimates differ slightly because the data are at the individual level). Panel B reports the same analysis as Table 6 (again, at the individual level), while Panel C reports results using the interactive specifications from Table 7. Here, because our main goal is to contrast the results with homogeneous vs. heterogeneous effects, we just report estimate for the 10^{th} and 90^{th} percentiles of the share black.[46]

Given that we walked through the calculation before, in reference to Table 6, we just jump

[46] Here, these percentiles are estimated at the individual level. But the PUMA estimates were weighted, and hence they are very comparable.

to the bottom line, which is similar. With heterogeneous minimum wage effects, the more adverse effects of minimum wages on blacks sometimes loom larger in explaining the difference in employment rates between areas at the 10^{th} vs. 90^{th} percentiles of the share black; for the three comparisons in Table 8, this is the case for the high school dropout, under 30 estimates, for which the impact of the simulated minimum wage increase lowers the employment rate in black areas by 3.3 percentage points with heterogeneous minimum wage effects (3.9 – 0.6), compared with 2.8 percentage points (3.1 – 0.3) with homogeneous minimum wage effects. For teens and male teens, however, we do not see this, reflecting the absence of a negative interaction between the minimum wage and the percent black for teens, and the very small negative interaction for male teens.

Finally, Figure 15 presents this comparison for more groups. For most groups aside from teenagers (with a couple exceptions), the implied effect of the simulated minimum wage increase on employment in black vs. white areas is larger with heterogeneous minimum wage effects.[47] But we reiterate that the statistical evidence for heterogeneous effects is weak, and the main reason higher minimum wages adversely affect black areas is because they have high concentrations of blacks and employment effects of minimum wages are more adverse for blacks.

Conclusions

There are a priori reasons to believe that the employment effects of minimum wages could be more adverse for black workers than for white workers. These more adverse effects could occur because of skill differences, Becker-type discrimination whereby employers devalue black workers' productivity and hence minimum wages are more binding, or because employers choose to reduce employment relatively more among blacks when responding to a higher minimum wage.

[47] The large difference in the opposite direction for female teens is a reflection of the large positive interaction reported in Table 7. Recall, though, that the employment rates also affect the estimated elasticities.

Despite these possibilities, and despite the very large literature on employment effects of minimum wages for low-skilled workers, race differences in employment effects have received little attention.

In this paper, we turn to this question, using ACS data that provide very large samples of both blacks and whites. We estimate standard minimum wage-employment regressions, and then extend these analyses to the estimation of race differences in effects. Many of the estimates point to substantial disemployment effects for low-skilled black workers, with some elasticities in the −0.2 to −0.3 range or higher. Moreover, these effects are much larger than for whites, for whom we generally do not detect adverse employment effects of minimum wages. We do a number of analyses that bolster a causal interpretation of these results. In addition, the evidence of adverse effects of minimum wages mainly on low-skilled blacks – and more so on low-skilled black men – is reinforced by our estimated effects of minimum wages on both wages and earnings.

We also explore whether lower skills or lower wages (whether because of unmeasured skill or discrimination) explain the more adverse employment effects of minimum wages for blacks. There is not very much evidence of this, although it is hard to be definitive because we can only estimate wage elasticities for those who remain employed. Another factor, which we regard as plausible, is that employers simply choose to reduce employment of blacks more when reducing overall employment in response to minimum wage increases.

Our analysis also compares employment and wage elasticities. Our comparisons suggest that the adverse employment effects of minimum wages on blacks are in some cases sufficiently large, relative to the positive wage effects, that minimum wages likely reduce earnings of black workers, while being more likely to increase earnings of white workers. We then confirm directly that minimum wages tend to reduce earnings of low-skilled blacks, but are more likely to increase earnings of low-skilled whites.

Given extensive residential segregation by race in the United States, any adverse minimum wage effects for blacks imply that the effects of minimum wages will be much more adverse in areas with a higher black population share. We report illustrative calculations suggesting that large minimum wage differences can account for a sizable share of the employment rate differences, for lower-skilled workers, between PUMAs at the 10th vs. the 90th or the 10th vs. the 95th percentiles of the share black. When we estimate models that also allow employment effects to differ with the share black, although the evidence of heterogeneity is weak, it nonetheless accentuates this effect, in some cases suggesting that large minimum wage differences can account for about one-fifth of the employment rate differences, for lower-skilled workers, between PUMAs with very low and very high black population shares.

Recall that Milton Friedman called the minimum wage "the most anti-Negro law on our statute books." We cannot compare the effects of the minimum wage to other laws that may adversely affect blacks. And we do not believe higher minimum wages are enacted to harm blacks, or with knowledge that the benefits may accrue mainly to whites. But our evidence indicates that – when it comes to the labor market impacts of the minimum wage – there is evidence that blacks appear to bear the cost, while whites bear very little cost and more likely benefit.

Even if one takes the view that our evidence of adverse effects on blacks is not decisive because we do not find these effects for every low-skill group we consider, there is clearly some evidence of adverse effects for blacks, and little or no evidence of adverse effects for whites and some evidence of positive effects on their earnings. In our view, at a minimum this has to call into serious question the claim that a higher minimum wage narrows the gaps in labor market outcomes between blacks and whites, and make us more likely to believe that a higher minimum wage instead widens these gaps.

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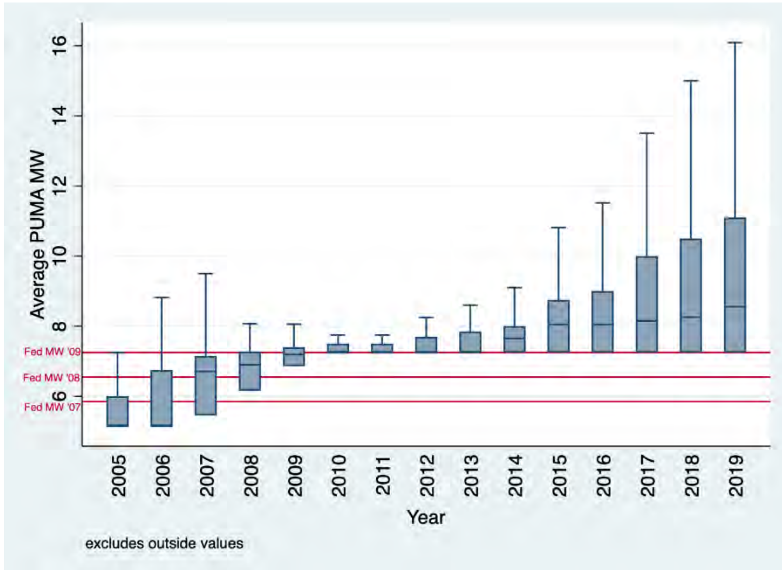
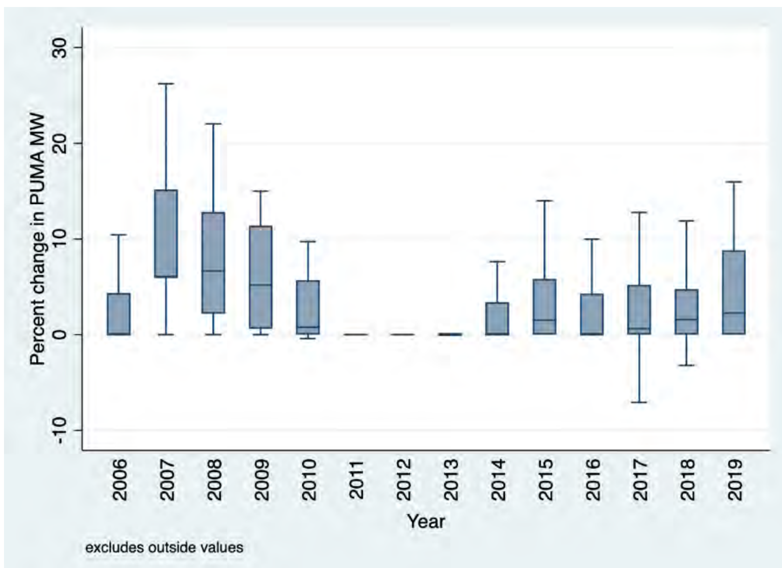
Figure 1: Box-and-Whisker Plots for Minimum Wages Levels and Percent Changes

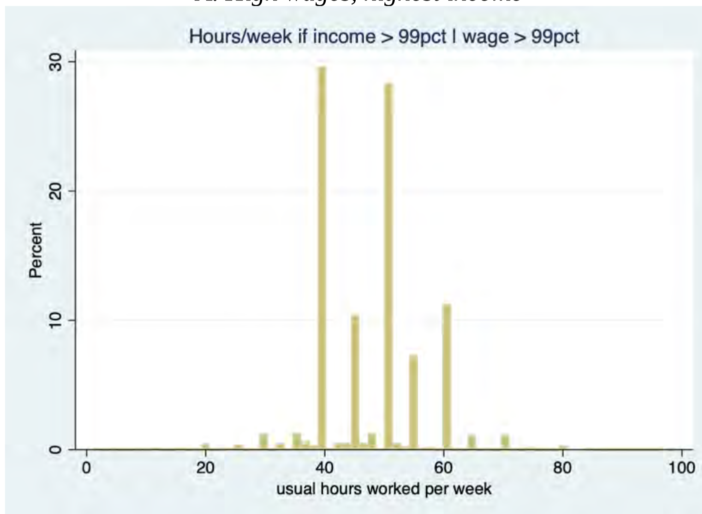




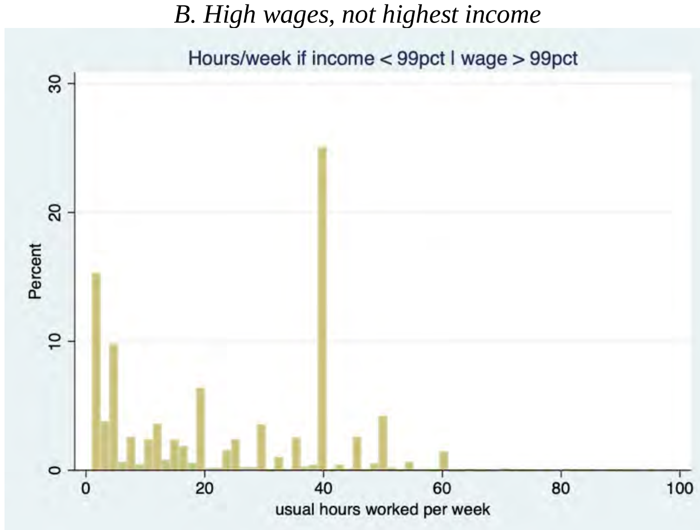
Notes: The rectangle extends from the 25th to the 75th percentile, the upper horizontal lines show the 75th percentile plus 1.5 times the interquartile range, and the lower horizontal lines show the 25th percentile minus this value. The latter is often not shown because of bunching attributable to the federal minimum wage. Note there are a few minimum wage declines owing to deflation for an indexed minimum wage (Colorado in 2010), and legislation (Iowa, in 2017) and a court ruling (Kentucky, in 2016) overturning local minimum wages. Note also that some PUMA definitions change in 2012, in which case the first percent change can be in 2013.

Figure 2: Reported Hours Distributions for High-Income and Lower-Income High-Wage Workers

A. High wages, highest income



B. High wages, not highest income



C. High wages, lower income

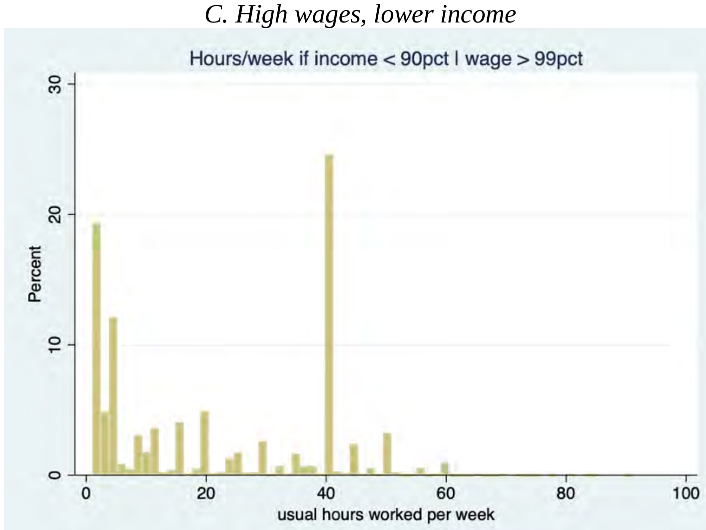


Figure 3: Distribution of Estimated Hourly Wages

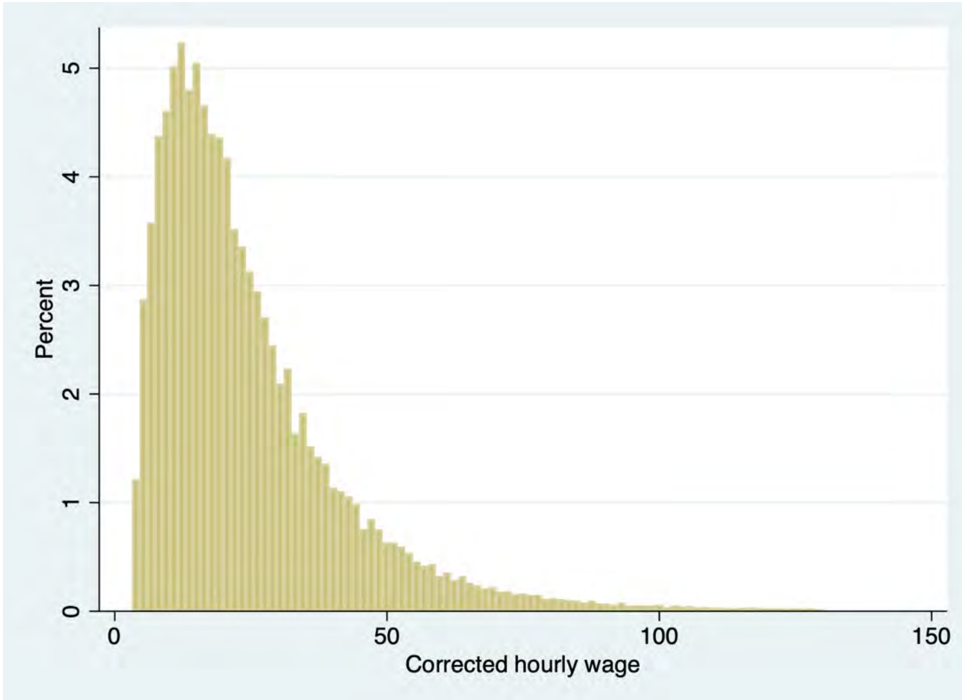
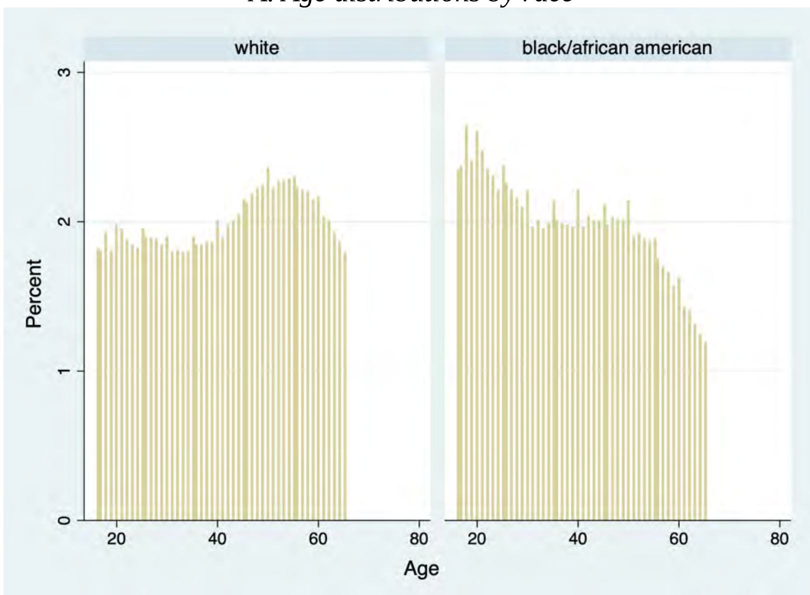


