Disaggregating city-level minimum wage impacts: How do young workers fare?

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Abstract

This study examines one possible policy that may affect youth employment: laws mandating higher minimum wages. Drawing on unique data from Seattle, the first major city to implement a $15 minimum hourly wage, we examine impacts of the minimum wage policy on young workers' continued employment, hours worked, and earnings. Employment records merged with demographic identifiers allow this study to include analyses of employees ages 16 to 24 at the time of the policy as well as to examine other demographic subgroups by age, sex, race, and industry. Using quasi-experimental triple difference models, we find that Seattle's $15 minimum wage ordinance reduced employment among young workers in the quarter after it took effect but not significantly in subsequent quarters. Young workers in Seattle worked significantly fewer hours but did not earn less. Subgroup analyses show that these effects were stronger for women and young Black workers.

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Data Availability

The authors will make data available to anyone who secures the approval of the Washington State Institutional Review Board and the state agency data owners.

Citation

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1. Introduction

For adolescents and young adults, finding and keeping a job has important developmental and instrumental implications (Leventhal, Graber, and Brooks-Gunn 2001; Mortimer 2010; Kahn 2006). However, labor force participation among workers aged 16-24 has dropped by 14 percent over the past two decades, the largest percentage drop for any age group (Abraham & Kearney, 2020). This drop is particularly strong for young men and White youth, although employment rates for Black, Latino, and Asian youth have been lower than rates for White youth over this century (Fernandes-Alcantara 2018). Employment matters for youth because early labor market experiences resonate over a career and hence lifetime. Young adults dissatisfied with their employment situations are at greater risk of mood or substance use disorders, predecessor conditions of premature deaths (Dupéré et al. 2024). Fewer experiences to learn on the job early in life can reduce long-run skill acquisition (Jovanovic & Nyarko 1996). Evidence from recessions shows that workers who enter labor markets marked by higher unemployment see lower earnings for years into the future, and these early labor market experiences can spill over into negative effects on health and family formation (von Wachter 2020).

This study examines one possible policy that may affect youth employment: laws mandating higher minimum wages. Drawing on unique data from Seattle, the first major city to implement a $15 minimum hourly wage, we examine impacts of the minimum wage policy on young workers' continued employment, hours worked, and earnings. Employment records merged with demographic identifiers allow this study to include analyses of employees ages 16 to 24 at the time of the policy as well as to examine other demographic subgroups by age, sex, race, and industry. Using quasi-experimental triple difference models, we find that Seattle's $15 minimum wage ordinance reduced employment among young workers in the quarter after it took effect but not significantly in subsequent quarters. Young workers worked significantly fewer hours but did not earn less. Subgroup analyses show that these effects were stronger for women, young Black workers, and workers with jobs in retail trade or health care and social assistance at baseline.

1.1. Minimum wage policy and research

By aiming to improve the sufficiency of the lowest-paid workers' income, minimum wage laws target overall earnings inequality and may reduce longstanding gender and racial disparities in the labor market (Derenoncourt and Montialoux 2020). Several dozen localities including the nation's three largest cities– New York, Los Angeles, and Chicago – all have adopted minimum wages higher than their relevant state minimum wages (Economic Policy Institute, 2024). Evidence from these policies enacted in local "laboratories of democracy" can inform national policy deliberations.

Classical economic theories of supply and demand predict that higher minimum wages will reduce employment by raising the cost of workers relative to other operating costs. Youth workers – who likely have less skill due to their relatively low experience levels – may be particularly susceptible to suppressed employment opportunities. On the other hand, monopsony models of the economy hold that raising wages could possibly increase employment by reducing the power of employers to artificially restrict workers' wages and boosting demand for goods and services by giving workers more money to spend. If the correction caused by raising wages increases all workers' wages, young workers might benefit from increased labor market opportunities. As might be expected from this clash in theoretical perspectives, the empirical literature on minimum wage impacts is heavily contested, with many (but not all) studies showing modest negative impacts on young workers.

While city-level minimum wages may operate differently than state- or federal efforts, evidence to date suggests that city minimum wages laws have raised wages for the lowest-earning workers without decreasing their employment rate (Dube and Lindner 2021; Karageorgiou 2004; Jardim et al. 2022; Dube, Naidu, and Reich 2007). However, minimum wage increases may simultaneously increase earnings for low-paid workers overall and harm some less-advantaged low-paid workers, including economically or racially disadvantaged youth and young adults. Research has yet to examine whether local wage laws vary in their effects on workers from different demographic groups, but there are some suggestions that youth may be at risk. Early findings from a study of Seattle's $15 minimum wage ordinance showed gains only for workers who had worked an above-median number of hours in recent quarters, a marker that likely aligns with age (Jardim et al., 2022).

Data limitations have constrained our understanding of the impact of local wage policies on important subgroups such as age and race. While minimum wage research based on federal or state variation has examined subgroups of workers by age and other characteristics (Allegretto, Dube, and Reich 2011; Derenoncourt and Montialoux 2020), studies of city-level wage policies focus on the workforce or population as a whole or within specific sectors such as food service (e.g., Dube et al., 2007, Karabarbounis et al., 2021). Research questions about the heterogeneous effects of city-level minimum wages demand more and better data than is commonly available through national survey data, which lack sufficient local sample sizes for subgroup analyses. State-level UI records offer the density needed to study city-level wages but lack demographic details. American legacies of white supremacy and colonialism show up in data as well (Urban Indian Health Institute 2021). National survey data sources lack sufficient sample sizes to describe the well-being of Asian/Pacific Islander (API) and American Indian/Alaska Native (AI/AN) populations despite these groups' ongoing and growing importance and presence in the population (Kauh, Read, and Scheitler 2021; Alegria et al. 2004). These same data limitations affect studies of other policy interventions.

1.2. Young workers and the minimum wage

Data limitations have heretofore precluded analysis of the impact of city-level minimum wages on young workers. Instead, existing evidence on how the minimum wage affects young workers reflects minimum wage changes at the state and federal levels. Studies about minimum wage impacts on teenagers and other young workers oscillate between finding small and null effects. Early studies finding no or positive effects on teenage employment (e.g. Card 1992) gave rise to findings of small unemployment effects as well as suggestions that more advantaged teens are displacing less-advantaged teens and slightly older workers (Neumark and Wascher 2007; Giuliano 2013). A recent review of published research finds that, in the majority of studies that focus on teens and young adults, younger worker employment drops as minimum wages rise (Neumark and Shirley 2021). However, many of these studies rely on variation in state laws over time, and a re-analysis of previously analyzed Current Population Survey (CPS) waves suggests that real effects on employment are statistically indistinguishable from zero when taking state heterogeneity and selectivity into account (Allegretto, Dube, and Reich 2011).

While overall effects are seemingly small, impacts may fall more heavily on certain subgroups. Younger workers – those with the least experience – may be more affected by minimum wage increases. Neumark and Wascher (1995) found that higher minimum wage laws had stronger negative employment effects on 16-17 year olds, relative to 18-19 year-olds, an effect that they posit is due to employers shifting their hiring to more experienced workers when mandated wages are higher. Young workers of color perennially have lower employment rates than White youth (Fernandes-Alcantara 2018). Hence employment among youth of color may also be particularly sensitive to changes in the minimum wage (Turner and Demiralp 2001).

The focal age period for this study – young people in their late teens through early 20s – is also a time in which many young people are in secondary or post-secondary education. While decisions about work and schooling are likely connected, our data do not include information on educational enrollment or attainment. However, studies that model the transition between different combinations of education and employment do suggest that minimum wage laws matter. In modelling transitions between employment and school enrollment, school without employment, employment without school, and neither employed nor in education or training (NEET), several studies find that minimum wage increases lead to small net decreases in teen employment but do not increase educational enrollment. This is true for samples of mostly White youth (Neumark and Wascher 1995; Neumark and Shupe 2018) and one analysis of youth of color found that Black and Hispanic teens who are NEET are less likely to become employed after a wage increase than they were before (Turner and Demiralp 2001).

1.3. The Seattle Minimum Wage Ordinance

This study focuses on the 2014 Seattle Minimum Wage Ordinance (hereafter, the Ordinance), the first effort by a major city to increase the minimum wage to $15 per hour. The Seattle City Council passed its own Minimum Wage Ordiance in June 2014. Figure N depicts the initial step-ups in the highest minimum wages, including the initial step-up to $11.00 in April 2015 (from the state minimum of $9.47) and the subsequent step-ups in January 2016 and 2017. While the full ordinance laid out different wage increase schedules depending on employer size and whether or not employees received employer-provided health insurance or tips, interviews with employers and workers suggest that the highest wage at each step-up prevailed (The Seattle Minimum Wage Study Team 2016). For simplicity, Figure 1 and the text refer only to the highest minimum wage at each time period. The Seattle wage mandate took place in the context of a relatively high state minimum wage. Since the 1990s, Washington state's minimum wage has been higher than the federal minimum, and it is indexed to inflation with increases every January 1. In November 2016, Washington voters approved a ballot initiative to further increase the state minimum wage; this initiative went into effect January 1, 2017.

Prior research on the Seattle Ordinance examined overall employment effects. Jardim and colleagues (2022) found that workers with less than the median amount of work hours in the two quarters prior to the implementation of the MWO saw greater reductions in hours worked relative to workers with more intense recent employment experience. They termed these workers "less experienced" and found that this group experienced slight negative or nonsignificant net impacts on total earnings. In contrast the "more experienced" workers posted modest earnings increases in the range of $115-$395 per quarter. With only UI earnings data, cannot distinguish workers who work intensely because they are young from other workers who are part-time or otherwise modestly attached to the labor market.