Figure 4: Race Differences in Age and Education

A. Age distributions by race



B. Education distributions by race

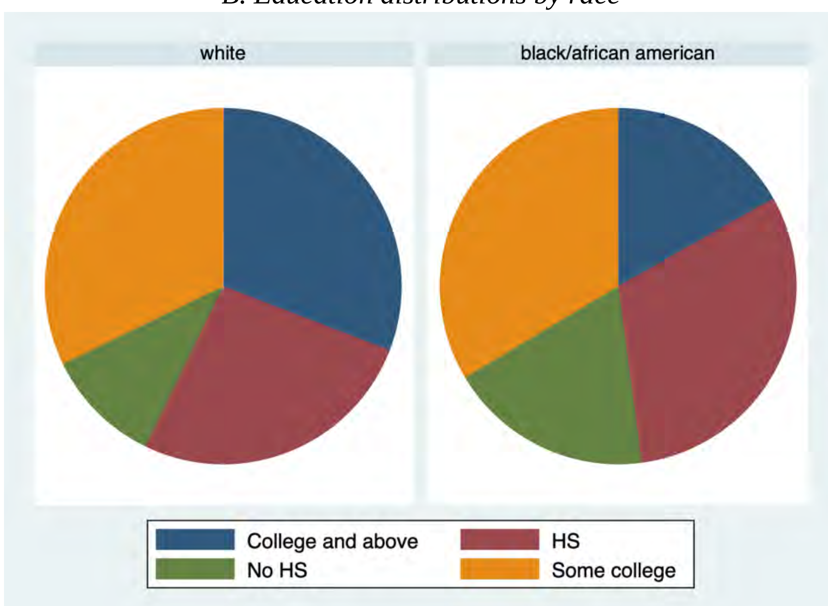
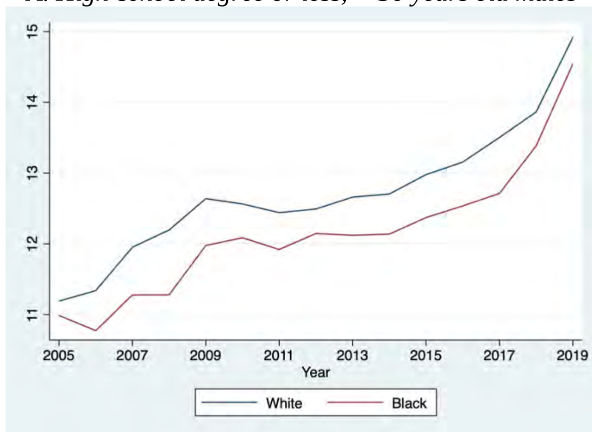
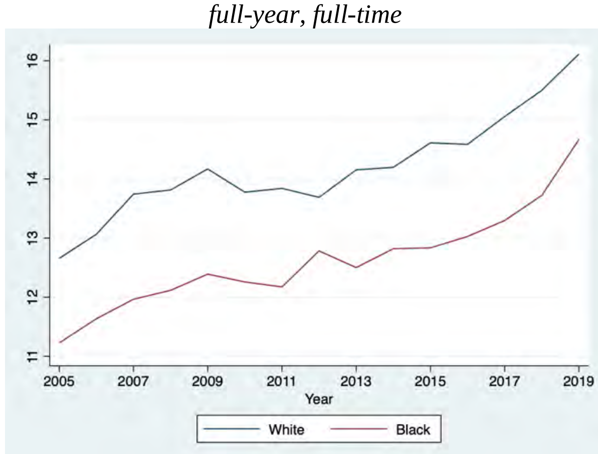


Figure 5: Hourly Wages by Year, Blacks and Whites

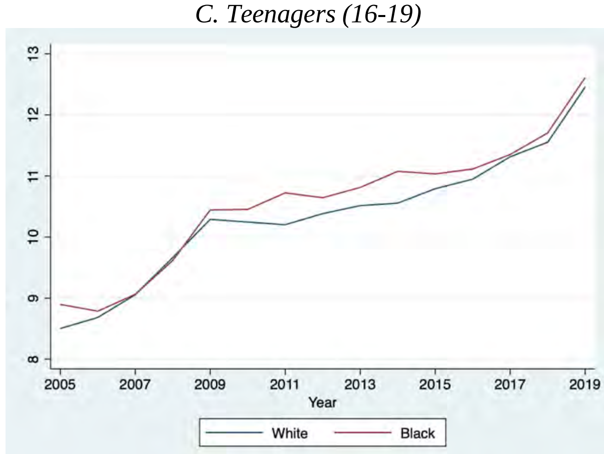
A. High-school degree or less, < 30 years old males



B. High-school degree or less, < 30 years old males, full-year, full-time



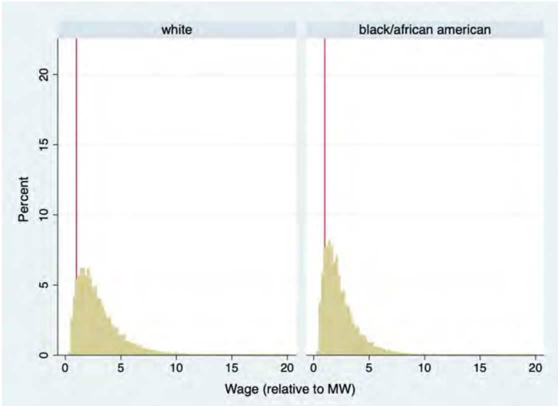
C. Teenagers (16-19)



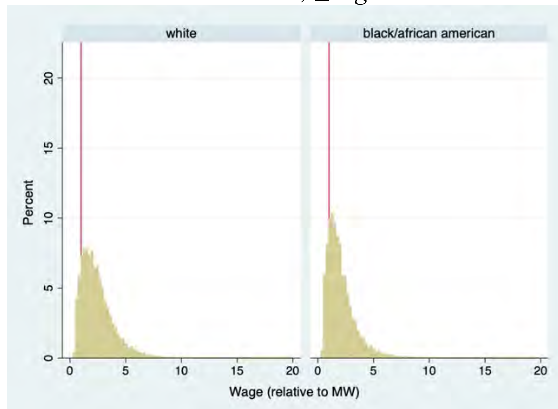
Note: Wages in each year are in nominal terms (in the respective year's dollar value) and weighted by individual person weights.

Figure 6: Wage Distributions of Blacks and Whites

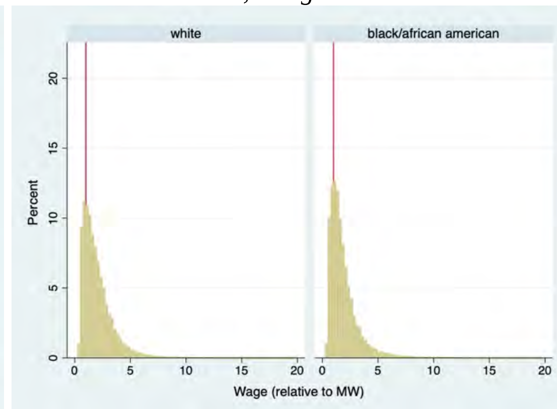
A. All



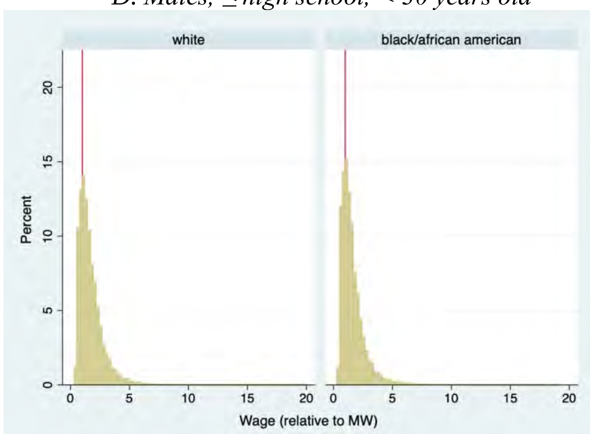
B. Males, ≤ high school



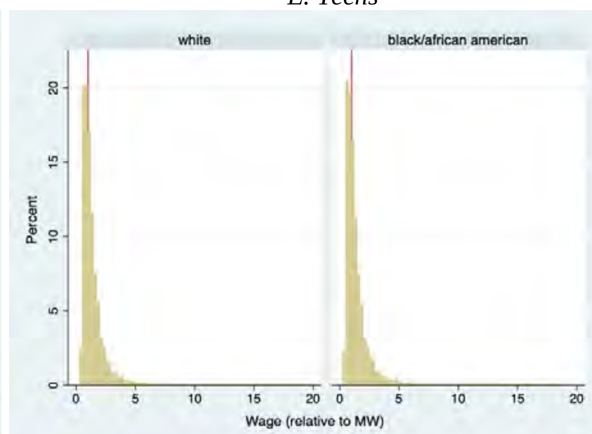
C. Males, < high school



D. Males, ≤ high school, < 30 years old

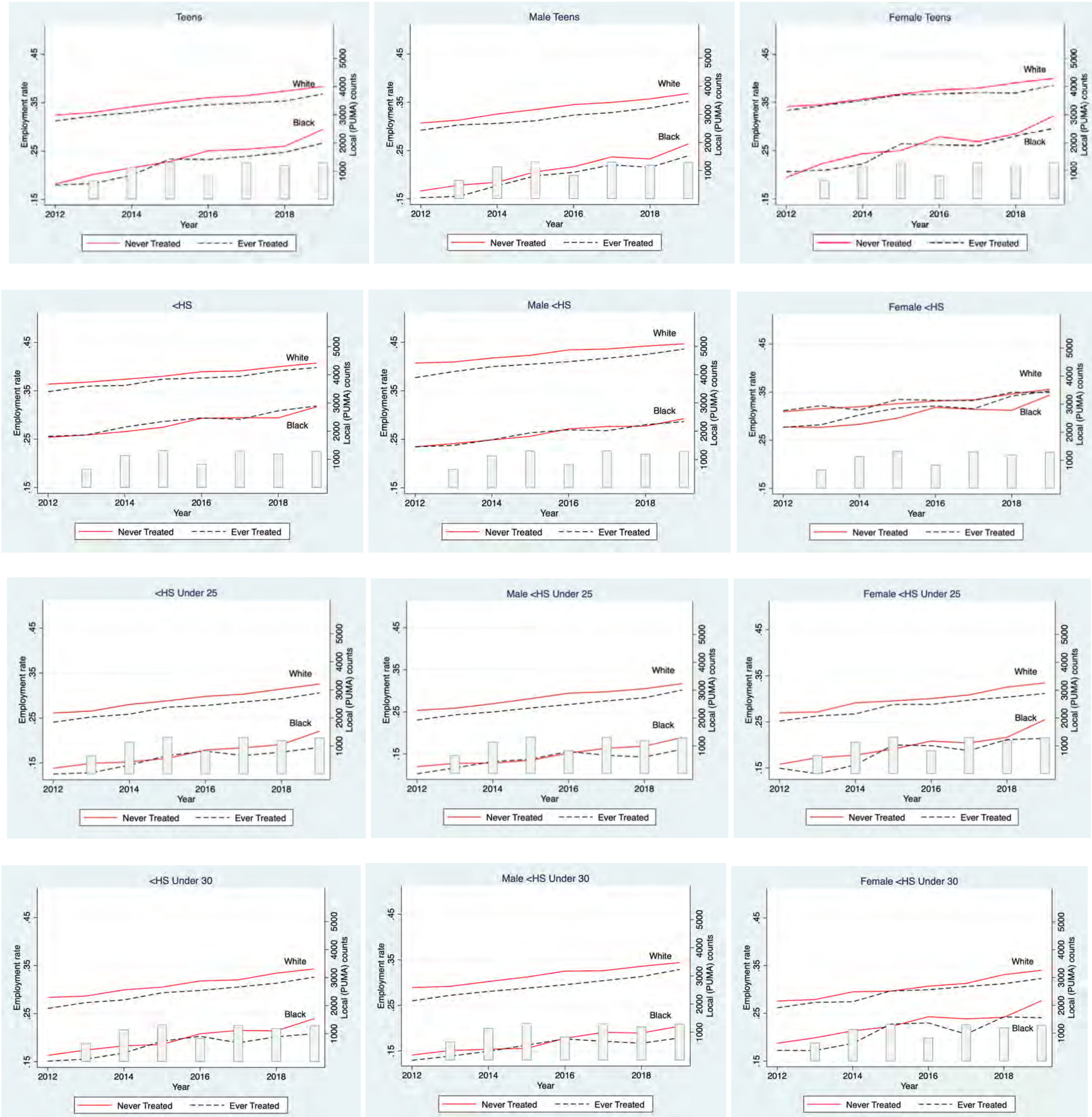


E. Teens



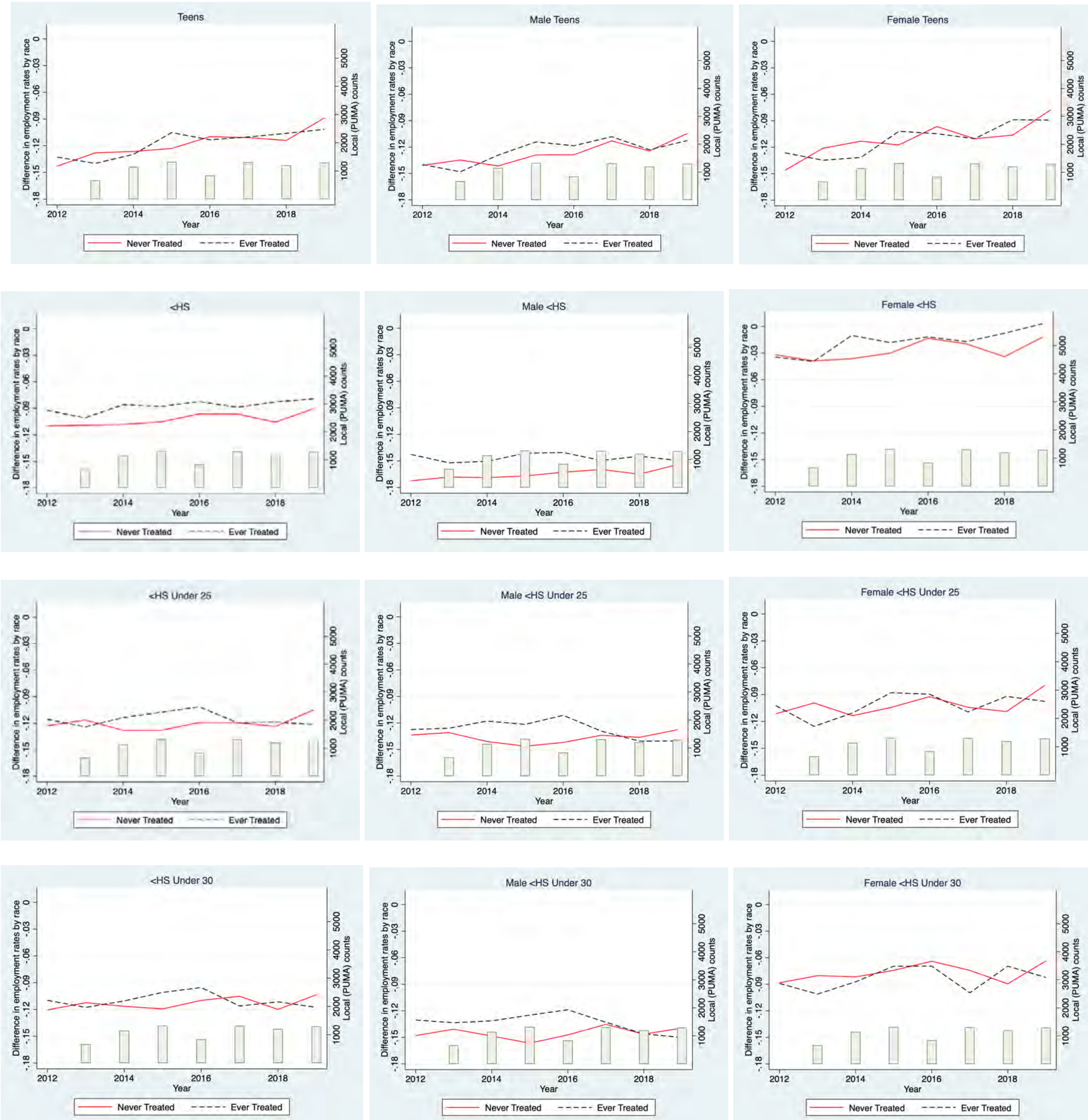
Note**:** Wages on the x-axis are defined as relative to minimum wage in each year, i.e., we construct wage/minimum wage and then pool across years. Thus, the red spike represents relative wage = 1 (or wage = minimum wage) in any year.

Figure 7: Employment Rates by Race and Treatment, and Local (PUMA) MW increases (2012-19)



Note: Shaded bars show number of minimum wage increases in each year.

Figure 8: Difference in Employment Rates between Blacks & Whites by Treatment, and PUMA MW increases (2012-19)



Note: Same as Figure 7.

Figure 9: Shares below 110% of the Minimum Wage and Estimated Employment Elasticities

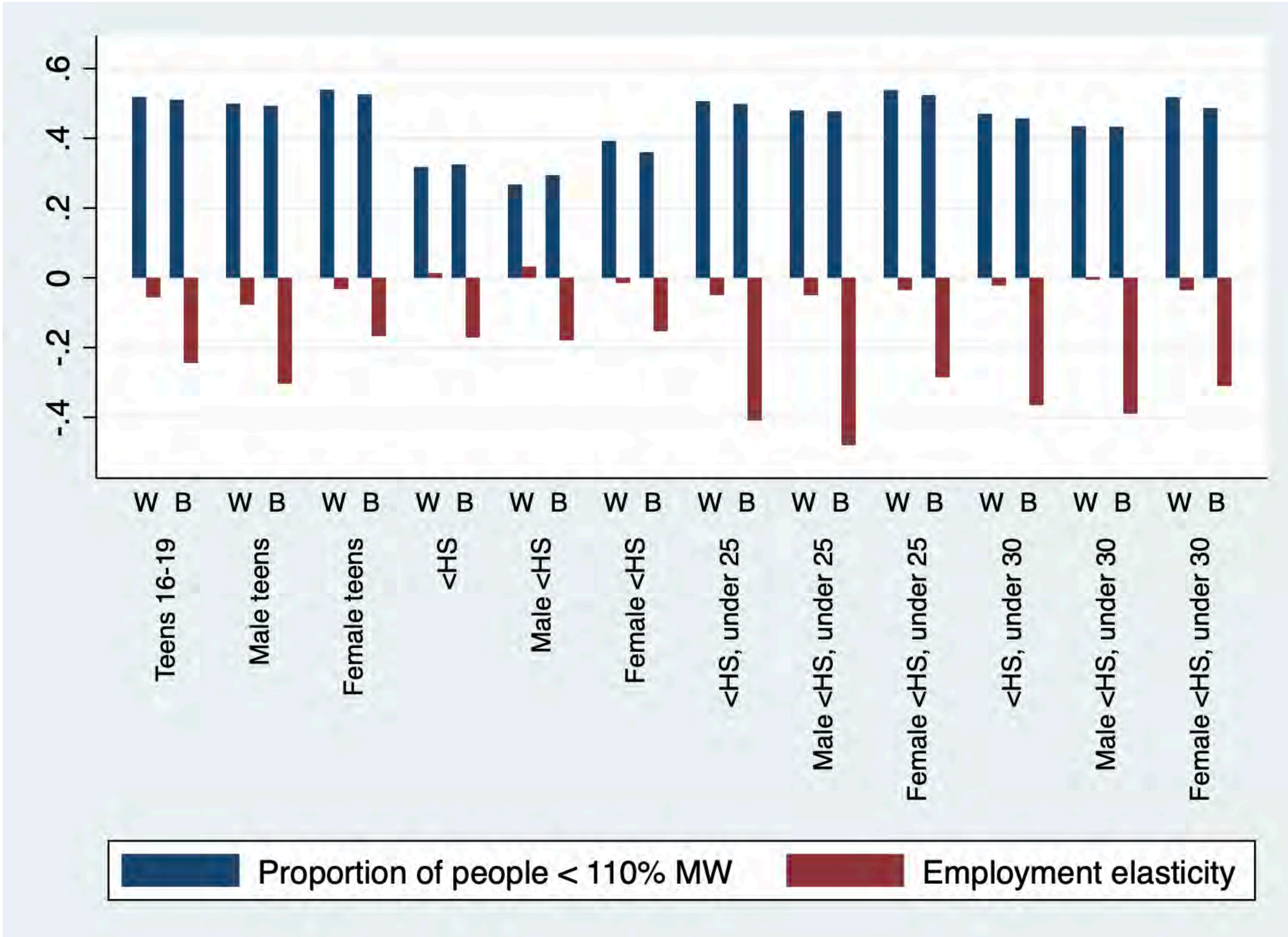
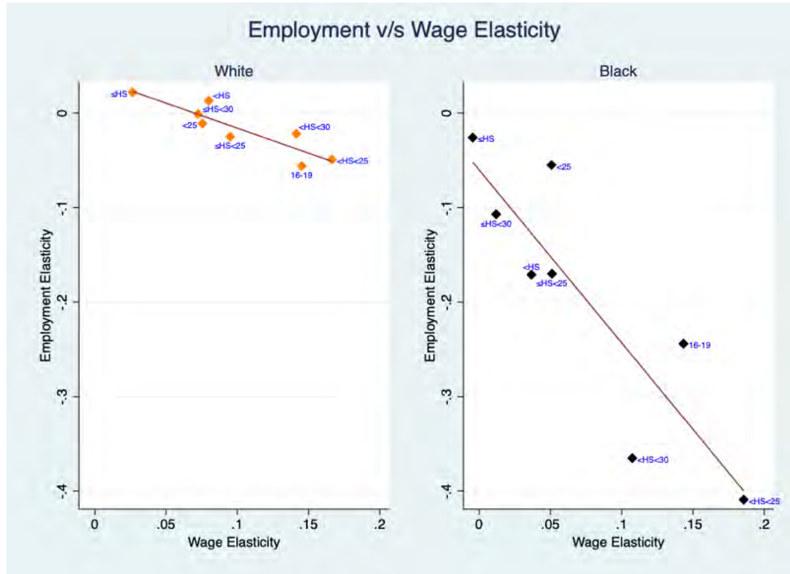
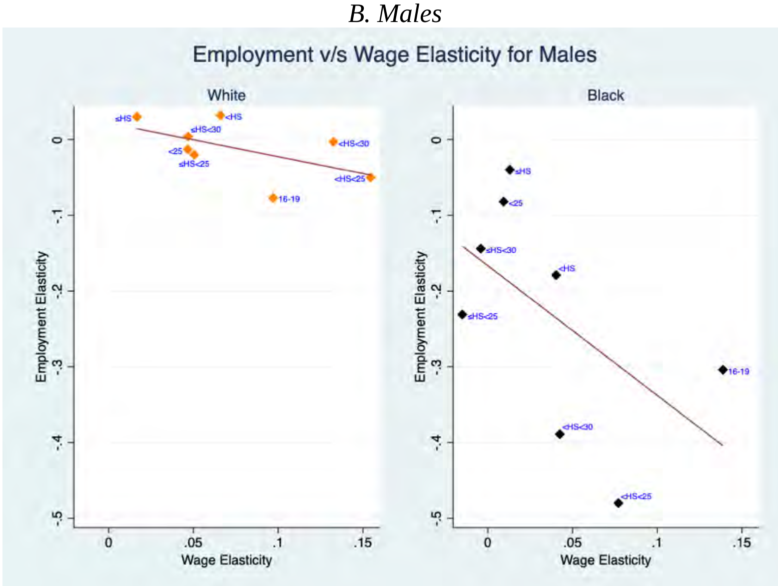