1.4. This Study

This study adds to evidence about the Seattle Minimum Wage Ordinance by using unique merged administrative data that allows the examination of impacts across different demographic groups. To our knowledge, this is the first study to focus on the impact of a city level minimum wage on young workers, which advances overall knowledge about minimum wage effects. We address two questions: (1) How did the Seattle minimum wage ordinance affect the employment, hours worked, and total earnings of young Seattle workers?, and (2) Did the effects vary by age, gender, race/ethnicity, or industry?

2. Methods

2.1. Data

We use the Washington Merged Longitudinal Administrative Dataset (WMLAD), which contains individual-level data linked by unique person identifiers across multiple Washington state agencies. WMLAD combines records on employment and public assistance use combined with detailed demographic and geographic information collected administratively. WMLAD was compiled as a collaboration between the University of Washington and the Research and Data Analysis Division at DSHS (J. Romich et al. 2018). The data span the first quarter of 2010 through the last quarter of 2017. WMLAD contains information on over 10 million individuals, representing a near-census of Washington's working-aged residents during this time (Long, Pelletier, and Romich 2022).

We define young workers as those who were aged 16 through 24 in January through March of 2015, the baseline quarter of analysis. WMLAD created demographic indicators by combining using year-of-birth information collected through driver's license records from Department of Licensing (DOL), voter records from the Secretary of State (SOS), vital statistics records from the Department of Health (DOH) and public assistance use records from the Department of Social and Health Services (DSHS) (Pelletier and Romich in press). Because employment data do not contain their own age records, we are unable to identify the ages of seven percent of the employed population in Washington state (see **Table 1**). The individuals missing age data are those who were working in Washington but either were not matched based on name and Social Security Number to another record or did not have a driver's license, were not registered to vote, did not appear as a parent on a birth certificate, and did not use public assistance during the eight-year window of the data.

2.2. Measures

We examine three employment outcomes following the implementation of Seattle's minimum wage increase: earnings (in 2015.2[1] dollars), hours worked, and employment status. For workers with multiple jobs, we sum earnings and hours across all jobs worked. We top-code earnings and hours worked to the 99th percentile. Each measure is reported quarterly to the Employment Security Department (ESD) to workers covered by the state's Unemployment Insurance (UI) program, which by state law is all workers who file a W-2. Contracted employees, gig workers, people who are self-employed, and people who work in the informal labor force are excluded from these data.

We include three sets of covariates to facilitate subgroup analysis: industry of primary job at baseline, binary sex, and race and ethnicity. Employment records include a five-digit North American Industry Classification System (NAICS) code that allows us to broadly identify industry. We categorize industries into four groups, the three industries that employ the greatest proportion of youth in the baseline quarter (2015.1) plus all other industries combined: Accommodation and Food Services (32.5% of young workers), Retail Trade (22.8%), Health Care and Social Assistance (9.9%), and Other Industries (34.8%). Binary sex (female/male) is provided from driver's license records (DOL), voter records (SOS), and public assistance records (DSHS). Six-category race and ethnicity (White, Black, Asian or Pacific Islander, Native American, Hispanic, or Other and Multiracial) is provided by public assistance use records (DSHS) and other records maintained by this department. Data on race and ethnicity based on information reported to vital statistics or public assistance systems are available for just under half of the population (Pelletier and Romich in press). For others, race and ethnicity is imputed by combining information on residential location and last name using the Bayesian Improved Surname Geocoding (BISG) method (Elliott et al. 2009). Information on residential address and last name are drawn from DSHS, SOS, DOL, and Department of Health (DOH) records.

[1] Throughout this manuscript, we refer to years and quarters as "Year.Quarter." Here, 2015.2 represents the second quarter of 2015.

2.3. Analytic Approach

We take a quasi-experimental, difference-in-difference-in-difference (triple difference, or DDD) approach to estimate the effect of Seattle's minimum wage increases on young workers' employment outcomes. The first difference compares outcomes in the post period (2015.2 through 2016.4) to outcomes in the quarter prior to the implementation of Seattle's minimum wage increases (2015.1, the "baseline quarter"). The second difference compares outcomes for young workers whose primary job was in Seattle in the baseline quarter, to outcomes for young workers whose primary job was in Washington state, but outside of Seattle and its surrounding counties in the baseline quarter. The third difference compares outcomes for young workers in the seven quarters following Seattle's minimum wage increase (2015.2 through 2016.4) to the outcomes of a "pseudo-cohort" of young workers in seven quarters during which no minimum wage changes were enacted (2011.2 through 2012.4). We estimate the triple difference equation for each quarter of the post-period, an event study framework, to avoid the serial correlation issues that have raised concern in the difference-in-differences literature (Zhao 2004; Callaway and Sant'Anna 2021).

The DDD approach provides strong but imperfect evidence about the causal impact of the Seattle wage ordinance on young workers. By including these three levels of differencing, this quasi-experimental approach will allow us to estimate the impact of the minimum wage ordinance net of any expected changes in employment, time trends that affected the full state labor market during the implementation period, or persistent differences between the Seattle youth labor market and the market for young workers in other parts of the state. This approach cannot account for Seattle-specific changes in the youth labor market that happened only in Seattle during the post-period (2015.2-2016.4) but were not caused by the wage change policy.

2.3.1. Treatment and Comparison Group Selection

We identify as our treatment group young workers who were most likely to be exposed to Seattle's minimum wage increases: people ages 16 to 24 who were employed and earning less than $11 per hour across all hours in the baseline quarter (2015.1) prior to the minimum wage increases, whose primary job (job with the highest hours worked that quarter) was located within the city limits of Seattle. An important but unavoidable limitation of the UI employment records is that job location is not identifiable for approximately one-third of young workers (see **Table 1**). Job locations are "non-locatable" when firms are multi-site establishments that file their employees' W-2s under one ambiguous address. Since job location is required to identify treatment status, we follow Jardim et al. (2022) and drop "non-locatable" workers from the analysis.

From a comparison pool of young workers outside of Seattle and its surrounding counties[2] , we identify a comparison group for analysis using a combination of nearest-neighbor and exact matching. We match exactly on employment status in the baseline and two prior quarters. We also match exactly on a binary variable indicating workers whose primary job was in the "Accommodation and Food Services" industries (NAICS sector 72) versus other industries because this is the sector that employs the greatest number of young workers and is seen as particularly sensitive to wage changes. Additionally, we match on earnings and hours in the baseline quarter, using Mahalanobis distance to match with one nearest neighbor (Zhao 2004). We use normalized differences to assess match quality (Imbens 2015). The normalized difference is the mean difference divided by the square root of the average of the variances. It is recommended over a t-statistic for assessing match quality because the calculation does not rely on sample size. As normalized differences increase, match quality decreases.

2.3.2. Pseudo-Cohort

For the third difference in the triple differences approach, we create a "pseudo-cohort" of workers inside Seattle (pseudo-treatment) and outside of Seattle and its surrounding counties (pseudo-comparison) during a period when Seattle's minimum wage did not change. We construct the pseudo-cohort following the same procedures we used to construct the "minimum wage cohort," described above, instead using 2011.1 for the pseudo-cohort baseline quarter. The pseudo-cohort allows us to adjust for factors that may

[2] We exclude the counties surrounding Seattle (King, Snohomish, Kitsap, and Pierce) out of concern that businesses near Seattle may raise wages to compete for workers (i.e. spillover effects of the minimum wage). As a robustness check, we conduct analyses that exclude only King County workers from the comparison group, but include workers from Snohomish, Kitsap, and Pierce counties.

bias the simple difference-in-differences estimation of the minimum wage cohort, such as unobserved but persistent differences between Seattle and non-Seattle workforce dynamics and time trends unrelated to Seattle's minimum wage increase that may have affected young workers' employment outcomes (Jardim et al., 2022).

2.3.3. Model Specification

We estimate the effect of Seattle's minimum wage increases on three outcomes for young workers: earnings, hours worked, and employment status. We estimate the triple difference using ordinary least squares[3] with this equation:

$$Y_{iq} = a + \beta_1 Seattle_i + \beta_2 Post_q + \beta_3 (Seattle_i \times Post_q)$$
$$+ \beta_5 (Seattle_i \times Cohort_i) + \beta_6 (Post_q \times Cohort_i)$$
$$+ \beta_7 (Seattle_i + Post_q + Cohort_i) + \beta_8 \mathrm{X}_i + \varepsilon_{iq}$$

where Y_{iq} represents the outcome for individual *i* in quarter *q*. *Seattle* is the treatment cohort indicator, identifying the workers whose primary jobs were in Seattle during the baseline quarter (2015.1) compared to those whose primary jobs were in Washington state outside of Seattle and its surrounding counties at baseline. *Post* equals one during the post period (2015.2 through 2016.4 for the cohort of interest; 2011.2 through 2013.4 in the pseudo-cohort) and zero at baseline (2015.1 in the cohort of interest; 2011.1 in the pseudo-cohort). *Cohort* identifies those in the minimum wage cohort—those treated by the actual Seattle minimum wage ordinance in 2015 and 2016—and was zero for those in the pseudo-cohort. The variable X is a vector of time-invariant demographic indicators that includes age at baseline (16-17, 18-20, and 21-24), binary sex (male and female), race and ethnicity (White, Black, Hispanic, Native American, Hispanic, and Multiple or Other Racial or Ethnic Identities), and industry of primary job at baseline (Accommodation and Food Services, Retail Trade, Health Care and Social Assistance, and Other Industries). The error term is designated by ε_{iq}.