Figure 10: Employment and Wage Elasticities

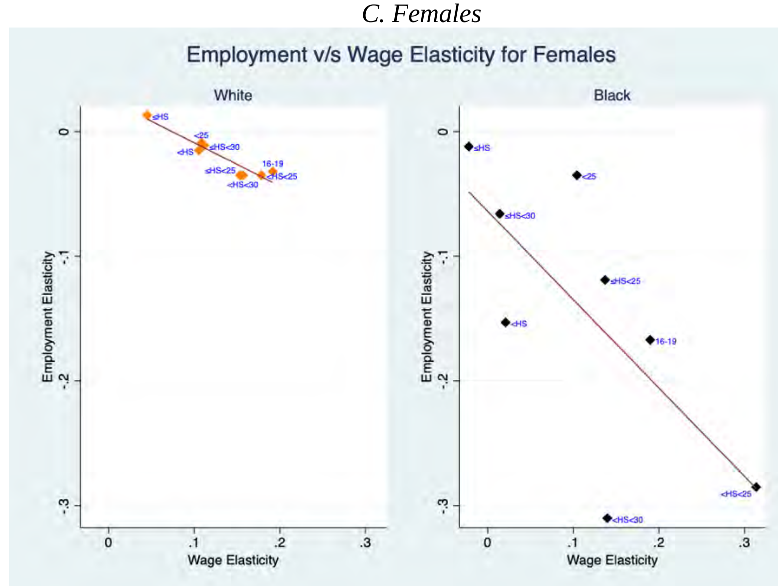
A. All



B. Males

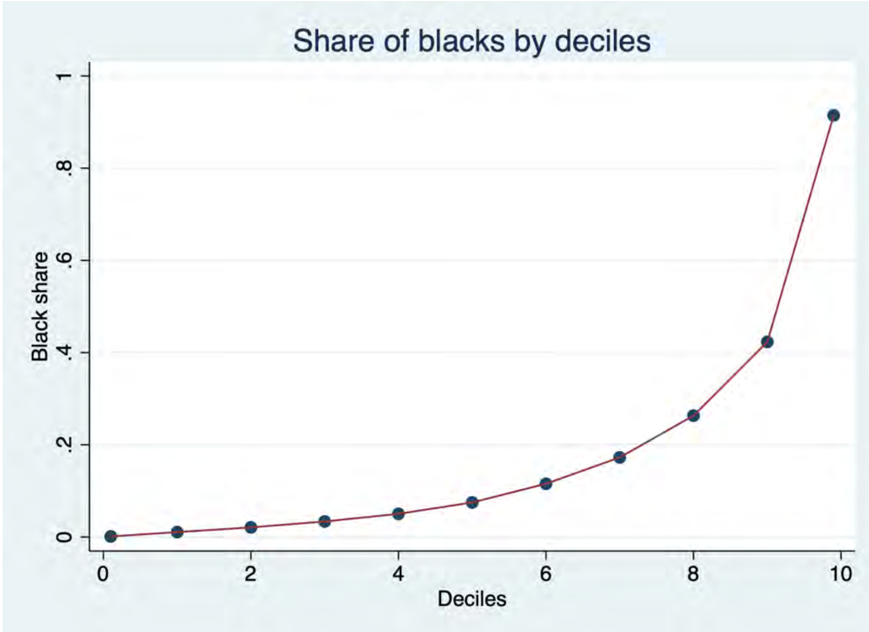


C. Females



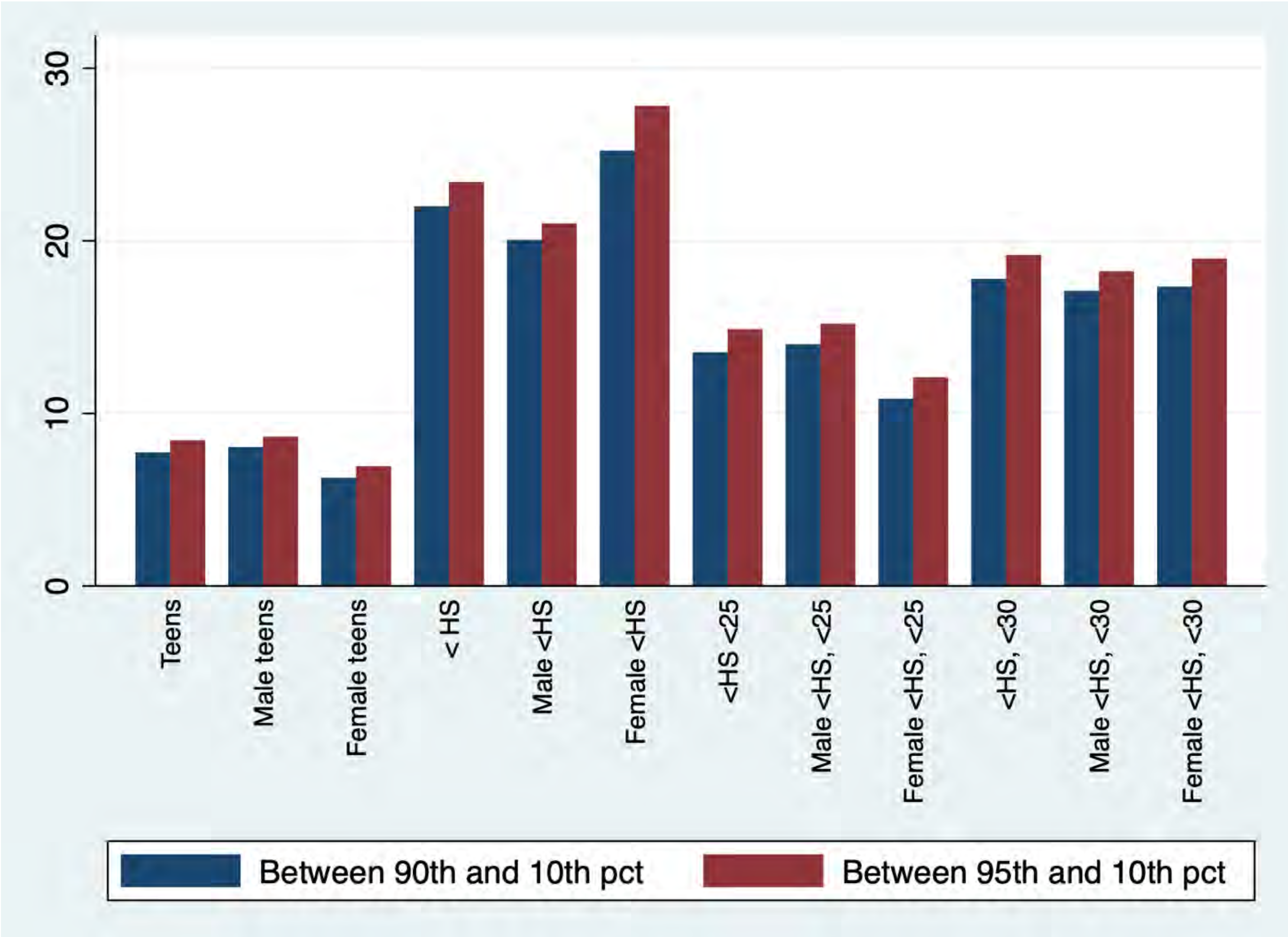
Note: Average wage elasticities for Panel A: 0.10 (Whites) 0.07 (Blacks), Panel B: 0.08 (Whites) 0.04 (Blacks), Panel C: 0.13 (Whites) 0.11 (Blacks).

Figure 11: Share of Black Population by PUMA Deciles



Notes: The first point in the graph corresponds to the 1st percentile and the last point corresponds to the 99th percentile of share black at the PUMA level. The other points are the deciles (10th, 20th, etc., percentiles). All deciles are computed as the weighted percentile of share black across PUMAs, where the weights correspond to the PUMA population every year.

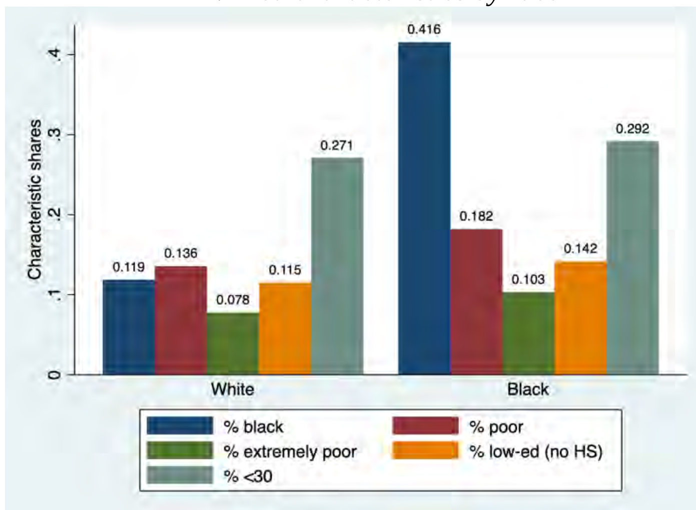
Figure 12: Percent of Difference in Employment Rates between High Share Black and Low Share Black Areas Explained by a Large Minimum Wage Increase ($7.25 to $12)



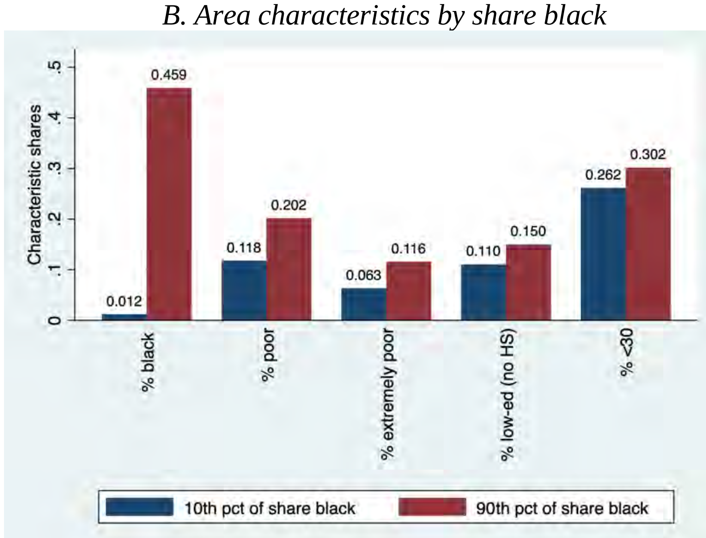
Notes: The estimates used to determine the percentage of variation explained are derived from the calculations presented in Table 6. The 10th, 90th and 95th percentiles are computed as the weighted percentile of share black across PUMAs, where the weights correspond to the PUMA population every year.

Figure 13: PUMA Share Black, Poor, Extremely Poor, Low-Skilled, and Young by Race and Share Black

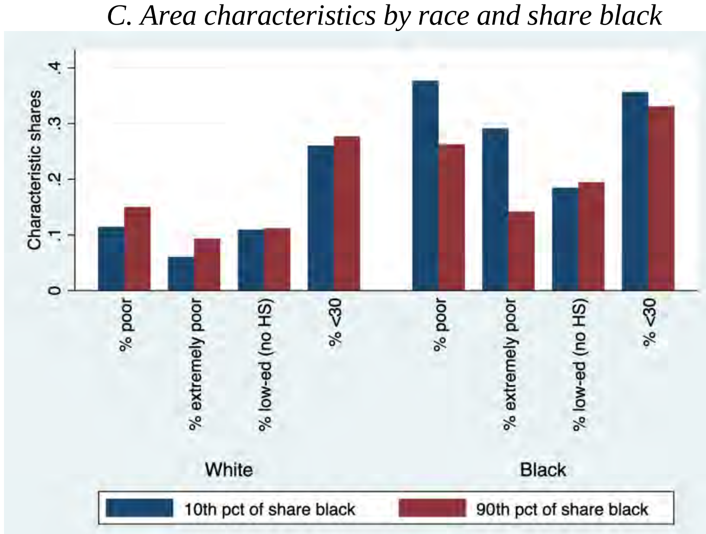
A. Area characteristics by race



B. Area characteristics by share black



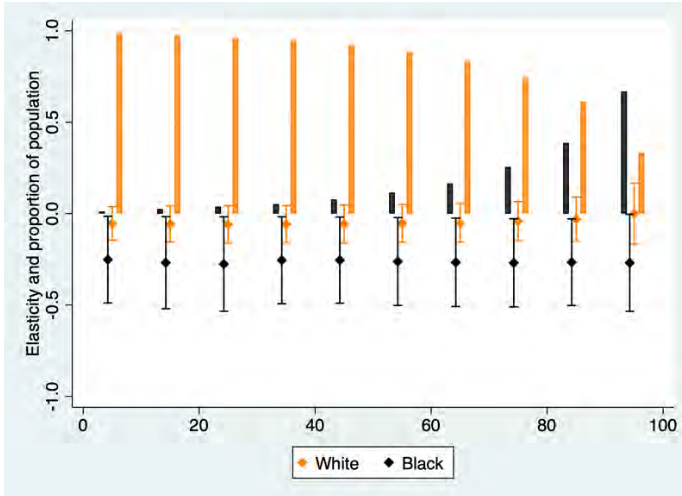
C. Area characteristics by race and share black



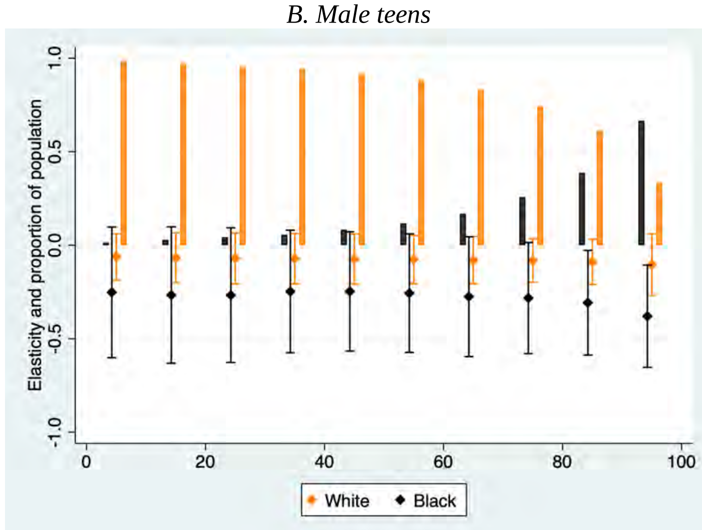
Note: All characteristic shares are estimated using individual-level data weighted by individual person weights. All shares are measured in a ± 5 percentile interval around the specified percentile; e.g., the share poor in the 10th percentile is computed as the weighted average between 5th and 15th percentiles of the share black.

Figure 14: Estimated Minimum Wage Employment Effects for Blacks and Whites by Percent Black in Area (Selected Groups)

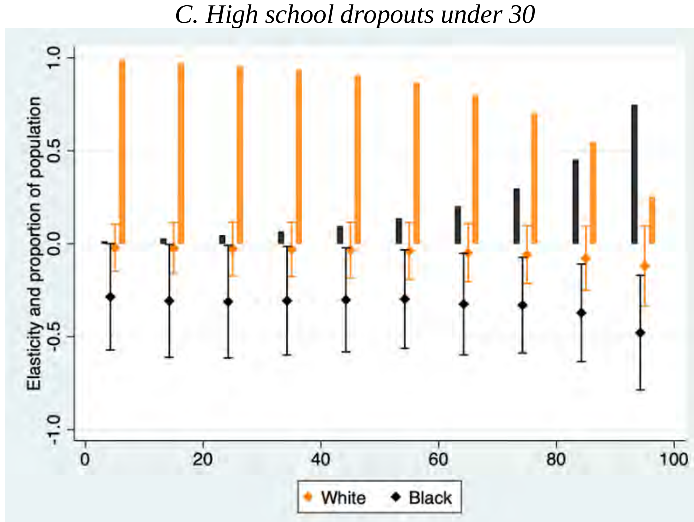
A. Teens



B. Male teens

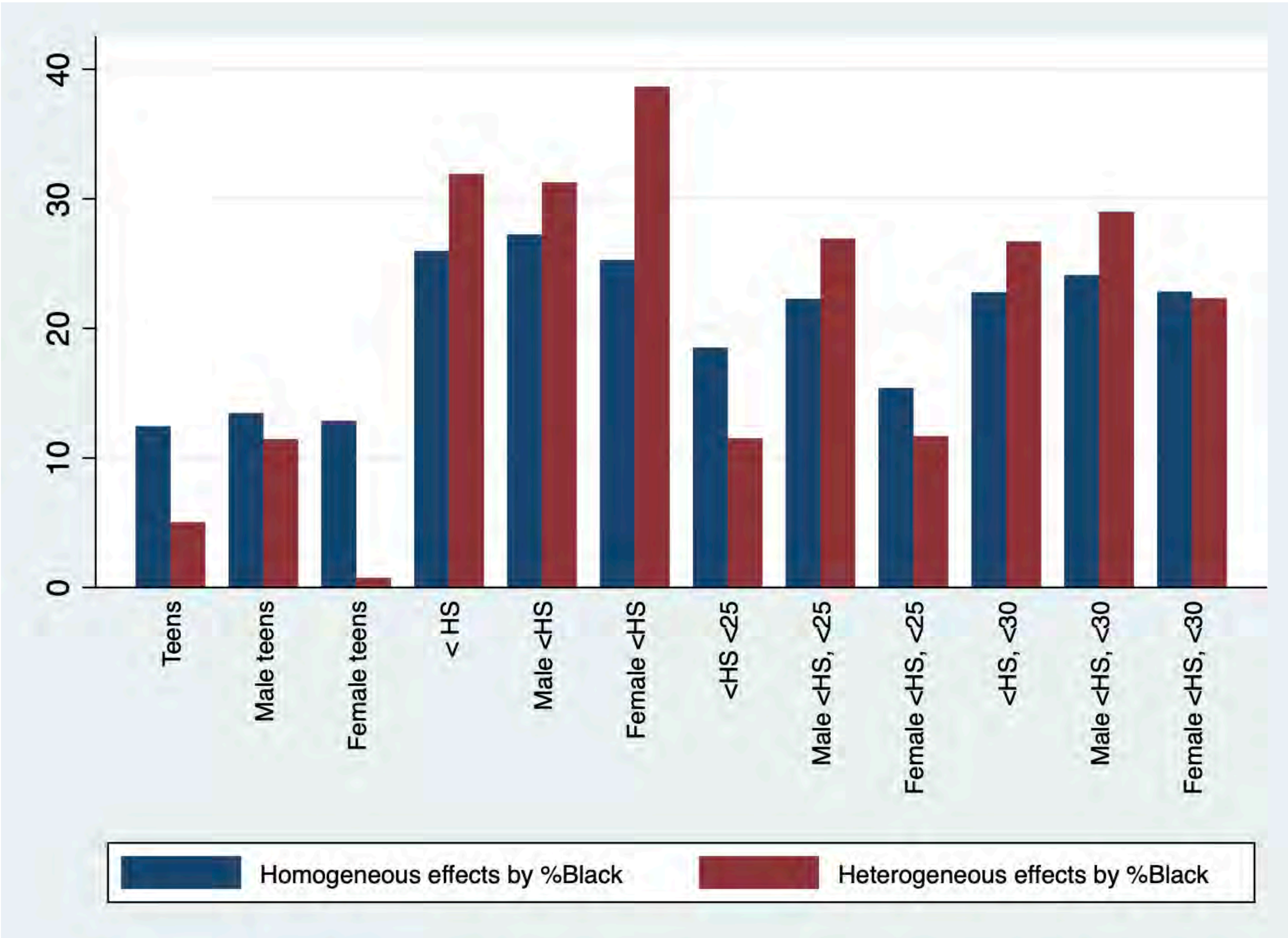


C. High school dropouts under 30



Notes: The horizontal axis corresponds to the decile of the share black across PUMAS (calculated using individual-level data with person weights). Elasticities are measured at the midpoint of each decile (e.g., at the 5th percentile for the first 1st decile). The employment rate is the average share employed in each decile weighted by individual person weights.