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The triple difference is estimated by coefficient β_7, which estimates the outcome for Seattle-based young workers from the minimum wage cohort in the post-period, relative to the three comparison points: (1) the pre-period, (2) the comparison group of young workers located outside of Seattle and its surrounding counties, and (3) the pseudo-cohort. The third difference may also be understood as the difference between the simple difference-in-difference (DD) estimates for the minimum wage and pseudo-cohorts. We conduct this analysis seven times, once for each quarter of the post-period. For models where the outcome is a binary indicator of employment status, we use a linear probability model.

2.3.4. Subgroup Analyses and Robustness Checks

To understand the possible heterogeneous impacts of Seattle's minimum wage on different groups of young workers, we conduct the analyses described in this section by four different subgroups: binary sex, race and ethnicity (White alone, Black alone, Asian or Pacific Islander alone, Hispanic alone, Multiracial or other race and ethnicity, and missing race and ethnicity information), age at baseline (16-17, 18-20, 21-24), and four-category job industry at baseline (Accommodation and Food Services, Health Care and Social Assistance, Retail Trade, and Everything Else). We are unable to conduct subgroup analyses for young workers identified as Native American alone due to small sample size.

To create the subgroups, we begin with the complete cohort of locatable young low-wage workers in the main cohort (as described in Table 1) and the pseudo-cohort prior to matching. We then create subsets of these cohorts by subgroup characteristic, such that male young workers and female young workers, for example, are in separate subgroups. We conduct the matching procedure within each subgroup, so Black young workers in Seattle at baseline, for example, are matched with Black young workers outside of Seattle at baseline who have comparable employment and earnings histories. We conduct the triple differences analyses, as described above, within each matched subgroup, controlling for the remaining unmatched demographic characteristics.

We conduct robustness checks to confirm the core conclusion remains valid despite changes to certain analytical decisions. For the first robustness check, we do not control for demographic indicators including age, binary sex, race and ethnicity, and industry. Second, we use earnings and hours worked without topcoding as employment outcome variables for the final robustness check. The final robustness check uses the full comparison group of young workers instead of selecting a subset of comparison workers through the matching procedure.

3. Results

3.1. Cohort Characteristics

We compare the employment characteristics and average age of the treatment and comparison groups in the minimum wage cohort (baseline 2015.1) before and after matching in **Table 2.** Matching on exactly on employment history and two-category job industry at baseline eliminates differences between the treatment and comparison groups. Likewise, nearest-neighbor matching on hours worked and age in the baseline eliminates differences between the cohorts on these variables. After nearest-neighbor matching on earnings in the baseline quarter, the treatment group has slightly lower quarterly earnings than the comparison group (-$3), but the normalized difference between these groups is zero, indicating a strong match (Imbens 2015). As shown in **Appendix Table 1**, matching also eliminates differences for the pseudo-cohort.

Although we do not match on demographic variables other than age, we report demographic characteristics and four-category job industry at baseline after matching for the minimum wage cohort (**Table 3**). There are slightly more women than men in both the treatment and comparison groups. The treatment group is more racially diverse than the comparison group, with fewer Seattle-based young workers identifying as white alone. The treatment group has more young workers who identify as Asian or Pacific Islander alone, Black alone, or multiracial or another racial identity, while the comparison group has more young workers who identify as Hispanic alone or Native American alone. These patterns likely reflect the relative concentration of some populations of color in metro Seattle relative to the rest of the state. After matching exactly on two-category primary job industry (Accommodation and Food Services vs. everything else), treated workers have a slightly more diverse industry mix than workers in the comparison group. The comparison group has more young workers with primary jobs in retail trade

(18 percent) than the treatment group (12 percent). The pseudo-cohort follows similar patterns (**Appendix Table 2**).

We visually inspect employment outcomes for evidence of parallel trends prior to the implementation of Seattle's minimum wage ordinance in **Figures 1 through 3.** There is evidence of parallel trends in the employment rate (Figure 1) between the treatment and comparison group from 2010.1 through 2013.3, with treated workers having a lower employment rate than comparison group workers. Starting in 2013.4, the employment rate between the treated and comparison group begin to converge and become equal from 2014.3 through 2015.1, when we match exactly on employment status. We see strong evidence of parallel trends in quarterly earnings (Figure 2) and hours worked (Figure 3) between the treatment and comparison groups, with treated Seattle-based workers earning less and working fewer hours than workers outside of Seattle from 2010.1 through 2014.4, until they converge in the matching quarter (2015.1).

3.2. Main Results

Triple difference estimates for each employment outcome are presented in **Tables 4 through 6**. In each table, we contextualize the triple difference estimates with the simple difference-in-difference estimates from the minimum wage and pseudo-cohorts. The triple difference estimate represents the difference between the two simple difference-in-differences estimates.

We find Seattle's minimum wage increases are associated with a decrease in employment among young workers (-2 percentage points) in the first quarter of the post-period (Table 4), relative to young workers outside of Seattle and its surrounding counties and to a cohort of workers four years earlier (the pseudo-cohort) who were not subject to a local minimum wage increase. However, for the remainder of the post-period, our estimates are not statistically significant. These results suggest that employment among young workers based in Seattle faced an initial relative decline in employment immediately following the implementation of a higher local minimum wage, but these minimum wage-associated employment losses were only temporary and soon rebounded to typical patterns. Turning to the simple difference-in-difference estimates, we find significant and positive or null associations between employment and treatment for both the minimum wage and pseudo-cohort. These estimates indicate that young workers who were employed in Seattle at baseline tended to have similar or higher employment rates compared to young workers employed outside of Seattle at baseline, a pattern that is likely unrelated to Seattle's minimum wage increases.

Unlike the employment results, the triple difference estimates presented in Table 5 show that declines in young workers' hours worked associated with Seattle's minimum wage increases were persistently statistically significant in most quarters of post-period. Young workers with jobs in Seattle at baseline worked an estimated -14.1 fewer hours in Q1, -8.8 fewer hours in Q2, -12.12 fewer hours in Q5 and -11.40 fewer hours in Q6 of the post-period relative to baseline, a comparison group of young workers in Washington state outside of Seattle, and the pseudo-cohort. The estimates in post-period quarters three, four, and six are also negative, but do not reach the statistical significance threshold ($p < 0.05$). Averaging all estimates to a weekly basis, we find that Seattle's minimum wage increases were associated with –0.4 to –1.1 fewer hours worked per week among young workers. This represents decreases of 2.7 to 7.4 percent from baseline weekly hours.

Despite estimated declines in hours worked associated with Seattle's minimum wage increases, we do not find any significant changes in young workers' quarterly earnings throughout the post period (Table 6). The simple difference-in-difference estimates show that, for both the minimum wage cohort (baseline: 2015.1) and the pseudo-cohort (baseline: 2011.1), Seattle workers tend to have significantly higher earnings than non-Seattle workers in most quarters, regardless of time period or minimum wage policy. Differencing the estimates for the two cohorts, the estimates are null, suggesting that young workers with jobs in Seattle at baseline did not earn more each quarter as a result of the higher minimum wage.

3.3. Subgroup Analyses

Tables 7 through 9 display triple difference results for each employment outcome by subgroup. Table 7 shows that employment reductions associated with Seattle's minimum wage increases were concentrated among female and Black young workers, workers aged 21 to 24 at baseline, workers in health care and social assistance or retail trade jobs at baseline, and workers missing information on their race and ethnicity in WMLAD. Significant reductions in the employment rate occurred in the initial quarters of minimum wage implementation for young workers identified as female (-3 percentage points, Q1 and Q2), Black (-7 percentage points, Q1 and Q2), aged 21 to 24 at baseline (-3 percentage points, Q1), working in health care and social assistance at baseline (-6 percentage points, Q1; -7 percentage points, Q2), and working in retail trade at baseline (-5 percentage points, Q2; -10 percentage points, Q3). These decreases did not persist throughout the remainder of the study period. Young workers without race and ethnicity information in WMLAD—including those who do not have driver's licenses, are not registered to vote, and do not participate in public assistance programs—saw large and significant reductions in employment in four quarters throughout the post-period, ranging from -12 percentage points in quarter six to -18 percentage points in quarter seven.

Only one other subgroup saw significant changes in employment associated with Seattle's minimum wage. The triple difference estimates in Table 7 show that workers aged 16 to 17 at baseline had significant increases in employment in quarter two (+9 percentage points), quarter six (+11 percentage points), and quarter seven (+20 percentage points) of the post-period, relative to baseline, the comparison group, and the pseudo-cohort. The triple difference estimates show no significant differences in employment associated with Seattle's minimum wage increases for the other subgroups.

Significant decreases in hours worked associated with Seattle's minimum wage increase, as shown in Table 8, were spread across multiple subgroups and quarters. Young workers who were female, Asian or Pacific Islander, or aged 21 to 24 at baseline all experienced signification declines in quarterly hours worked during the first five of the seven post-period quarters. Significant declines for these groups ranged from -13.96 to -22.08 hours per quarter (-1.07 to -1.70 hours per week) for female young workers,

-24.77 to -33.24 hours per quarter (-1.90 to -2.56 hours per week) for Asian and Pacific Islander young workers, and -13.22 to -22.53 hours per quarter (-1.02 to -1.73 hours per week) for young workers aged 21 to 24 at baseline. Additionally, male young workers experienced significant hours decreases associated with Seattle's minimum wage in quarters one, five, and seven of the post-period (ranging -12.85 to -17.85 hours per quarter), white young workers in quarters one (-11.5 hours) and five (-17.5 hours), Hispanic young workers in quarter one (-29.22 hours), and young workers missing race and ethnicity data in quarters four (-46.02 hours) and seven (-55.68 hours). Triple difference estimates show no statistically significant changes to hours worked among young workers identified as Black, multiracial, or another racial or ethnicity identity, and workers aged 16 to 20 at baseline. Young workers in all industries faced declines in hours worked across the post-period, but declines were persistently statistically significant and largest for those working in retail trade at baseline. For these workers, significant declines in hours worked ranged from –17.83 hours to –37.81 hours per quarter (-1.37 hours to –2.91 hours per week). No groups or industries experienced increases in quarterly hours worked.