Figure 15: Percent of Difference in Employment Rates Explained by a Large Minimum Wage Increase ($7.25 to $12) – Homogeneous Minimum Wage Effects vs. Heterogeneous Effects by %Black



Note: The estimates used to determine the percentage of variation explained are derived from the calculations presented in Table 8.

Table 1: Baseline Minimum Wage-Employment Regressions

Population	Employment effect (β)	Black effect (γ_B)	Average Employment rate	Employment elasticity
Teens 16-19	-0.026	-0.086^{***}	0.334	-0.079
	(0.019)	(0.004)		(0.056)
Male teens	-0.032	-0.097^{***}	0.314	-0.102
	(0.021)	(0.004)		(0.068)
Female teens	-0.018	-0.074^{***}	0.354	-0.052
	(0.019)	(0.004)		(0.052)
<25	-0.009	-0.089^{***}	0.520	-0.018
	(0.014)	(0.004)		(0.028)
Male <25	-0.011	-0.119^{***}	0.507	-0.021
	(0.018)	(0.005)		(0.035)
Female <25	-0.007	-0.059^{***}	0.532	-0.014
	(0.014)	(0.003)		(0.026)
< HS	-0.008	-0.065^{***}	0.369	-0.022
	(0.020)	(0.006)		(0.053)
Male < HS	-0.001	-0.107^{***}	0.395	-0.004
	(0.023)	(0.005)		(0.057)
Female < HS	-0.014	-0.012^{*}	0.334	-0.040
	(0.019)	(0.007)		(0.055)
≤ HS	0.008	-0.031^{***}	0.570	0.014
	(0.016)	(0.006)		(0.028)
Male ≤ HS	0.011	-0.089^{***}	0.606	0.019
	(0.019)	(0.006)		(0.031)
Female ≤ HS	0.007	0.014^{**}	0.526	0.012
	(0.014)	(0.006)		(0.027)
< HS, < 25	-0.023	-0.103^{***}	0.271	-0.084
	(0.020)	(0.005)		(0.075)
Male < HS, < 25	-0.023	-0.127^{***}	0.261	-0.088
	(0.022)	(0.005)		(0.086)
Female < HS, < 25	-0.018	-0.077^{***}	0.281	-0.065
	(0.023)	(0.005)		(0.080)
≤ HS, < 25	-0.017	-0.111^{***}	0.417	-0.040
	(0.019)	(0.004)		(0.046)
Male ≤ HS, < 25	-0.019	-0.143^{***}	0.423	-0.046
	(0.022)	(0.005)		(0.052)
Female ≤ HS, < 25	-0.017	-0.071^{***}	0.407	-0.043
	(0.019)	(0.004)		(0.047)
< HS, < 30	-0.020	-0.103^{***}	0.293	-0.069
	(0.023)	(0.004)		(0.078)
Male < HS, < 30	-0.015	-0.137^{***}	0.291	-0.052
	(0.024)	(0.005)		(0.083)
Female < HS, < 30	-0.022	-0.065^{***}	0.293	-0.074
	(0.025)	(0.005)		(0.084)
≤ HS, < 30	-0.006	-0.106^{***}	0.470	-0.013
	(0.018)	(0.005)		(0.039)
Male ≤ HS, < 30	-0.008	-0.150^{***}	0.488	-0.016
	(0.021)	(0.005)		(0.043)
Female ≤ HS, < 30	-0.006	-0.053^{***}	0.444	-0.014
	(0.018)	(0.005)		(0.041)

Notes: The sample consists of ACS micro-data at the PUMA-by-year level from 2005-2019 restricting to those aged between 16 to 65. ACS person sampling weights are used while collapsing the micro-data. The demographic controls included are a dummy variable for PUMA cell means for blacks, and the proportion of males, average number of children, average age, proportion of people in each category of marital status and education in each PUMA by year and race. Fixed effects are at PUMA and year level. Minimum wages can vary across PUMAs over years. Employment regressions are weighted by PUMA population for each group in each year. Employment elasticity for each population group is computed by dividing the employment effect (β) by the average employment rate of the group weighted by its PUMA population every year. Reported standard errors are clustered at the state level. The coefficients are statistically significant at the ***1%, **5%, or *10% level.

Table 2: Minimum Wage-Employment Regressions with Separate Effects by Race

Population	White empl. effect	Black empl. effect	Avg white empl. rate	Avg black empl. rate	White empl. elas.	Black empl. elas.	White sub-pop. share	Black sub-pop. share
Teens 16-19	-0.020	-0.054**††	0.357	0.222	-0.056	-0.244**	0.074	0.098
	(0.019)	(0.022)			(0.053)	(0.099)		
Male teens	-0.026	-0.060**†	0.338	0.197	-0.077	-0.304**	0.038	0.050
	(0.021)	(0.028)			(0.062)	(0.142)		
Female teens	-0.012	-0.041*	0.377	0.245	-0.032	-0.167*	0.036	0.048
	(0.020)	(0.022)			(0.053)	(0.090)		
<25	-0.006	-0.022	0.545	0.399	-0.011	-0.055	0.169	0.218
	(0.014)	(0.023)			(0.026)	(0.058)		
Male <25	-0.007	-0.030	0.537	0.365	-0.013	-0.082	0.087	0.111
	(0.018)	(0.026)			(0.034)	(0.071)		
Female <25	-0.005	-0.015	0.552	0.430	-0.009	-0.035	0.082	0.107
	(0.014)	(0.023)			(0.025)	(0.053)		
< HS	0.005	-0.049**†††	0.393	0.287	0.013	-0.171**	0.108	0.190
	(0.018)	(0.021)			(0.046)	(0.073)		
Male < HS	0.014	-0.048**†††	0.433	0.268	0.032	-0.179**	0.060	0.104
	(0.022)	(0.023)			(0.051)	(0.086)		
Female < HS	-0.005	-0.047*†	0.342	0.307	-0.015	-0.153*	0.048	0.086
	(0.017)	(0.026)			(0.050)	(0.085)		
≤ HS	0.013	-0.012††	0.592	0.464	0.022	-0.026	0.377	0.505
	(0.016)	(0.021)			(0.027)	(0.045)		
Male ≤ HS	0.019	-0.018††	0.640	0.447	0.030	-0.040	0.204	0.271
	(0.019)	(0.023)			(0.030)	(0.051)		
Female ≤ HS	0.007	-0.006	0.535	0.481	0.013	-0.012	0.173	0.234
	(0.013)	(0.024)			(0.024)	(0.050)		
< HS, < 25	-0.015	-0.068***††	0.297	0.166	-0.049	-0.409***	0.051	0.078
	(0.021)	(0.024)			(0.072)	(0.146)		
Male < HS, < 25	-0.015	-0.070**††	0.291	0.147	-0.050	-0.480**	0.027	0.043
	(0.023)	(0.027)			(0.079)	(0.185)		
Female < HS, < 25	-0.011	-0.053*	0.303	0.187	-0.035	-0.285*	0.023	0.035
	(0.025)	(0.028)			(0.0840	(0.151)		
≤ HS, < 25	-0.011	-0.051**††	0.444	0.300	-0.025	-0.170**	0.092	0.138
	(0.019)	(0.023)			(0.043)	(0.077)		
Male ≤ HS, < 25	-0.009	-0.065**††	0.457	0.281	-0.020	-0.231**	0.051	0.076
	(0.022)	(0.029)			(0.048)	(0.103)		
Female ≤ HS, < 25	-0.015	-0.038	0.427	0.319	-0.035	-0.119	0.041	0.062
	(0.020)	(0.026)			(0.047)	(0.082)		
< HS, < 30	-0.007	-0.070**†††	0.319	0.192	-0.022	-0.365**	0.057	0.093
	(0.022)	(0.026)			(0.069)	(0.136)		
Male < HS, < 30	-0.001	-0.066**†††	0.325	0.170	-0.003	-0.389**	0.031	0.052
	(0.024)	(0.028)			(0.074)	(0.165)		

Population	White empl. effect	Black empl. effect	Avg white empl. rate	Avg black empl. rate	White empl. elas.	Black empl. elas.	White sub-pop. share	Black sub-pop. share
Female < HS, < 30	-0.011	-0.067**††	0.311	0.216	-0.035	-0.310**	0.026	0.041
	(0.025)	(0.030)			(0.080)	(0.139)		
≤ HS, < 30	-0.0003	-0.038††	0.498	0.356	-0.001	-0.107	0.121	0.188
	(0.017)	(0.026)			(0.034)	(0.073)		
Male ≤ HS, < 30	0.002	-0.048*††	0.527	0.334	0.004	-0.144*	0.068	0.104
	(0.020)	(0.027)			(0.038)	(0.081)		
Female ≤ HS, < 30	-0.005	-0.025	0.460	0.378	-0.011	-0.066	0.053	0.084
	(0.018)	(0.031)			(0.039)	(0.082)		

Notes: Same as Table 1. The employment regressions are run separately by race. The sub-population shares represent the proportion of individuals within each race that belong to the specified sub-group. These shares are computed as the weighted average of sub-group shares across PUMAs, with weights based on the PUMA population in each year. The daggers represent the statistical significance of the differential effect of a Black PUMA, on employment. For this, the following model is estimated: $Y = \alpha + \beta \cdot \ln(MW) + \beta_B \cdot \ln(MW) \cdot Black + X\delta + X \cdot Black \cdot \delta_B + D_P \cdot \lambda + D_P \cdot Black \cdot \lambda_B + D_T\tau + D_T \cdot Black \cdot \tau_B + \varepsilon$, where Black is an indicator for PUMA cell means for blacks. The daggers represent the statistical significance of the black-minimum wage interaction estimate in a pooled model. The coefficients are statistically significant at the †††1%, ††5%, or †10% level.

Table 3: Minimum Wage-Employment Regressions with Separate Effects by Race, TWFE and 2S-DID, 2012-19

Population	TWFE White	TWFE Black	2S-DID White	2S-DID Black
Teens 16-19	-0.032*	-0.056***	-0.012	-0.051*
	(0.017)	(0.018)	(0.018)	(0.029)
Male teens	-0.032	-0.060**	-0.016	-0.061**
	(0.022)	(0.026)	(0.020)	(0.031)
Female teens	-0.030	-0.050**	-0.013	-0.043
	(0.019)	(0.022)	(0.019)	(0.034)
< 25	-0.016	-0.021	-0.0004	-0.018
	(0.013)	(0.018)	(0.015)	(0.024)
Male < 25	-0.014	-0.042**	0.003	-0.030
	(0.015)	(0.017)	(0.017)	(0.020)
Female < 25	-0.017	-0.001	-0.005	-0.014
	(0.018)	(0.021)	(0.017)	(0.027)
< HS	-0.008	-0.044**	0.012	-0.027
	(0.019)	(0.019)	(0.017)	(0.025)
Male < HS	0.004	-0.043**	0.026	-0.029
	(0.023)	(0.020)	(0.018)	(0.022)
Female < HS	-0.022	-0.036	-0.005	-0.018
	(0.018)	(0.027)	(0.017)	(0.036)
≤ HS	0.008	-0.007	0.015	0.0001
	(0.017)	(0.021)	(0.013)	(0.024)
Male ≤ HS	0.017	-0.015	0.023	-0.001
	(0.018)	(0.020)	(0.014)	(0.023)
Female ≤ HS	0.0002	0.003	0.007	0.007
	(0.017)	(0.024)	(0.012)	(0.027)
< HS, < 25	-0.035*	-0.070***	-0.010	-0.037
	(0.020)	(0.022)	(0.021)	(0.028)
Male < HS, < 25	-0.031	-0.086***	-0.012	-0.068***
	(0.022)	(0.022)	(0.021)	(0.024)
Female < HS, < 25	-0.035	-0.037	-0.010	-0.031
	(0.025)	(0.030)	(0.025)	(0.039)
≤ HS, < 25	-0.025	-0.059***	-0.012	-0.047
	(0.019)	(0.019)	(0.017)	(0.031)
Male ≤ HS, < 25	-0.025	-0.084***	-0.012	-0.071***
	(0.020)	(0.020)	(0.018)	(0.022)
Female ≤ HS, < 25	-0.028	-0.031	-0.016	-0.032
	(0.019)	(0.027)	(0.019)	(0.044)
< HS, < 30	-0.030	-0.079***	-0.002	-0.051
	(0.022)	(0.025)	(0.022)	(0.032)
Male < HS, < 30	-0.018	-0.080***	-0.001	-0.067**
	(0.025)	(0.023)	(0.022)	(0.026)
Female < HS, < 30	-0.037	-0.060*	-0.006	-0.041
	(0.025)	(0.035)	(0.025)	(0.046)
≤ HS, < 30	-0.016	-0.046**	-0.006	-0.031
	(0.017)	(0.023)	(0.016)	(0.031)
Male ≤ HS, < 30	-0.014	-0.057**	-0.005	-0.047**
	(0.019)	(0.021)	(0.016)	(0.023)
Female ≤ HS, < 30	-0.020	-0.026	-0.009	-0.018
	(0.018)	(0.031)	(0.017)	(0.049)

Notes: Same as Table 1. The TWFE and 2S-DID regressions are run separately by race. The sample is restricted to 2012-19. The treatment considered in the second-stage in the 2S-DID regressions is the continuous variation in minimum wages across PUMAs over years, as in the preceding tables.

Table 4: Minimum Wage-Earnings Regressions with Separate Effects by Race

Population	White earnings effect	Black earnings effect	Avg white earnings	Avg black earnings	White earnings elas.	Black earnings elas.
Teens 16-19	35.998	-612.797††	2640.209	1896.586	0.014	-0.323
	(279.356)	(370.488)			(0.106)	(0.195)
Male teens	-117.227	-741.829†	2822.392	1844.554	-0.042	-0.402
	(330.106)	(543.500)			(0.117)	(0.295)
Female teens	192.384	-416.399†	2440.836	1934.950	0.079	-0.215
	(261.476)	(298.743)			(0.107)	(0.154)
< 25	939.839*	318.483	8676.030	6031.754	0.037*	0.053
	(517.908)	(697.871)			(0.080)	(0.116)
Male < 25	448.190	123.422	9623.366	5984.711	0.047	0.021
	(633.799)	(778.004)			(0.066)	(0.130)
Female < 25	1480.214***	647.825	7660.065	6000.218	0.193***	0.108
	(432.617)	(631.297)			(0.056)	(0.105)
$<$ HS	811.411	17.003	8690.869	6333.952	0.093	0.003
	(581.289)	(516.490)			(0.067)	(0.082)
Male $<$ HS	1046.429	-169.553	11555.160	6767.432	0.091	-0.025
	(1083.148)	(617.788)			(0.094)	(0.091)
Female $<$ HS	493.368*	244.518	5132.512	5756.000	0.096*	0.042
	(282.040)	(849.824)			(0.055)	(0.148)
$\leq$ HS	1360.760	988.486*	18624.130	12535.590	0.073	0.079*
	(880.165)	(555.824)			(0.047)	(0.044)
Male $\leq$ HS	1679.668	1064.680	23586.980	13519.480	0.071	0.079
	(1187.086)	(650.327)			(0.050)	(0.048)
Female $\leq$ HS	942.915*	778.618	12782.820	11294.870	0.074*	0.069
	(541.727)	(693.116)			(0.042)	(0.061)
$<$ HS, < 25	125.954	-556.097**†	2268.569	1660.537	0.056	-0.335**
	(325.578)	(256.000)			(0.144)	(0.154)
Male $<$ HS, < 25	161.933	-865.167**††	2669.260	1683.668	0.061	-0.514**
	(428.130)	(327.361)			(0.160)	(0.194)
Female $<$ HS, < 25	29.658	6.095	1776.222	1615.762	0.017	0.004
	(258.356)	(264.905)			(0.145)	(0.164)
$\leq$ HS, < 25	33.959	-712.720	5952.965	4196.963	0.006	-0.170
	(557.356)	(426.887)			(0.094)	(0.102)
Male $\leq$ HS, < 25	-261.338	-1089.338*	7206.097	4361.004	-0.036	-0.250*
	(709.196)	(550.444)			(0.098)	(0.126)
Female $\leq$ HS, < 25	296.583	24.562	4379.560	3921.598	0.068	0.006
	(406.719)	(539.130)			(0.093)	(0.137)
$<$ HS, < 30	9.068	-622.497*†	3343.383	2581.987	0.003	-0.241*
	(376.321)	(315.114)			(0.113)	(0.122)
Male $<$ HS, < 30	44.180	-1202.012***††	4199.405	2617.352	0.011	-0.459***
	(545.023)	(430.417)			(0.130)	(0.164)
Female $<$ HS, < 30	-58.043	377.258	2293.107	2477.299	-0.025	0.152
	(241.620)	(374.101)			(0.105)	(0.151)
$\leq$ HS, < 30	249.445	-372.692	9031.919	6445.887	0.028	-0.058
	(591.005)	(499.563)			(0.065)	(0.078)
Male $\leq$ HS, < 30	84.220	-581.322	11255.210	6725.209	0.007	-0.086
	(767.322)	(579.069)			(0.068)	(0.086)
Female $\leq$ HS, < 30	369.357	82.789	6164.913	5976.081	0.060	0.014
	(431.618)	(653.240)			(0.070)	(0.109)

Notes: Same as Table 2.

Table 5: Minimum Wage-Earnings Regressions with Separate Effects by Race, TWFE and 2S-DID from 2012-19

Population	TWFE White	TWFE Black	2S-DID White	2S-DID Black
Teens 16-19	20.214	-750.792**	148.021	-597.298
	(315.336)	(356.611)	(313.605)	(417.891)
Male teens	0.271	-842.777	155.592	-620.804
	(347.207)	(631.637)	(298.745)	(591.369)
Female teens	16.197	-639.264**	122.176	-642.507**
	(337.023)	(296.379)	(384.063)	(261.131)
< 25	1148.685**	543.932	1266.903**	315.726
	(517.502)	(698.735)	(514.477)	(720.943)
Male < 25	753.172	306.244	1059.441*	-133.447
	(622.329)	(800.054)	(603.090)	(776.338)
Female < 25	1604.207***	1009.718	1550.092***	926.029
	(444.956)	(687.724)	(438.710)	(656.686)
< HS	591.435	173.036	1079.771**	288.580
	(579.944)	(385.885)	(542.799)	(524.651)
Male < HS	446.705	-199.987	1265.388	-534.323
	(1091.81)	(633.273)	(949.577)	(857.999)
Female < HS	650.232	683.210	846.273**	1433.779**
	(399.809)	(782.107)	(399.586)	(628.074)
≤ HS	1431.544*	1218.682**	1563.307**	1305.119**
	(791.858)	(570.412)	(613.765)	(565.804)
Male ≤ HS	1428.616	1133.514	1511.819*	817.811
	(1020.28)	(699.79)	(901.725)	(807.113)
Female ≤ HS	1341.306**	1283.572*	1529.689***	1945.44***
	(577.928)	(707.648)	(387.145)	(564.674)
< HS, < 25	-56.720	-857.857***	267.214	-359.948
	(371.367)	(221.945)	(330.914)	(280.201)
Male < HS, < 25	-78.768	-1357.487***	477.728	-745.021**
	(487.524)	(369.294)	(442.589)	(370.995)
Female < HS, < 25	-207.253	74.438	-27.159	45.786
	(319.603)	(268.736)	(267.120)	(288.142)
≤ HS, < 25	-127.147	-933.461**	218.218	-929.191
	(660.447)	(373.579)	(578.853)	(625.545)
Male ≤ HS, < 25	-482.665	-1336.227**	60.344	-1486.761**
	(816.290)	(569.994)	(715.226)	(706.964)
Female ≤ HS, < 25	96.550	-17.132	346.458	-214.426
	(502.843)	(487.099)	(465.655)	(474.009)
< HS, < 30	-303.915	-799.624***	83.551	-589.746**
	(425.204)	(228.450)	(422.913)	(290.744)
Male < HS, < 30	-475.255	-1657.256***	178.646	-1118.307***
	(635.789)	(374.844)	(592.784)	(405.134)
Female < HS, < 30	-181.359	842.915**	-20.393	648.410
	(286.223)	(391.788)	(257.550)	(409.988)
≤ HS, < 30	-150.098	-437.255	51.463	-672.293
	(634.734)	(392.979)	(627.839)	(452.045)
Male ≤ HS, < 30	-630.903	-522.221	-291.528	-1268.684**
	(799.03)	(561.696)	(751.428)	(584.151)
Female ≤ HS, < 30	267.568	188.068	280.257	363.038
	(483.475)	(483.583)	(475.677)	(508.244)

Notes: Same as Table 3.

Table 6: "Simulated" Minimum Wage Effects on Employment in White vs. Black Areas for Subgroups, Increase from $7.25 (Federal Minimum Wage) to $12 (California Minimum Wage in 2019)

	Teens			Male teens			< HS, < 30		
Share black percentile	**10th**	**90th**	**95th**	**10th**	**90th**	**95th**	**10th**	**90th**	**95th**
White sub-population share	0.985	0.488	0.340	0.983	0.493	0.344	0.982	0.423	0.269
Black sub-population share	0.015	0.512	0.660	0.017	0.507	0.656	0.018	0.577	0.731
White employment rate	0.403	0.302	0.293	0.381	0.292	0.280	0.365	0.276	0.268
Black employment rate	0.261	0.216	0.198	0.212	0.195	0.179	0.166	0.200	0.186
Weighted employment rate	0.401	0.258	0.230	0.379	0.243	0.214	0.362	0.232	0.208
White MW-empl. elas.	-0.050	-0.066	-0.068	-0.068	-0.089	-0.093	-0.019	-0.025	-0.026
Black MW-empl. elas.	-0.207	-0.250	-0.273	-0.282	-0.308	-0.335	-0.421	-0.351	-0.377
Weighted empl. elas.	**-0.052**	**-0.160**	**-0.203**	**-0.072**	**-0.200**	**-0.252**	**-0.026**	**-0.213**	**-0.282**
Impact of MW increase ($7.25 to $12) on empl. rate	**-0.013**	**-0.025**	**-0.028**	**-0.017**	**-0.028**	**-0.032**	**-0.005**	**-0.028**	**-0.035**

Notes: All measures are computed as the weighted average across PUMAs, with weights as the PUMA population for each group in each year. "Sub-population shares" include only blacks and whites, and refer to shares of black/white individuals among teens, male teens, and high school dropouts under 30. All percentiles are computed as the weighted percentiles of share black across PUMAs, where the weights correspond to the PUMA population every year. Employment rate is measured in a ± 5 percentile interval around the specified percentile – for e.g., the employment rate for the 10th percentile is computed as the weighted average employment in the interval between 5th and 15th percentile of share black. Minimum wage-employment elasticities are based on the estimates in Table 2. Weighted employment rate and weighted employment elasticities are based on the sub-population shares. The last row is computed using separate elasticities and employment rates by race.

Table 7: Minimum Wage-Employment Regressions with Separate Effects by Race & Share Black in Area

	Empl. effect, white (β)	Black-MW interaction (β_B)	%Black-MW interaction ($\beta_{\%B}$)	Effect at percentile of %Black	Avg. white empl. rate	Avg. black empl. rate	White empl. elas.	Black empl. elas.	Black − white empl. elas.
Teens	-0.023	-0.051*	0.037	10th	0.398	0.292	-0.056	-0.251**	-0.196
	(0.019)	(0.026)	(0.040)				(0.047)	(0.118)	
				50th	0.350	0.275	-0.055	-0.257**	-0.202
							(0.052)	(0.118)	
				90th	0.303	0.217	-0.019	-0.263**	-0.244
							(0.068)	(0.119)	
Teens Male	-0.024	-0.036	-0.008	10th	0.375	0.237	-0.065	-0.256	-0.192
	(0.024)	(0.028)	(0.051)				(0.064)	(0.176)	
				50th	0.333	0.248	-0.075	-0.248	-0.173
							(0.065)	(0.156)	
				90th	0.295	0.197	-0.095	-0.327**	-0.232
							(0.066)	(0.133)	
Teens Female	-0.021	-0.082**	0.096	10th	0.422	0.364	-0.047	-0.279**	-0.232
	(0.021)	(0.035)	(0.062)				(0.048)	(0.108)	
				50th	0.368	0.303	-0.035	-0.312**	-0.277
							(0.054)	(0.121)	
				90th	0.313	0.237	0.072	-0.251*	-0.322
							(0.093)	(0.127)	
< HS	0.008	-0.039*	-0.043	10th	0.417	0.279	0.017	-0.113	-0.131
	(0.020)	(0.020)	(0.033)				(0.048)	(0.117)	
				50th	0.385	0.294	0.011	-0.118	-0.129
							(0.048)	(0.106)	
				90th	0.373	0.300	-0.031	-0.168*	-0.137
							(0.044)	(0.085)	
< HS Males	0.017	-0.048**	-0.049	10th	0.454	0.258	0.037	-0.120	-0.157
	(0.023)	(0.021)	(0.042)				(0.050)	(0.122)	
				50th	0.424	0.274	0.031	-0.126	-0.157
							(0.052)	(0.109)	
				90th	0.426	0.293	-0.011	-0.179*	-0.168
							(0.058)	(0.093)	
< HS Females	0.001	-0.024	-0.050	10th	0.371	0.323	0.001	-0.073	-0.074
	(0.020)	(0.033)	(0.044)				(0.052)	(0.132)	
				50th	0.337	0.321	-0.010	-0.085	-0.075
							(0.052)	(0.125)	
				90th	0.308	0.308	-0.071	-0.148	-0.078
							(0.057)	(0.097)	
< HS, < 25	-0.025	-0.079***	0.032	10th	0.398	0.292	-0.061	-0.354***	-0.292
	(0.023)	(0.028)	(0.046)				(0.058)	(0.125)	
				50th	0.350	0.275	-0.063	-0.367***	-0.304
							(0.064)	(0.124)	
				90th	0.303	0.217	-0.035	-0.411***	-0.377

	Empl. effect, white (β)	Black-MW interaction (β_B)	%Black-MW interaction ($\beta_{\%B}$)	Effect at percentile of %Black	Avg. white empl. rate	Avg. black empl. rate	White empl. elas.	Black empl. elas.	Black − white empl. elas.
							(0.089)	(0.121)	
< HS, < 25, Males	-0.013	-0.049	-0.062	10th	0.333	0.179	-0.041	-0.348*	-0.308
	(0.025)	(0.036)	(0.060)				(0.076)	(0.207)	
				50th	0.277	0.179	-0.065	-0.374*	-0.309
							(0.091)	(0.191)	
				90th	0.250	0.158	-0.162	-0.565***	-0.404
							(0.140)	(0.168)	
< HS, < 25, Females	-0.019	-0.083**	0.055	10th	0.348	0.251	-0.052	-0.402**	-0.350
	(0.028)	(0.034)	(0.062)				(0.080)	(0.191)	
				50th	0.289	0.228	-0.049	-0.425**	-0.376
							(0.088)	(0.195)	
				90th	0.238	0.184	0.024	-0.417**	-0.441
							(0.103)	(0.171)	
< HS, < 30	-0.008	-0.055**	-0.042	10th	0.360	0.221	-0.023	-0.286**	-0.263
	(0.024)	(0.022)	(0.039)				(0.065)	(0.141)	
				50th	0.307	0.221	-0.036	-0.299**	-0.263
							(0.075)	(0.135)	
				90th	0.279	0.203	-0.095	-0.401***	-0.306
							(0.093)	(0.134)	
< HS, < 30, Males	-0.003	-0.047	-0.068	10th	0.365	0.198	-0.011	-0.257	-0.246
	(0.026)	(0.035)	(0.064)				(0.071)	(0.181)	
				50th	0.314	0.201	-0.029	-0.277*	-0.248
							(0.084)	(0.163)	
				90th	0.297	0.189	-0.114	-0.427***	-0.313
							(0.128)	(0.138)	
< HS, < 30, Females	-0.012	-0.073*	0.007	10th	0.354	0.268	-0.035	-0.317	-0.283
	(0.027)	(0.037)	(0.058)				(0.077)	(0.193)	
				50th	0.299	0.248	-0.039	-0.341*	-0.302
							(0.084)	(0.196)	
				90th	0.257	0.220	-0.036	-0.373**	-0.337
							(0.100)	(0.165)	

Notes: The sample consists of ACS micro-data from 2005-2019 restricting to those aged between 16 to 65. Employment estimates are from linear probability models for an indicator of employment. The demographic controls included are race, sex, number of children, marital status, age and education. Additional controls include share black in the PUMA every year. Fixed effects are at PUMA and year level. All controls and fixed effects are interacted with race and share black. Percentiles of share black are computed using individual-level data weighted by individual person weights. Employment rate is measured in a ± 5 percentile interval around the specified percentile – for e.g., employment rate for 10th percentile is calculated by taking the weighted average employment (weighted by individual person weights) in the interval between 5th and 15th percentile. Employment elasticity for each population group is computed by dividing the employment effect (β) by the average employment rate of the group. ACS person sampling weights are used in the regressions. Reported standard errors are clustered at the state level.