Despite some declines in employment and widespread declines in hours worked across groups, the triple difference estimates show few statistically significant changes in quarterly earnings (Table 9). The large standard errors suggest that the within-group variability in earnings are too great, and the sample sizes too small, to result in statistically significant estimates. There are, however, a few notable exceptions. In the first quarter of the post-period, the estimates show earnings declines for female young workers (-\$140.41) and Hispanic young workers (-\$281.18). For female young workers, Black and Asian or Pacific Islander young workers, young workers without race and ethnicity information in WMLAD, and workers aged 21 to 24 at baseline, the triple difference point estimates were consistently negative but not statistically significant in most or all quarters. These earnings declines largely reflect employment and hours patterns described above. In contrast, workers aged 18 to 20 at baseline experienced significant earnings increases in quarters four (+\$252.81) and six (+\$287.50) of the post-period. There were also significant earnings increases for young workers with jobs in accommodation and food services in quarter six (+\$254.34) and in health care and social assistance in quarter seven (+\$476.02). Unlike the findings for earnings declines, the findings for earnings increases do not reflect significant changes in employment or hours worked for these groups.

3.4. Robustness Checks

Table 10 displays the results of three robustness checks to our main analytic approach. The alternative specifications produce triple difference estimates that are generally similar in significance, magnitude, and direction compared to the main specification, with a few minor exceptions. Together, the robustness checks suggest our main results are generally stable to alternative specifications.

Excluding covariates in our triple difference model does not change the magnitude or statistical significance of the point estimates. Estimates that do not top-code earnings at the 99th percentile, thus preserving the influence of high-earning outliers and possible data entry errors, mostly mirror the results from the main specification with two exceptions. Without top-coding, Seattle's minimum wage is associated with a significant decline in earnings in the first quarter of the post-period (-$94.78) and larger declines in hours worked throughout the post-period. Five out of seven quarters show significant declines in hours worked among Seattle's young workers without top-coding, compared to four out of seven quarters when earnings data are top-coded. Using the full comparison pool of young workers with jobs outside of Seattle and its surrounding counties at baseline results in triple difference estimates that are mostly consistent with the main specification, which selects a comparison group through a matching procedure that more closely resembles young workers with jobs in Seattle at baseline. There are two main differences in the triple difference estimates when using the full comparison group: (1) there is a moderately significant decrease in employment (-2 percentage points) in the fourth quarter of the post-period, whereas the fourth quarter decline is not significant in the main specification, and (2) there are significant declines in hours worked across all quarters of the post-period, whereas the main specification shows significant declines in hours worked in four of the seven quarters of the post-period. These minor differences suggest that matching on baseline employment characteristics results in more conservative estimates, but do not substantively change the results.

4. Discussion

In this study, we used linked administrative data from Washington state to estimate the causal impact of Seattle's minimum wage ordinances on the employment outcomes of workers aged 16 to 24 ("young workers"). With a combined matching and triple-difference approach, we found that employment significantly declined by two percentage points for young workers in Seattle during the first quarter following the implementation of a higher minimum wage. This initial employment decline was concentrated among female young workers, young workers identified as Black alone, workers aged 21 to 24 at baseline, and young workers with jobs in health care, social assistance, and retail trade at baseline. However, these declines in employment were short-lived and did not persist beyond the second quarter of the post-period. Seattle's minimum wage increases were also associated with significant declines in quarterly hours worked for young workers overall and for most subgroups in multiple quarters throughout the post-period. Despite declines in employment and hours worked, we found no significant association between Seattle's minimum wage increases and quarterly earnings overall and for most groups. There are, however, a few notable exceptions. In the first quarter of the post-period, the estimates show earnings declines for female (-$140.41) and Hispanic young workers (-$281.18). For female young workers, Black and Asian or Pacific Islander young workers, young workers without race and ethnicity information, workers aged 21 to 24 at baseline, and young workers with jobs in retail trade at baseline, the triple difference point estimates for earnings were consistently negative but not statistically significant in most or all quarters. These earnings declines are largely consistent with declines in employment and hours worked for these groups.

Taken together, our results suggest that Seattle's minimum wage increases had a mixed impact on most young workers in the first two years of implementation. Because declines in hours worked did not co-occur with declines in earnings or employment other than in the first quarter following implementation, we view declines in hours worked among young workers as a potentially positive outcome of Seattle's minimum wage increases. Working fewer hours without losing earnings may allow young adults to spend time on other pursuits, including education and family. However, some patterns are still cause for concern. Although earnings declines among female, Black, Asian or Pacific Islander young workers, young workers without race and ethnicity information, and workers aged 21 to 24 at baseline were largely not statistically significant, the persistence of earnings declines for these groups in the post-period raise concerns about negative impacts of Seattle's minimum wage increases that may not be reflected in the average treatment effect. That statistically significant employment and earnings losses in the first two quarters of the post-period were concentrated among female, Black, and Hispanic young workers also raises concern, particularly given that sexism and racism contribute to labor market discrimination, structural oppression, and economic precarity for these groups. Although the negative impacts did not last throughout the post-period, even one quarter of employment or earnings losses may have led these young workers to experience housing or food insecurity, or to lose public assistance like SNAP or childcare subsidies that generally require employment. (Jardim et al. 2022; 2024)

Although we show that our estimates are robust and consistent across a variety of specifications, the data and analytic approach we use in this study have some limitations that may threaten the validity of our estimates. First, there may be unobserved differences between the labor markets within and outside of Seattle for young workers, and these differences may result in systematic time trends that are unrelated to the minimum wage (Jardim et al. 2022) (Jardim et al., 2022, 2024). We match workers on pre-treatment employment outcomes and employ a triple difference approach to account for these differences. Robustness checks with unmatched data suggest that the main specification with matching may be a more conservative approach. Similarly, the triple difference approach represents a conservative estimation strategy by eliminating the statistical significance of the simple DD estimate by differencing out time trends unrelated to Seattle's minimum wage increases.

Data limitations prevent us from conducting the full population analysis desired when using administrative data. Due to a limitation of the UI data we use to identify job location, we are unable to identify a treatment status for about one-third of young workers in Washington and must drop these workers from analysis. The UI data also exclude workers who are self-employed or otherwise not covered by the state's UI program. Further, we do not have age data for seven percent of the total employed population and cannot determine if they are young workers for the purpose of this study. Our subgroup analyses are also limited by the data available. Data on young workers' race ethnicity are limited to seven mutually exclusive categories: White alone, Black alone, Asian or Pacific Islander alone, Hispanic alone, Native American or American Indian alone, Multiracial or Other Racial and Ethnic Identity, and missing race and ethnicity information. Due to small population size, we are unable to produce subgroup analyses for young workers who are Native American or American Indian alone. Like the concepts of race and ethnicity themselves, these categories are socially constructed and do not reflect the complexities of how people identify or how others perceive them. Additionally, subgroup analyses by race and ethnicity do not capture the mechanisms of racism and structural oppression, like employment discrimination, that contribute to disparate outcomes by race and ethnicity. Similarly, the measure of binary sex used in these analyses do not reflect individuals' gender identities or discrimination and oppression on the basis of sex and gender identity. We also do not have education data, which would shed light on trade-offs young workers may be making between education and employment in light of rising wages. Finally, the data and these estimates represent what was happening in Seattle and the rest of Washington state during a unique time in Seattle's history that was marked by low unemployment, increasing population, and rapidly rising housing costs. Generalizability may be limited to similar contexts, and other city-level minimum wage ordinances may affect young workers differently.

Despite these limitations, this study adds novel and valuable evidence to the contested literature on how raising the minimum wage affects the employment outcomes of different groups of young workers. The density and detail afforded by WMLAD's linked administrative data allow us to contribute the first evidence, to our knowledge, of the heterogeneous impacts of a city-level minimum wage increase on young workers. Our finding that the short-term negative employment and earnings effects associated with raising Seattle's minimum wage were concentrated among female, Black, and Hispanic young workers is consistent with the hypothesis that raising the minimum wage disadvantages some groups, compounding other types of employment discrimination and structural oppression that these groups experience. The heterogeneity analyses by industry also suggest that industry-specific approaches to understanding the impact of raising the minimum wage masks important variation. Notably, we find null employment effects for young workers with jobs in accommodation and food services, an industry often singled out for minimum wage studies. Instead, we find that young workers in the retail trade and health care and social assistance industries may be most vulnerable to job loss when the minimum wage goes up.