Table 8: "Simulated" Minimum Wage Effects on Employment in White vs. Black Areas for High School Dropouts under Age 30, Increase from $7.25 (Federal Minimum Wage) to $12 (California Minimum Wage in 2019)

A. Population Shares and Employment Descriptives

	Teens		Male Teens		<HS, <30	
Share black percentile	**10th**	**90th**	**10th**	**90th**	**10th**	**90th**
White sub-population share	0.983	0.451	0.981	0.455	0.981	0.387
Black sub-population share	0.017	0.549	0.019	0.545	0.019	0.613
White employment rate	0.398	0.303	0.375	0.295	0.360	0.279
Black employment rate	0.292	0.217	0.237	0.197	0.221	0.203
Weighted employment rate	0.396	0.256	0.372	0.242	0.357	0.232

B. Homogeneous Effects by %Black

	Teens		Male Teens		<HS, <30	
Share black percentile	**10th**	**90th**	**10th**	**90th**	**10th**	**90th**
White MW-empl. elas.	-0.035	-0.046	-0.056	-0.071	-0.008	-0.011
Black MW-empl. elas.	-0.219	-0.295	-0.304	-0.365	-0.344	-0.374
Weighted empl. elas.	**-0.038**	**-0.183**	**-0.061**	**-0.231**	**-0.015**	**-0.234**
Impact of MW increase ($7.25 to $12) on empl. rate	**-0.010**	**-0.027**	**-0.014**	**-0.032**	**-0.003**	**-0.031**

C. Heterogeneous Effects by %Black

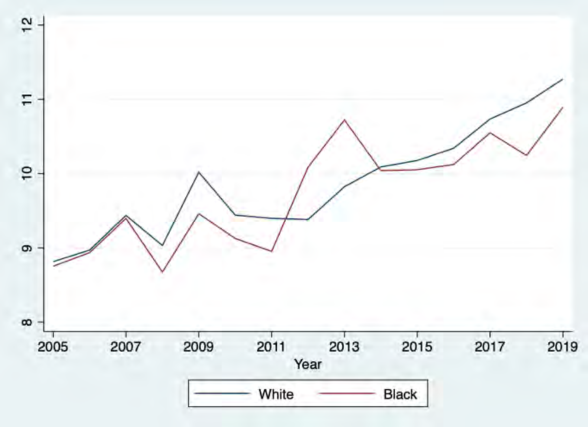
	Teens		Male Teens		<HS, <30	
Share black percentile	**10th**	**90th**	**10th**	**90th**	**10th**	**90th**
White MW-empl. elas.	-0.056	-0.019	-0.065	-0.095	-0.023	-0.095
Black MW-empl. elas.	-0.251	-0.263	-0.256	-0.327	-0.286	-0.401
Weighted empl. elas.	**-0.059**	**-0.153**	**-0.069**	**-0.221**	**-0.028**	**-0.283**
Impact of MW increase ($7.25 to $12) on empl. rate	**-0.015**	**-0.022**	**-0.016**	**-0.031**	**-0.006**	**-0.039**

Notes: All measures and percentiles are based on individual-level data using ACS person weights. "Sub-population shares" include only blacks and white, and refer to shares among teens, male teens and high school dropouts under 30. Employment rate is measured in a ± 5 percentile interval around the specified percentile – for e.g., employment rate for 10th percentile is calculated by taking the average employment weighted by individual person weights in the interval between 5th and 15th percentile. Minimum wage-employment elasticities for homogeneous effect by %Black are based on estimates of the similar model as in Table 2, but estimated at the individual level, and for heterogeneous effect by %Black are based on estimates in Table 7. Weighted employment rate and weighted elasticities are based on the sub-population shares. The last row is computed using separate elasticities and employment rates by race.

Appendix A: Figures and Tables

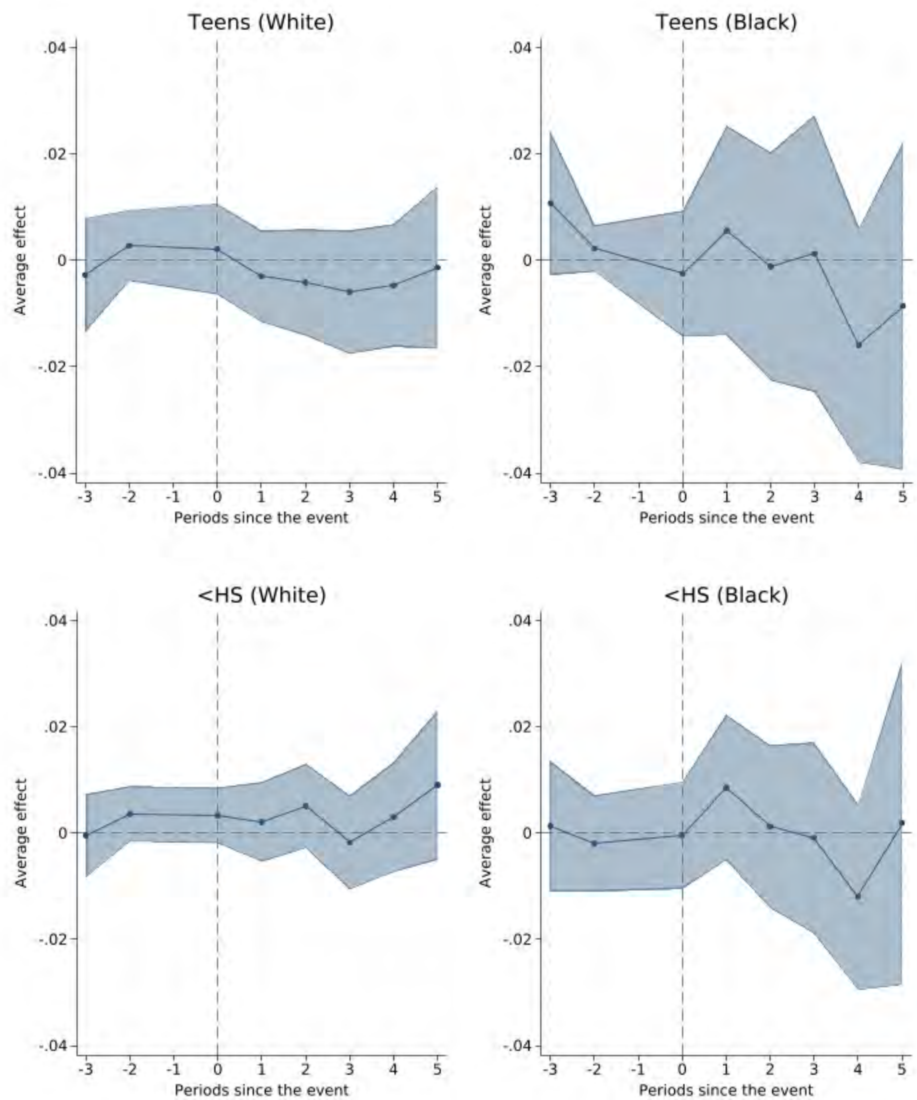
Appendix Figure A1: Hourly Wages by Year, Blacks and Whites

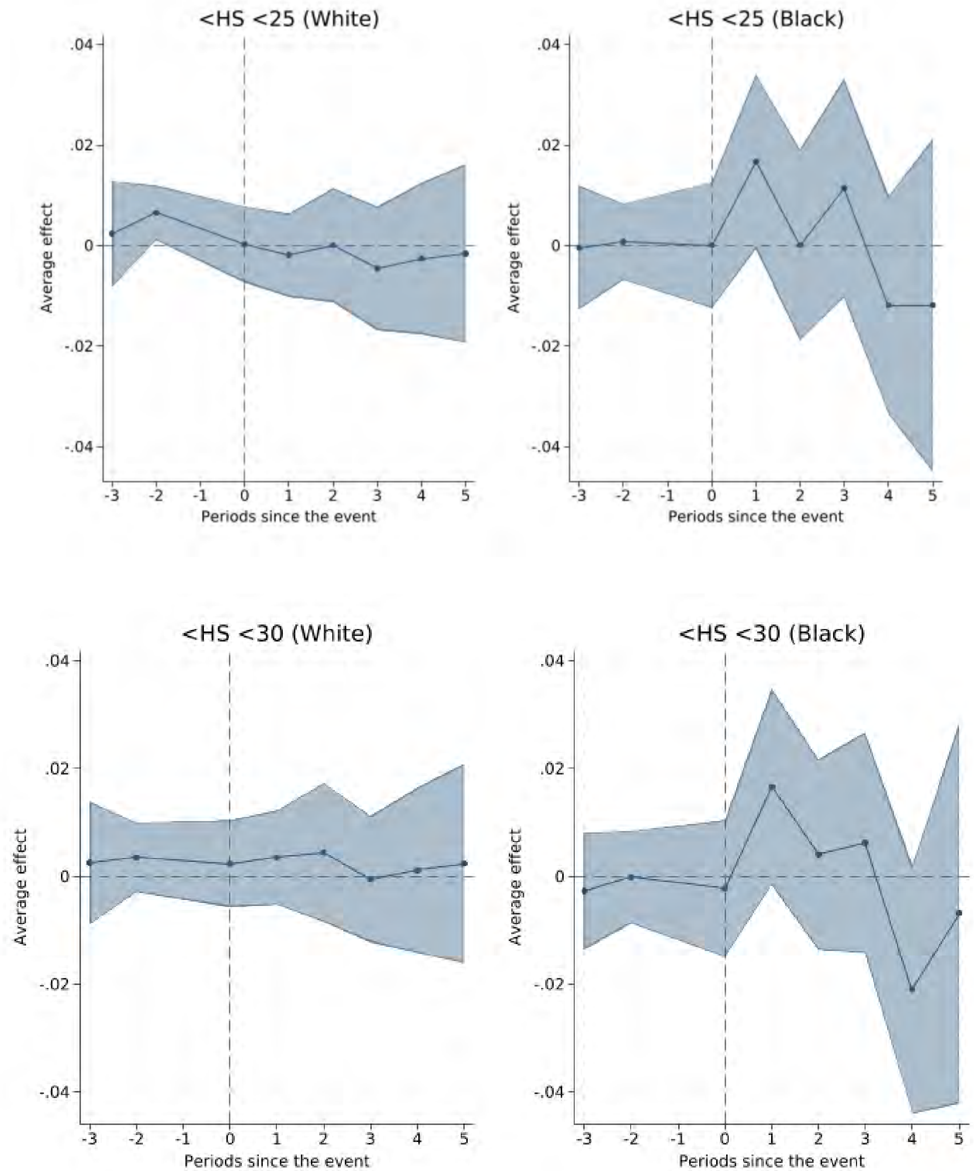
Teenagers (16-19), full-year, full-time



Note: Wages in each year are in nominal terms (in the respective year's dollar value) and weighted by individual person weights.

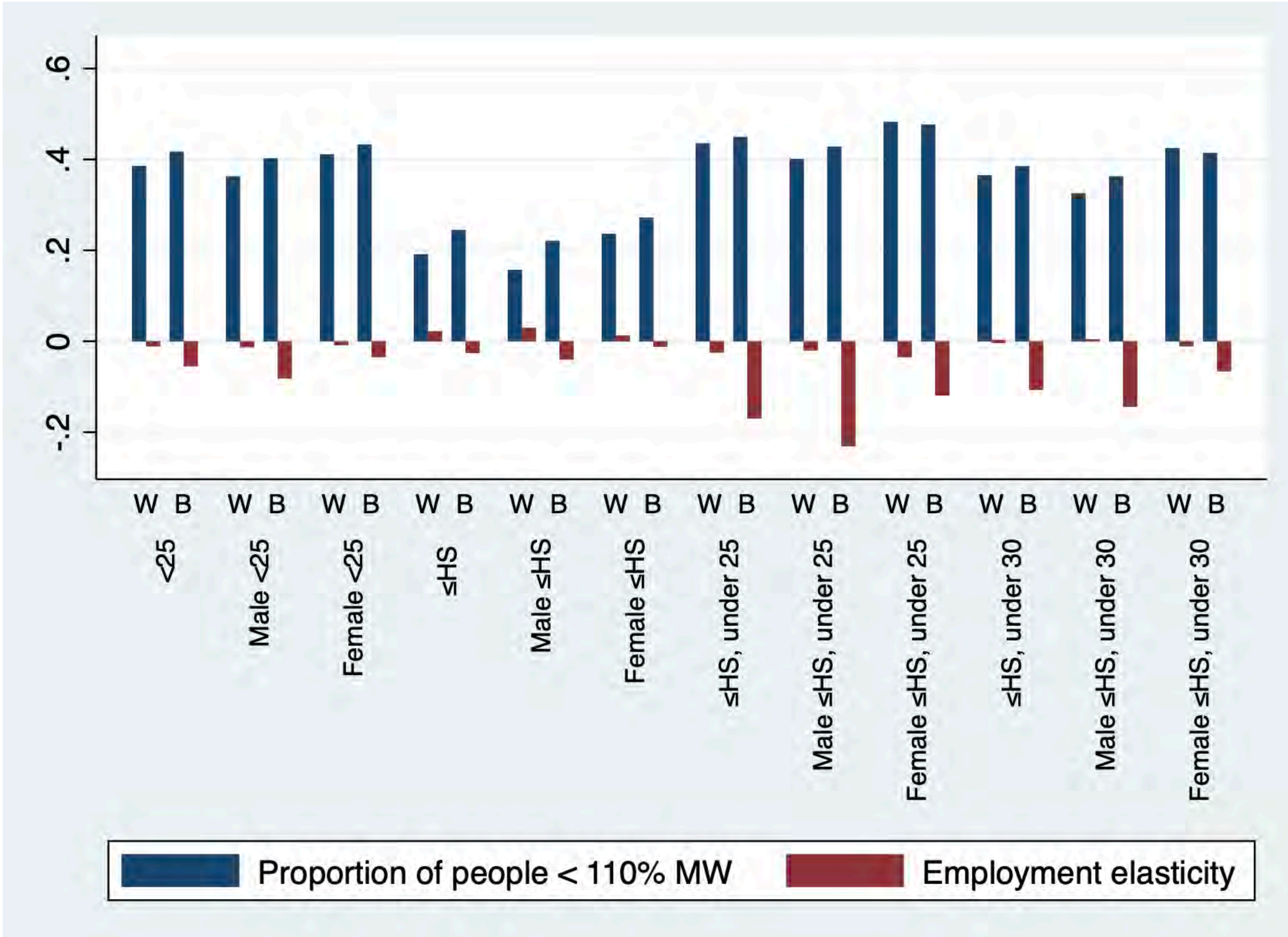
Appendix Figure A2: Event-study Graphs for Select Groups (Discrete Treatment, 2012-19)





Note: The event-study estimates exclude one year prior to treatment, thereby constraining the pre-treatment coefficients to zero. However, the graph displays a continuous line connecting all the estimates, which may give the appearance of a non-zero value in the pre-treatment year, even though no estimate is reported for that period.