One argument against raising minimum wages is that they can disproportionately harm young workers or others at risk of exclusion from the labor market (e.g. Gipson 2010; Cooper 2016)), our findings do not support this claim. Young workers in Seattle generally maintained their employment and earnings levels over a 21-month period when the minimum wage increased by a total of 37% (from 9.47 to $13). Furthermore, these results do not support the idea of a training wage or similar lower minimum wage for young workers, a measure taken by some European countries (Bellmann et al. 2017). As has been argued elsewhere, arguments about possible minimum wage impacts often reflect the arguers' political interest rather than a clear-eyed assessment of the likely impacts (J. L. Romich 2017). While policy debates over minimum wage laws often feature claims about large and negative impacts, the experienced effects of minimum wage increases – as we find here – are typically quite modest. Those who support raising minimum wages based on values of equality should not be distracted by claims of harm to young workers.

5. References

Alegria, Margarita, David Takeuchi, Glorisa Canino, Naihua Duan, Patrick Shrout, Xiao-Li Meng, William Vega, et al. 2004. “Considering Context, Place and Culture: The National Latino and Asian American Study.” *International Journal of Methods in Psychiatric Research* 13 (4): 208–20. https://doi.org/10.1002/mpr.178.

Allegretto, Sylvia A., Arindrajit Dube, and Michael Reich. 2011. “Do Minimum Wages Really Reduce Teen Employment? Accounting for Heterogeneity and Selectivity in State Panel Data.” *Industrial Relations: A Journal of Economy and Society* 50 (2): 205–40. https://doi.org/10.1111/j.1468-232X.2011.00634.x.

Bellmann, Lutz, Mario Bossler, Hans-Dieter Gerner, and Olaf Hübler. 2017. “Training and Minimum Wages: First Evidence from the Introduction of the Minimum Wage in Germany.” *IZA Journal of Labor Economics* 6 (1): 8. https://doi.org/10.1186/s40172-017-0058-z.

Callaway, Brantly, and Pedro H. C. Sant’Anna. 2021. “Difference-in-Differences with Multiple Time Periods.” *Journal of Econometrics*, Themed Issue: Treatment Effect 1, 225 (2): 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001.

Card, David. 1992. “Using Regional Variation in Wages to Measure the Effects of the Federal Minimum Wage.” *ILR Review* 46 (1): 22–37. https://doi.org/10.1177/001979399204600103.

Cooper, Preston. 2016. “Raising Minimum Wage Would Drive out Youngest Workers.” The Seattle Times. August 15, 2016. https://www.seattletimes.com/opinion/raising-minimum-wage-would-drive-out-youngest-workers/.

Derenoncourt, Ellora, and Claire Montialoux. 2020. “Minimum Wages and Racial Inequality*.” *The Quarterly Journal of Economics* 136 (1): 169–228. https://doi.org/10.1093/qje/qjaa031.

Dube, Arindrajit, and Attila Lindner. 2021. “City Limits: What Do Local-Area Minimum Wages Do?” *Journal of Economic Perspectives* 35 (1): 27–50. https://doi.org/10.1257/jep.35.1.27.

Dube, Arindrajit, Suresh Naidu, and Michael Reich. 2007. “The Economic Effects of a Citywide Minimum Wage” 60 (4): 1–43.

Dupéré, Véronique, Nancy Beauregard, Mathieu Pelletier-Dumas, Éliane Racine, and Kristel Tardif-Grenier. 2024. “Employment Wages and Diseases of Despair in Early Adulthood: Links through Subjective Socioeconomic Status and Cumulative Stressor Exposure.” *SSM - Mental Health* 5 (June):100324. https://doi.org/10.1016/j.ssmmh.2024.100324.

Economic Policy Institute,. 2024. “Minimum Wage Tracker.” Economic Policy Institute. 2024. https://www.epi.org/minimum-wage-tracker/.

Elliott, Marc N., Peter A. Morrison, Allen Fremont, Daniel F. McCaffrey, Philip Pantoja, and Nicole Lurie. 2009. “Using the Census Bureau’s Surname List to Improve Estimates of Race/Ethnicity and Associated Disparities.” *Health Services and Outcomes Research Methodology* 9 (2): 69–83. https://doi.org/10.1007/s10742-009-0047-1.

Fernandes-Alcantara, Adrienne L. 2018. “Youth and the Labor Force: Background and Trends.” R42519. Washington, DC: Congressional Research Service. https://crsreports.congress.gov/product/pdf/R/R42519/15.

Gipson, Carl. 2010. “Washington’s Minimum Wage Is on the Rise and Hurting Young People’s Prospects.” The Seattle Times. November 19, 2010. https://www.seattletimes.com/opinion/washingtons-minimum-wage-is-on-the-rise-and-hurting-young-peoples-prospects/.

Giuliano, Laura. 2013. “Minimum Wage Effects on Employment, Substitution, and the Teenage Labor Supply: Evidence from Personnel Data.” *Journal of Labor Economics* 31 (1): 155–94. https://doi.org/10.1086/666921.

Imbens, Guido W. 2015. “Matching Methods in Practice: Three Examples.” *Journal of Human Resources* 50 (2): 373–419. https://doi.org/10.3368/jhr.50.2.373.

Jardim, Ekaterina, Mark C. Long, Robert Plotnick, Emma van Inwegen, Jacob Vigdor, and Hilary Wething. 2022. “Minimum-Wage Increases and Low-Wage Employment: Evidence from Seattle.”

American Economic Journal: Economic Policy 14 (2): 263–314. https://doi.org/10.1257/pol.20180578.

Jardim, Ekaterina, Mark C. Long, Robert Plotnick, Jacob Vigdor, and Emma Wiles. 2024. "Local Minimum Wage Laws, Boundary Discontinuity Methods, and Policy Spillovers." *Journal of Public Economics* 234 (June):105131. https://doi.org/10.1016/j.jpubeco.2024.105131.

Kahn, Lisa B. 2006. "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy." SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.2139/ssrn.702463.

Karageorgiou Λ. 2004. "The Impact of Minimum Wage on Youth and Teenage Employment in Greece." *Spoudai* 54:39–67.

Kauh, Tina J., Jen'nan Ghazal Read, and A. J. Scheitler. 2021. "The Critical Role of Racial/Ethnic Data Disaggregation for Health Equity." *Population Research and Policy Review* 40 (1): 1–7. https://doi.org/10.1007/s11113-020-09631-6.

Leventhal, Tama, Julia A. Graber, and Jeanne Brooks-Gunn. 2001. "Adolescent Transitions to Young Adulthood: Antecedents, Correlates, and Consequences of Adolescent Employment." *Journal of Research on Adolescence* 11 (3): 297–323. https://doi.org/10.1111/1532-7795.00014.

Long, Mark C., Elizabeth Pelletier, and Jennifer Romich. 2022. "Constructing Monthly Residential Locations of Adults Using Merged State Administrative Data." *Population Studies* 76 (2): 253–72. https://doi.org/10.1080/00324728.2022.2085776.

Mortimer, Jeylan T. 2010. "The Benefits and Risks of Adolescent Employment." *The Prevention Researcher* 17 (2): 8–11.

Neumark, David, and Peter Shirley. 2021. "Myth or Measurement: What Does the New Minimum Wage Research Say about Minimum Wages and Job Loss in the United States?" Working Paper 28388. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w28388.

Neumark, David, and Cortnie Shupe. 2018. "Declining Teen Employment: Minimum Wages, Other Explanations, and Implications for Human Capital Investment." SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.2139/ssrn.3169558.

Neumark, David, and William Wascher. 1995. "Minimum-Wage Effects on School and Work Transitions of Teenagers." *The American Economic Review* 85 (2): 244–49.

———. 2007. "Minimum Wages, the Earned Income Tax Credit, and Employment: Evidence from the Post-Welfare Reform Era." *The Institute for the Study of Labor (IZA) Discussion Paper*, no. 2610.

Pelletier, Elizabeth, and Jennifer Romich. in press. "Supplementing State Employment Records with Demographic Data." Monthly Labor Review.

Romich, Jennifer L. 2017. "Is Raising the Minimum Wage a Good Idea? Evidence and Implications for Social Work." *Social Work* 62 (4): 367–70. https://doi.org/10.1093/sw/swx033.

Romich, Jennifer, Mark Long, Scott Allard, and Anne Althauser. 2018. "The Washington State Merged Longitudinal Administrative Database," no. 51 (November). https://repository.upenn.edu/handle/20.500.14332/1282.

The Seattle Minimum Wage Study Team. 2016. "Report on Baseline Employer Survey and Worker Interviews." Seattle.

Turner, Mark D., and Berna Demiralp. 2001. "Do Higher Minimum Wages Harm Minority and Inner-City Teens?" *The Review of Black Political Economy* 28 (4): 95–116. https://doi.org/10.1007/s12114-001-1010-8.

Urban Indian Health Institute. 2021. "Data Genocide of American Indians and Alaska Natives in COVID-19 Data." Seattle, WA: Urban Indian Health Institute.

Wachter, Till von. 2020. "The Persistent Effects of Initial Labor Market Conditions for Young Adults and Their Sources." *Journal of Economic Perspectives* 34 (4): 168–94. https://doi.org/10.1257/jep.34.4.168.

Zhao, Zhong. 2004. "Using Matching to Estimate Treatment Effects: Data Requirements, Matching Metrics, and Monte Carlo Evidence." *The Review of Economics and Statistics* 86 (1): 91–107.

6. Tables and Figures

Table 1. Analytic Population Selection Prior to Matching

Characteristics at Baseline (2015.1)	Treatment	Comparison Pool	Total	Percent of Total Employed Population
Employed workers, all ages (including missing age)	584,018	951,279	1,535,297	100%
Employed workers, all ages (not missing age)	559,071	871,218	1,430,289	93%
Employed young[a] worker	49,095	126,892	175,987	11%
Locatable[b] young worker	23,446	95,816	119,262	8%
Locatable young low-wage[c] worker	5,608	52,070	57,678	4%

Notes. Treatment and comparison pools are Unemployment Insurance-covered workers in Washington state at baseline. Treated workers are those whose highest-hour job in 2015.1 was located within the city of Seattle. Comparison workers are those whose highest-hour job in 2015.1 was located in Washington state outside of Seattle and its surrounding counties (King, Snohomish, Kitsap, and Pierce).