Appendix Figure A3: Shares below 110% of the Minimum Wage and Estimated Employment Elasticities



Appendix Table A1: Minimum Wage-Annual Employment Regressions with Separate Effects by Race

Population	White empl. effect	Black empl. effect	Avg white empl. rate	Avg black empl. rate	White empl. elas.	Black empl. elas.
Teens 16-19	0.001	-0.050*	0.554	0.358	0.002	-0.138*
	(0.021)	(0.026)			(0.038)	(0.073)
Male teens	-0.001	-0.073**	0.542	0.333	-0.002	-0.221**
	(0.022)	(0.030)			(0.040)	(0.091)
Female teens	0.005	-0.014	0.567	0.385	0.008	-0.035
	(0.023)	(0.030)			(0.041)	(0.079)
<25	0.011	-0.015	0.714	0.544	0.016	-0.027
	(0.014)	(0.023)			(0.020)	(0.042)
Male <25	0.009	-0.034	0.713	0.514	0.012	-0.065
	(0.016)	(0.025)			(0.023)	(0.048)
Female <25	0.014	0.007	0.715	0.573	0.020	0.012
	(0.015)	(0.026)			(0.021)	(0.045)
< HS	0.013	-0.040	0.507	0.389	0.026	-0.103
	(0.019)	(0.028)			(0.038)	(0.071)
Male < HS	0.021	-0.035	0.555	0.380	0.038	-0.093
	(0.021)	(0.030)			(0.038)	(0.079)
Female < HS	0.004	-0.044	0.447	0.397	0.010	-0.111
	(0.020)	(0.029)			(0.045)	(0.074)
≤ HS	0.017	-0.011	0.683	0.563	0.025	-0.020
	(0.014)	(0.024)			(0.020)	(0.042)
Male ≤ HS	0.020	-0.017	0.736	0.555	0.028	-0.030
	(0.015)	(0.026)			(0.020)	(0.046)
Female ≤ HS	0.014	-0.006	0.620	0.569	0.023	-0.010
	(0.013)	(0.024)			(0.022)	(0.043)
< HS, < 25	-0.005	-0.065**	0.450	0.279	-0.011	-0.232**
	(0.024)	(0.032)			(0.053)	(0.114)
Male < HS, < 25	0.004	-0.068*	0.454	0.267	0.008	-0.254*
	(0.026)	(0.034)			(0.057)	(0.128)
Female < HS, < 25	-0.010	-0.049	0.445	0.295	-0.021	-0.166
	(0.026)	(0.038)			(0.058)	(0.130)
≤ HS, < 25	0.010	-0.046*	0.604	0.436	0.017	-0.105*
	(0.019)	(0.026)			(0.032)	(0.059)
Male ≤ HS, < 25	0.012	-0.067**	0.622	0.422	0.019	-0.158**
	(0.021)	(0.027)			(0.033)	(0.065)
Female ≤ HS, < 25	0.006	-0.014	0.583	0.452	0.011	-0.031
	(0.021)	(0.034)			(0.037)	(0.076)
< HS, < 30	0.003	-0.057*	0.470	0.313	0.007	-0.183*
	(0.023)	(0.033)			(0.050)	(0.106)
Male < HS, < 30	0.013	-0.048	0.485	0.298	0.027	-0.160
	(0.025)	(0.037)			(0.051)	(0.125)
Female < HS, < 30	-0.003	-0.066*	0.452	0.331	-0.007	-0.198*
	(0.027)	(0.036)			(0.059)	(0.109)
≤ HS, < 30	0.017	-0.036	0.645	0.491	0.026	-0.073
	(0.017)	(0.029)			(0.026)	(0.060)
Male ≤ HS, < 30	0.015	-0.049*	0.677	0.474	0.022	-0.103*
	(0.018)	(0.029)			(0.026)	(0.061)
Female ≤ HS, < 30	0.019	-0.011	0.605	0.509	0.031	-0.022
	(0.019)	(0.038)			(0.032)	(0.075)

Notes: Same as Table 2. The employment measure is annual employment, defined as individuals who reported working more than zero weeks in the past 12 months.

Appendix Table A2: Minimum Wage-Annual Hours Regressions with Separate Effects by Race

Population	White empl. effect	Black empl. effect	Avg white empl. rate	Avg black empl. rate	White empl. elas.	Black empl. elas.
Teens 16-19	-39.664	-83.431**	341.129	234.366	-0.116	-0.356**
	(25.344)	(33.169)			(0.074)	(0.142)
Male teens	-41.268	-95.667**	350.593	221.087	-0.118	-0.433**
	(29.458)	(44.423)			(0.084)	(0.201)
Female teens	-36.160	-65.685**	330.601	246.574	-0.109	-0.266**
	(24.405)	(29.160)			(0.074)	(0.118)
<25	-29.736	-54.067	796.678	603.135	-0.037	-0.090
	(29.904)	(40.429)			(0.038)	(0.067)
Male <25	-35.111	-57.023	849.620	583.402	-0.041	-0.098
	(38.735)	(42.746)			(0.046)	(0.073)
Female <25	-24.689	-47.046	739.600	616.844	-0.033	-0.076
	(24.177)	(41.760)			(0.033)	(0.068)
< HS	-6.740	-94.378**	648.316	513.739	-0.010	-0.184**
	(36.554)	(43.187)			(0.056)	(0.084)
Male < HS	2.707	-88.239*	794.155	516.571	0.003	-0.171*
	(49.389)	(48.443)			(0.062)	(0.094)
Female < HS	-16.775	-88.317*	466.069	506.970	-0.036	-0.174*
	(27.532)	(46.464)			(0.059)	(0.092)
≤ HS	4.070	-58.417	1153.493	897.361	0.004	-0.065
	(36.532)	(52.398)			(0.032)	(0.058)
Male ≤ HS	10.816	-52.970	1344.370	911.955	0.008	-0.058
	(46.782)	(59.011)			(0.035)	(0.065)
Female ≤ HS	-0.311	-62.921	928.390	874.468	0.000	-0.072
	(26.808)	(47.405)			(0.029)	(0.054)
< HS, < 25	-19.717	-74.258***	272.986	194.682	-0.072	-0.381***
	(23.804)	(24.489)			(0.087)	(0.126)
Male < HS, < 25	-17.422	-74.047**	304.560	192.199	-0.057	-0.385**
	(29.527)	(33.841)			(0.097)	(0.176)
Female < HS, < 25	-23.311	-52.810**	233.924	196.271	-0.100	-0.269**
	(23.076)	(26.272)			(0.099)	(0.134)
≤ HS, < 25	-35.944	-103.587***	613.561	453.227	-0.059	-0.229***
	(35.277)	(37.688)			(0.057)	(0.083)
Male ≤ HS, < 25	-34.991	-110.794**	700.470	453.962	-0.050	-0.244**
	(43.789)	(47.878)			(0.063)	(0.105)
Female ≤ HS, < 25	-43.061	-76.802*	504.023	445.087	-0.085	-0.173*
	(29.428)	(38.866)			(0.058)	(0.087)
< HS, < 30	-11.345	-88.580**	353.012	269.773	-0.032	-0.328**
	(29.647)	(33.428)			(0.084)	(0.124)
Male < HS, < 30	-3.116	-89.415**	414.417	265.304	-0.008	-0.337**
	(36.588)	(43.535)			(0.088)	(0.164)
Female < HS, < 30	-19.339	-73.430**	277.218	270.801	-0.070	-0.271**
	(26.853)	(35.969)			(0.097)	(0.133)
≤ HS, < 30	-27.628	-98.864*	793.360	603.038	-0.035	-0.164*
	(33.527)	(50.847)			(0.042)	(0.084)
Male ≤ HS, < 30	-29.133	-107.318*	924.972	603.393	-0.031	-0.178*
	(42.221)	(56.655)			(0.046)	(0.094)
Female ≤ HS, < 30	-27.624	-72.597	623.394	593.494	-0.044	-0.122
	(29.551)	(51.108)			(0.047)	(0.086)

Notes: Same as Table 2. The employment measure is usual hours worked in the past 12 months.

Appendix Table A3: Minimum Wage-Employment Regressions with Separate Effects by Race, TWFE and 2S-DID (Discrete Treatment) from 2012-19

Population	TWFE White	TWFE Black	2S-DID White	2S-DID Black
Teens 16-19	-0.006	-0.004	-0.002	-0.006
	(0.005)	(0.006)	(0.005)	(0.010)
Male teens	-0.008*	0.001	-0.004	-0.004
	(0.005)	(0.008)	(0.005)	(0.012)
Female teens	-0.005	-0.004	-0.002	-0.008
	(0.006)	(0.008)	(0.007)	(0.012)
< 25	-0.003	-0.002	0.002	-0.004
	(0.004)	(0.006)	(0.004)	(0.008)
Male < 25	-0.002	-0.003	0.003	-0.005
	(0.004)	(0.005)	(0.005)	(0.007)
Female < 25	-0.005	-0.001	0.001	-0.006
	(0.005)	(0.007)	(0.005)	(0.009)
< HS	-0.0002	0.001	0.005	-0.001
	(0.004)	(0.006)	(0.004)	(0.008)
Male < HS	0.002	-0.004	0.007	-0.004
	(0.004)	(0.007)	(0.005)	(0.007)
Female < HS	-0.002	0.011	0.003	0.008
	(0.004)	(0.008)	(0.005)	(0.012)
≤ HS	0.002	0.004	0.005	0.004
	(0.003)	(0.006)	(0.003)	(0.007)
Male ≤ HS	0.004	0.004	0.008**	0.005
	(0.004)	(0.006)	(0.004)	(0.007)
Female ≤ HS	0.001	0.005	0.002	0.005
	(0.003)	(0.006)	(0.003)	(0.009)
< HS, < 25	-0.005	-0.0003	-0.0003	-0.0002
	(0.005)	(0.007)	(0.006)	(0.009)
Male < HS, < 25	-0.006	-0.003	-0.001	-0.007
	(0.005)	(0.007)	(0.006)	(0.008)
Female < HS, < 25	-0.003	0.004	-0.00002	0.001
	(0.007)	(0.010)	(0.007)	(0.014)
≤ HS, < 25	-0.004	-0.009	0.001	-0.009
	(0.004)	(0.007)	(0.005)	(0.010)
Male ≤ HS, < 25	-0.003	-0.007	0.002	-0.010
	(0.005)	(0.006)	(0.007)	(0.008)
Female ≤ HS, < 25	-0.004	-0.010	-0.003	-0.012
	(0.006)	(0.011)	(0.006)	(0.014)
< HS, < 30	-0.001	-0.001	0.004	-0.002
	(0.005)	(0.007)	(0.006)	(0.009)
Male < HS, < 30	-0.002	-0.003	0.004	-0.007
	(0.005)	(0.008)	(0.006)	(0.009)
Female < HS, < 30	-0.001	0.003	0.003	0.001
	(0.007)	(0.011)	(0.007)	(0.016)
≤ HS, < 30	-0.001	-0.003	0.003	-0.003
	(0.004)	(0.007)	(0.005)	(0.010)
Male ≤ HS, < 30	-0.001	-0.001	0.005	-0.003
	(0.005)	(0.006)	(0.006)	(0.009)
Female ≤ HS, < 30	-0.001	-0.003	0.001	-0.004
	(0.005)	(0.011)	(0.005)	(0.015)

Notes: Same as Table 3. The treatment considered is discrete, defined as the first-time minimum wage increases in a PUMA.

Appendix Table A4: HHIs (for Various Industries) for PUMAs with 10th and 90th Percentiles of Share Black (in 2019)

A. 10th percentile of share black (each PUMA weighted by population)

	Retail (NAICS = 44,45)	Food & Accommodation (NAICS = 72)	Low wage (NAICS = 44,45,71,72,56,81)	All
HHI (estab)	128.76	105.34	38.45	31.38
HHI (firm)	249.59	117.03	58.54	64.16
Count (estab)	995	484	4787	11186
Employment	8583	6595	26566	79755

B. 90th percentile of share black (each PUMA weighted by population)

	Retail (NAICS = 44,45)	Food & Accommodation (NAICS = 72)	Low wage (NAICS = 44,45,71,72,56,81)	All
HHI (estab)	124.22	104.02	45.22	52.70
HHI (firm)	219.03	127.02	59.83	134.03
Count (estab)	1031	518	5353	11374
Employment	8729	8492	32530	101008

Notes: All measures (including percentiles of share black) are computed as weighted averages across PUMAs, where the weights correspond to the population of each PUMA in 2019. The HHI, establishment count, and employment are measured in a ± 5 percentile interval around the specified percentile— for e.g., the HHI for the 10th percentile is calculated by taking the weighted average HHI in the interval between 5th and 15th percentile of share black.