[a] "Young worker" refers to individuals aged 16 to 24 at baseline.

[b] "Locatable worker" refers to workers whose job location data is precise and unambiguous. "Non-locatable workers" are those who work at multi-site establishments whose employers report wage data to the Washington Employment Security Department under one, ambiguous address, thereby making it impossible to identify whether an employee was exposed to Seattle's minimum wage increases.

[c] "Low-wage worker" is defined as individuals earning less than $11 per hour (2015.2 dollars) at baseline.

Table 2. Comparison of Minimum Wage Cohort Characteristics Before and After Matching

	Before Matching					After Matching				
	Treatment		Comparison		Norm.	Treatment		Comparison		Norm.
	Mean	SD	Mean	SD	Diff.	Mean	SD	Mean	SD	Diff.
Employment History										
2014.3[a]	0.72	*(0.45)*	0.75	*(0.43)*	-0.09	0.72	*(0.45)*	0.72	*(0.45)*	0.00
2014.4[a]	0.79	*(0.41)*	0.83	*(0.38)*	-0.09	0.79	*(0.41)*	0.79	*(0.41)*	0.00
2015.1[a]	1.00	*(0.00)*	1.00	*(0.00)*	--	1.00	*(0.00)*	1.00	*(0.00)*	--
Industry at Baseline (2015.1)										
Accommodation and Food Service[a]	0.39	*(0.49)*	0.32	*(0.47)*	0.15	0.39	*(0.49)*	0.39	*(0.49)*	0.00
Characteristics at Baseline (2015.1)										
Quarterly Hours Worked[b]	193	*(163)*	223	*(161)*	-0.19	193	*(163)*	193	*(163)*	0.00
Quarterly Total Earnings[b,c]	1892	*(1606)*	2204	*(1601)*	-0.19	1892	*(1606)*	1895	*(1602)*	0.00
Age at Baseline (2015.1)[b]	20.77	*(2.12)*	20.53	*(2.12)*	0.11	20.77	*(2.12)*	20.77	*(2.11)*	0.00
N	5,608		52,068			5,608		5,608		

Notes. Treatment and comparison pools are Unemployment Insurance-covered workers in Washington earning less than $11 per hour in the first quarter of 2015 (2015.1) aged 16 to 24 at baseline. Treated workers are those whose highest-hour job in 2015.1 was located within the city of Seattle. Comparison workers are those whose highest-hour job in 2015.1 was located in Washington state outside of Seattle and its surrounding counties (King, Snohomish, Kitsap, and Pierce). The normalized difference divides the mean difference by the square root of the average of the variance (Imbens, 2015).

[a] Variables matched exactly.

[b] Variables matched with one nearest neighbor using Mahalanobis distance.

[c] Dollars adjusted for inflation using the CPI-W (2015.2)

Table 3. Demographic Characteristics of Minimum Wage Cohort After Matching

	Treatment		Comparison		Norm.
	Mean	SD	Mean	SD	Diff.
Female	0.52	*(0.50)*	0.54	*(0.50)*	-0.03
Race and Ethnicity					
White alone	0.56	*(0.50)*	0.66	*(0.47)*	-0.21
Black alone	0.08	*(0.27)*	0.01	*(0.12)*	0.30
Asian or Pacific Islander alone	0.13	*(0.33)*	0.03	*(0.16)*	0.38
Native American alone	0.00	*(0.06)*	0.01	*(0.09)*	-0.05
Hispanic alone	0.15	*(0.35)*	0.23	*(0.42)*	-0.21
Multiracial and Other	0.05	*(0.21)*	0.04	*(0.19)*	0.05
Missing Race and Ethnicity	0.04	*(0.20)*	0.03	*(0.16)*	0.09
Industry at Baseline (2015.1)					
Accommodation and Food Services	0.39	*(0.49)*	0.39	*(0.49)*	0.00
Health Care and Social Assistance	0.10	*(0.30)*	0.09	*(0.29)*	0.03
Retail Trade	0.12	*(0.33)*	0.18	*(0.38)*	-0.14
Everything Else	0.38	*(0.49)*	0.34	*(0.47)*	0.09
N	5,608		5,608		

Notes. Treatment and comparison workers are Unemployment Insurance-covered workers aged 16 to 24 in Washington earning less than $11 per hour in the first quarter of 2015 (2015.1). Treated workers are those whose highest-hour job in 2015.1 was located within the city of Seattle. Comparison workers are those whose highest-hour job in 2015.1 was located in Washington state outside of Seattle and its surrounding counties (King, Snohomish, Kitsap, and Pierce). The normalized difference divides the mean difference by the square root of the average of the variance (Imbens, 2015).

Table 4. Estimates of Seattle Minimum Wage Increases on Employment of Young Workers

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Outcome: Employment Status (0/1)							
Minimum Wage Cohort (N=11,216)							
DD Estimate (Seattle x Post)	-0.00	0.00	0.01	0.02*	-0.01	0.03***	0.01
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Pseudo-Minimum Wage Cohort (N=13,214)							
DD Estimate (Seattle x Post)	0.02***	0.01	0.02*	0.03***	0.00	0.02*	0.01
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Combined Cohorts (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-0.02**	-0.01	-0.01	-0.01	-0.01	0.02	0.01
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

*** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$

Notes. Each point estimate represents a separate linear regression model that includes controls for age at baseline, binary sex, race and ethnicity, and industry. The first two rows show the difference-in-difference (DD) coefficient in which the two differences are time (pre- versus post-) and area (Seattle versus comparison). The third row shows the third difference (DDD) between the estimates for the minimum wage cohort and the pseudo cohort. Baseline quarter (pre-period, or quarter zero) is 2015.1 for the main cohort and 2011.1 for the pseudo-cohort. The post-period is indicated as Q1 through Q7, which is 2015.2 through 2016.4 for the minimum wage cohort, and 2011.2 through 2012.4 for the pseudo-cohort. Standard errors are block-bootstrapped with 1000 replications.

Table 5. Estimates of Seattle Minimum Wage Increases on Hours Worked of Young Workers

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Outcome: Hours Worked							
Minimum Wage Cohort (N=11,216)							
DD Estimate (Seattle x Post)	-19.71***	-13.65***	-4.81	-7.07*	-14.65***	-6.84	-9.74**
SE	(2.49)	(3.38)	(3.39)	(3.39)	(3.48)	(3.84)	(3.74)
Pseudo-Minimum Wage Cohort (N=13,214)							
DD Estimate (Seattle x Post)	-5.60*	-4.86	1.15	0.12	-2.53	-2.11	1.66
SE	(2.23)	(2.98)	(2.99)	(3.14)	(3.37)	(3.51)	(3.43)
Combined Cohorts (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-14.11***	-8.79*	-5.96	-7.19	-12.12*	-4.73	-11.40*
SE	(3.56)	(4.42)	(4.62)	(4.37)	(5.04)	(5.26)	(5.09)

*** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$

Notes. Each point estimate represents a separate linear regression model that includes controls for age at baseline, binary sex, race and ethnicity, and industry. The first two rows show the difference-in-difference (DD) coefficient in which the two differences are time (pre- versus post-) and area (Seattle versus comparison). The third row shows the third difference (DDD) between the estimates for the minimum wage cohort and the pseudo cohort. Baseline quarter (pre-period, or quarter zero) is 2015.1 for the main cohort and 2011.1 for the pseudo-cohort. The post-period is indicated as Q1 through Q7, which is 2015.2 through 2016.4 for the minimum wage cohort, and 2011.2 through 2012.4 for the pseudo-cohort. Standard errors are block-bootstrapped with 1000 replications.

Table 6. Estimates of Seattle Minimum Wage Increases on Earnings of Young Workers

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Outcome: Earnings (2015.2 Dollars)							
Minimum Wage Cohort (N=11,216)							
DD Estimate (Seattle x Post)	-82.19**	74.15	189.18***	238.52***	177.22**	310.89***	278.58***
SE	(29.87)	(43.22)	(48.23)	(46.86)	(54.21)	(60.84)	(61.35)
Pseudo-Minimum Wage Cohort (N=13,214)							
DD Estimate (Seattle x Post)	-10.24	57.12	128.06**	145.65***	148.85**	171.30***	257.96***
SE	(25.23)	(39.62)	(40.16)	(40.30)	(47.09)	(51.30)	(51.56)
Combined Cohorts (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-71.95	17.03	61.12	92.87	28.37	139.59	20.62
SE	(40.66)	(57.47)	(62.63)	(64.07)	(71.62)	(81.21)	(78.66)

*** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$

Notes. Each point estimate represents a separate linear regression model that includes controls for age at baseline, binary sex, race and ethnicity, and industry. The first two rows show the difference-in-difference (DD) coefficient in which the two differences are time (pre- versus post-) and area (Seattle versus comparison). The third row shows the third difference (DDD) between the estimates for the minimum wage cohort and the pseudo cohort. Baseline quarter (pre-period, or quarter zero) is 2015.1 for the main cohort and 2011.1 for the pseudo-cohort. The post-period is indicated as Q1 through Q7, which is 2015.2 through 2016.4 for the minimum wage cohort, and 2011.2 through 2012.4 for the pseudo-cohort. Standard errors are block-bootstrapped with 1000 replications. Earnings estimates in whole dollars adjusted for inflation using the CPI-W (2015.2).

Table 7. Estimates of Seattle Minimum Wage Increases on Employment of Young Workers by Subgroup

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Outcome: Employment Status (0/1)							
Sex							
Female Young Worker (N=13,154)							
DDD Estimate (Seattle x Cohort x Post)	-0.03*	-0.03*	-0.01	-0.01	-0.01	0.01	0.00
SE	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Male Young Worker (N=11,276)							
DDD Estimate (Seattle x Cohort x Post)	-0.02	-0.01	-0.01	-0.02	-0.03	0.01	0.00
SE	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Race and Ethnicity							
White Young Worker (N=14,310)							
DDD Estimate (Seattle x Cohort x Post)	-0.02	-0.01	-0.00	-0.01	-0.02	0.01	0.01
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Black Young Worker (N=1,732)							
DDD Estimate (Seattle x Cohort x Post)	-0.07*	-0.07*	-0.05	-0.03	-0.03	-0.03	-0.01
SE	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
Asian or Pacific Islander Young Worker (N=3,140)							
DDD Estimate (Seattle x Cohort x Post)	0.01	0.01	0.01	0.02	0.01	0.04	0.03
SE	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Hispanic Young Worker (N=3,060)							
DDD Estimate (Seattle x Cohort x Post)	-0.03	-0.04	-0.03	0.01	0.02	0.04	0.05
SE	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Multiracial or Other Young Worker (N=1,018)							
DDD Estimate (Seattle x Cohort x Post)	0.08	0.01	-0.01	-0.02	-0.01	-0.01	-0.04
SE	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Missing Race and Ethnicity Young Worker (N=1,044)							
DDD Estimate (Seattle x Cohort x Post)	-0.07	-0.03	-0.16**	-0.13*	-0.09	-0.12*	-0.18**
SE	(0.04)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
Age							
Young Worker aged 16 to 17 (N=1,434)							
DDD Estimate (Seattle x Cohort x Post)	0.06	0.09*	0.07	0.06	0.03	0.11*	0.20***
SE	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Young Worker aged 18 to 20 (N=9,000)							
DDD Estimate (Seattle x Cohort x Post)	-0.02	0.00	-0.01	-0.01	-0.00	0.01	-0.01
SE	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Young Worker aged 21 to 24 (N=13,996)							
DDD Estimate (Seattle x Cohort x Post)	-0.03*	-0.02	-0.01	-0.02	-0.02	0.00	0.00
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Industry							
Young Worker in Accommodation and Food Services (N=8,814)							
DDD Estimate (Seattle x Cohort x Post)	-0.02	0.01	-0.00	-0.00	-0.03	0.01	-0.02
SE	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Young Worker in Retail Trade (N=3,306)							
DDD Estimate (Seattle x Cohort x Post)	-0.04	-0.05*	-0.10***	-0.05	-0.04	-0.02	-0.04
SE	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Young Worker in Health Care and Social Assistance (N=2,788)							
DDD Estimate (Seattle x Cohort x Post)	-0.06*	-0.07*	-0.02	-0.05	-0.00	-0.00	0.02
SE	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Young Worker in Everything Else (N=9,522)							
DDD Estimate (Seattle x Cohort x Post)	-0.00	-0.01	0.01	-0.01	0.01	0.02	0.01
SE	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

*** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$

Note. Each point estimate represents a separate linear regression model that includes controls for age at baseline, binary sex, race and ethnicity, and industry. Each row shows the third difference (DDD) between the estimates for the minimum wage cohort and the pseudo cohort) by each sub-group. Baseline quarter (pre-period, or quarter zero) is 2015.1 for the main cohort and 2011.1 for the pseudo-cohort. The post-period is indicated as Q1 through Q7, which is 2015.2 through 2016.4 for the minimum wage cohort, and 2011.2 through 2012.4 for the pseudo-cohort. Standard errors are block-bootstrapped with 1000 replications. Shade represents each sub-group that shows statistically significant DDD results.

Table 8. Estimates of Seattle Minimum Wage Increases on Hours Worked of Young Workers by Subgroup

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Outcome: Hours Worked							
Sex							
Female Young Worker (N=13,154)							
DDD Estimate (Seattle x Cohort x Post)	-22.08***	-19.80***	-13.96*	-15.45**	-18.15**	-8.68	-9.36
SE	(4.60)	(5.81)	(6.24)	(5.95)	(6.54)	(7.20)	(7.14)
Male Young Worker (N=11,276)							
DDD Estimate (Seattle x Cohort x Post)	-12.85*	-12.78	-8.53	-9.57	-17.85*	-7.01	-17.63*
SE	(5.13)	(6.87)	(6.85)	(6.62)	(7.54)	(8.29)	(7.76)
Race and Ethnicity							
White Young Worker (N=14,310)							
DDD Estimate (Seattle x Cohort x Post)	-11.50**	-7.69	-9.41	-8.70	-17.05**	-6.81	-6.03
SE	(4.11)	(5.39)	(5.59)	(5.80)	(6.17)	(6.79)	(6.51)
Black Young Worker (N=1,732)							
DDD Estimate (Seattle x Cohort x Post)	-5.51	-5.41	-11.36	3.66	10.44	-0.55	-3.34
SE	(14.49)	(17.40)	(19.60)	(19.09)	(20.44)	(21.55)	(20.98)
Asian or Pacific Islander Young Worker (N=3,140)							
DDD Estimate (Seattle x Cohort x Post)	-24.77**	-26.63*	-33.24**	-32.02**	-29.69*	2.28	-21.18
SE	(9.21)	(12.57)	(12.30)	(11.90)	(13.78)	(14.70)	(15.07)
Hispanic Young Worker (N=3,060)							
DDD Estimate (Seattle x Cohort x Post)	-29.22**	-22.54	6.51	-1.27	-7.11	13.29	4.88
SE	(10.69)	(13.20)	(14.27)	(13.76)	(14.79)	(15.78)	(15.59)
Multiracial or Other Young Worker (N=1,018)							
DDD Estimate (Seattle x Cohort x Post)	-10.84	-11.87	-2.68	-25.39	-47.42	-29.42	-29.20
SE	(16.01)	(21.97)	(24.10)	(23.11)	(24.93)	(25.80)	(25.75)
Missing Race and Ethnicity Young Worker (N=1,044)							
DDD Estimate (Seattle x Cohort x Post)	-25.33	-20.21	-40.26	-46.02*	-29.80	-46.19	-55.68*
SE	(15.22)	(21.16)	(21.03)	(20.15)	(22.50)	(25.44)	(25.59)
Age							
Young Worker aged 16 to 17 (N=1,434)							
DDD Estimate (Seattle x Cohort x Post)	-2.73	0.72	3.22	-11.34	-9.68	1.93	21.10
SE	(7.37)	(12.46)	(9.34)	(9.30)	(11.23)	(15.78)	(16.22)
Young Worker aged 18 to 20 (N=9,000)							
DDD Estimate (Seattle x Cohort x Post)	-8.56	-0.42	-0.61	2.65	-4.49	1.54	-11.73
SE	(5.12)	(6.77)	(6.83)	(7.02)	(7.46)	(8.00)	(8.03)
Young Worker aged 21 to 24 (N=13,996)							
DDD Estimate (Seattle x Cohort x Post)	-14.14**	-13.22*	-13.97*	-16.92**	-22.53**	-10.95	-8.22
SE	(4.84)	(6.31)	(6.55)	(6.22)	(6.94)	(7.13)	(7.40)
Industry							
Young Worker in Accommodation and Food Services (N=8,814)							
DDD Estimate (Seattle x Cohort x Post)	-12.12*	-7.87	-7.11	-9.32	-19.10*	-3.36	-14.28
SE	(5.26)	(7.13)	(7.59)	(7.24)	(7.89)	(8.52)	(8.45)
Young Worker in Retail Trade (N=3,306)							
DDD Estimate (Seattle x Cohort x Post)	-17.83*	-22.87	-37.81**	-26.53*	-36.99**	-19.16	-30.39*
SE	(9.09)	(12.11)	(12.60)	(12.59)	(12.80)	(13.62)	(14.50)
Young Worker in Health Care and Social Assistance (N=2,788)							
DDD Estimate (Seattle x Cohort x Post)	-26.86*	-19.31	-8.10	-17.52	-13.43	-12.59	3.20
SE	(12.09)	(15.63)	(15.31)	(14.92)	(15.77)	(16.92)	(16.29)
Young Worker in Everything Else (N=9,522)							
DDD Estimate (Seattle x Cohort x Post)	-12.85*	-5.54	-0.24	-4.79	-6.82	-16.38	-15.20
SE	(6.00)	(7.71)	(7.46)	(7.36)	(8.14)	(8.58)	(8.85)

*** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$

Note. Each point estimate represents a separate linear regression model that includes controls for age at baseline, binary sex, race and ethnicity, and industry. Each row shows the third difference (DDD) between the estimates for the minimum wage cohort and the pseudo cohort) by each sub-group. Baseline quarter (pre-period, or quarter zero) is 2015.1 for the main cohort and 2011.1 for the pseudo-cohort. The post-period is indicated as Q1 through Q7, which is 2015.2 through 2016.4 for the minimum wage cohort, and 2011.2 through 2012.4 for the pseudo-cohort. Standard errors are block-bootstrapped with 1000 replications. Shade represents each sub-group that shows statistically significant DDD results.

Table 9. Estimates of Seattle Minimum Wage Increases on Earnings of Young Workers by Subgroup

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Outcome: Earnings (2015.2 Dollars)							
Sex							
Female Young Worker (N=13,154)							
DDD Estimate (Seattle x Cohort x Post)	-140.41**	-116.16	-38.09	-18.43	-37.06	70.69	49.48
SE	(48.34)	(71.73)	(81.36)	(81.00)	(94.18)	(102.87)	(110.03)
Male Young Worker (N=11,276)							
DDD Estimate (Seattle x Cohort x Post)	-92.29	-71.14	5.38	69.73	-71.08	68.43	-119.68
SE	(62.34)	(93.56)	(92.71)	(91.53)	(102.37)	(121.98)	(122.92)
Race and Ethnicity							
White Young Worker (N=14,310)							
DDD Estimate (Seattle x Cohort x Post)	-24.76	72.40	42.57	101.39	-31.88	139.76	59.85
SE	(50.04)	(74.10)	(83.20)	(86.05)	(93.89)	(106.24)	(110.57)
Black Young Worker (N=1,732)							
DDD Estimate (Seattle x Cohort x Post)	-98.88	-103.28	-348.25	-81.39	-14.71	-77.45	-113.26
SE	(147.02)	(190.91)	(213.44)	(219.24)	(232.47)	(270.08)	(278.95)
Asian or Pacific Islander Young Worker (N=3,140)							
DDD Estimate (Seattle x Cohort x Post)	-132.83	-77.33	-209.07	-186.73	-242.33	334.35	-35.26
SE	(98.42)	(157.48)	(167.85)	(171.79)	(186.04)	(221.01)	(230.93)
Hispanic Young Worker (N=3,060)							
DDD Estimate (Seattle x Cohort x Post)	-281.18*	-195.37	155.24	176.69	62.90	338.16	351.82
SE	(117.80)	(168.57)	(171.59)	(178.57)	(189.21)	(207.52)	(215.50)
Multiracial or Other Young Worker (N=1,018)							
DDD Estimate (Seattle x Cohort x Post)	13.91	24.15	108.99	-231.83	-398.97	-145.78	-82.48
SE	(169.38)	(228.60)	(280.18)	(283.62)	(300.65)	(350.91)	(350.40)
Missing Race and Ethnicity Young Worker (N=1,044)							
DDD Estimate (Seattle x Cohort x Post)	-107.58	90.38	-307.30	-137.63	56.15	-177.47	-559.43
SE	(189.29)	(297.01)	(328.33)	(321.53)	(358.85)	(432.23)	(437.44)
Age							
Young Worker aged 16 to 17 (N=1,434)							
DDD Estimate (Seattle x Cohort x Post)	40.32	76.95	29.87	-39.07	37.64	202.26	208.77
SE	(72.50)	(130.09)	(98.74)	(95.95)	(121.19)	(190.24)	(195.01)
Young Worker aged 18 to 20 (N=9,000)							
DDD Estimate (Seattle x Cohort x Post)	-19.80	120.55	127.74	252.81**	142.10	287.50**	113.30
SE	(54.83)	(83.47)	(83.57)	(83.56)	(93.23)	(110.31)	(110.27)
Young Worker aged 21 to 24 (N=13,996)							
DDD Estimate (Seattle x Cohort x Post)	-65.07	-57.44	-63.14	-6.42	-56.98	104.41	102.96
SE	(58.09)	(85.00)	(91.99)	(98.18)	(103.48)	(116.95)	(118.36)
Industry							
Young Worker in Accommodation and Food Services (N=8,814)							
DDD Estimate (Seattle x Cohort x Post)	0.65	52.10	65.79	36.47	-4.04	254.34*	50.58
SE	(57.33)	(91.52)	(92.91)	(96.62)	(111.85)	(124.18)	(131.82)
Young Worker in Retail Trade (N=3,306)							
DDD Estimate (Seattle x Cohort x Post)	-99.73	-136.47	-320.53	-130.02	-281.99	-152.63	-189.52
SE	(103.26)	(149.74)	(166.42)	(160.43)	(188.16)	(202.31)	(220.04)
Young Worker in Health Care and Social Assistance (N=2,788)							
DDD Estimate (Seattle x Cohort x Post)	-155.78	-77.31	34.51	87.83	186.59	269.86	476.02*
SE	(112.52)	(164.40)	(173.91)	(181.74)	(200.13)	(222.31)	(225.27)
Young Worker in Everything Else (N=9,522)							
DDD Estimate (Seattle x Cohort x Post)	-113.59	42.16	120.73	137.28	19.54	-35.96	-116.51
SE	(70.26)	(101.90)	(107.58)	(106.04)	(122.15)	(136.44)	(144.80)

*** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$

Note. Each point estimate represents a separate linear regression model that includes controls for age at baseline, binary sex, race and ethnicity, and industry. Each row shows the third difference (DDD) between the estimates for the minimum wage cohort and the pseudo cohort) by each sub-group. Baseline quarter (pre-period, or quarter zero) is 2015.1 for the main cohort and 2011.1 for the pseudo-cohort. The post-period is indicated as Q1 through Q7, which is 2015.2 through 2016.4 for the minimum wage cohort, and 2011.2 through 2012.4 for the pseudo-cohort. Standard errors are block-bootstrapped with 1000 replications. Shade represents each sub-group that shows statistically significant DDD results.

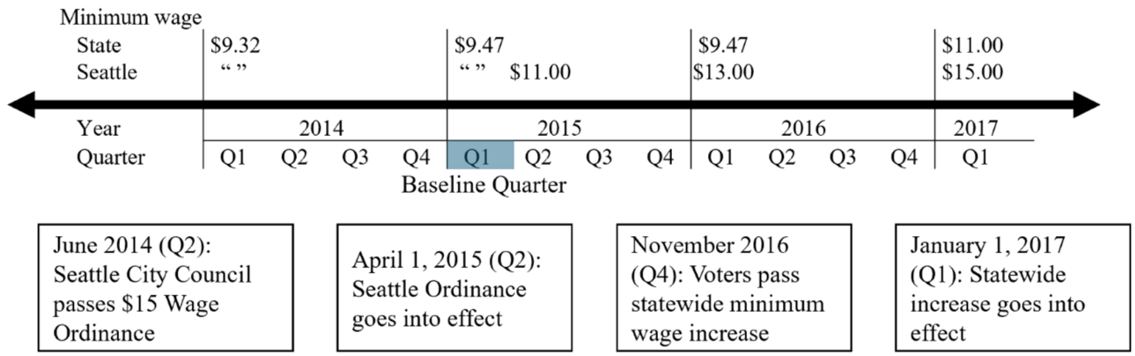
Table 10. Robustness Checks

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Outcome: Employment Status (0/1)							
Main Analytic Population and Specification (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-0.02**	-0.01	-0.01	-0.01	-0.01	0.02	0.01
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Main Analytic Population, No Covariates (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-0.02**	-0.01	-0.01	-0.01	-0.01	0.02	0.01
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Main Analytic Population, No Topcoding (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-0.02**	-0.01	-0.01	-0.01	-0.02	0.01	0.00
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Full Comparison Group, No Matching (N=115,531)							
DDD Estimate (Seattle x Cohort x Post)	-0.02***	-0.01	-0.01	-0.02	-0.01	0.01	-0.01
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Outcome: Hours Worked							
Main Analytic Population and Specification (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-14.11***	-8.79*	-5.96	-7.19	-12.12*	-4.73	-11.40*
SE	(3.56)	(4.42)	(4.62)	(4.37)	(5.04)	(5.26)	(5.09)
Main Analytic Population, No Covariates (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-14.11***	-8.79	-5.96	-7.19	-12.12*	-4.73	-11.40*
SE	(3.45)	(4.49)	(4.75)	(4.53)	(5.00)	(5.27)	(5.35)
Main Analytic Population, No Topcoding (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-16.93***	-14.18**	-9.30	-8.48	-14.03**	-10.42*	-15.17**
SE	(4.06)	(4.97)	(5.13)	(4.69)	(4.99)	(5.29)	(5.33)
Full Comparison Group, No Matching (N=115,531)							
DDD Estimate (Seattle x Cohort x Post)	-20.37***	-12.86**	-15.55**	-15.67**	-24.12***	-13.61**	-20.28***
SE	(4.48)	(4.78)	(4.97)	(4.77)	(4.78)	(5.04)	(5.00)
Outcome: Earnings (2015.2 Dollars)							
Main Analytic Population and Specification (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-71.95	17.03	61.12	92.87	28.37	139.59	20.62
SE	(40.66)	(57.47)	(62.63)	(64.07)	(71.62)	(81.21)	(78.66)
Main Analytic Population, No Covariates (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-71.95	17.03	61.12	92.87	28.37	139.59	20.62
SE	(39.72)	(57.00)	(65.72)	(63.40)	(67.62)	(79.09)	(79.58)
Main Analytic Population, No Topcoding (N=24,430)							
DDD Estimate (Seattle x Cohort x Post)	-94.78*	-3.65	50.41	72.57	13.38	84.67	-8.01
SE	(40.68)	(60.32)	(68.07)	(65.87)	(70.86)	(81.80)	(87.89)
Full Comparison Group, No Matching (N=115,531)							
DDD Estimate (Seattle x Cohort x Post)	-118.12*	-25.13	-64.28	0.96	-108.05	47.60	-79.94
SE	(48.12)	(57.28)	(61.39)	(63.12)	(62.21)	(68.50)	(69.46)

*** = p < 0.001, ** = p < 0.01, * = p < 0.05

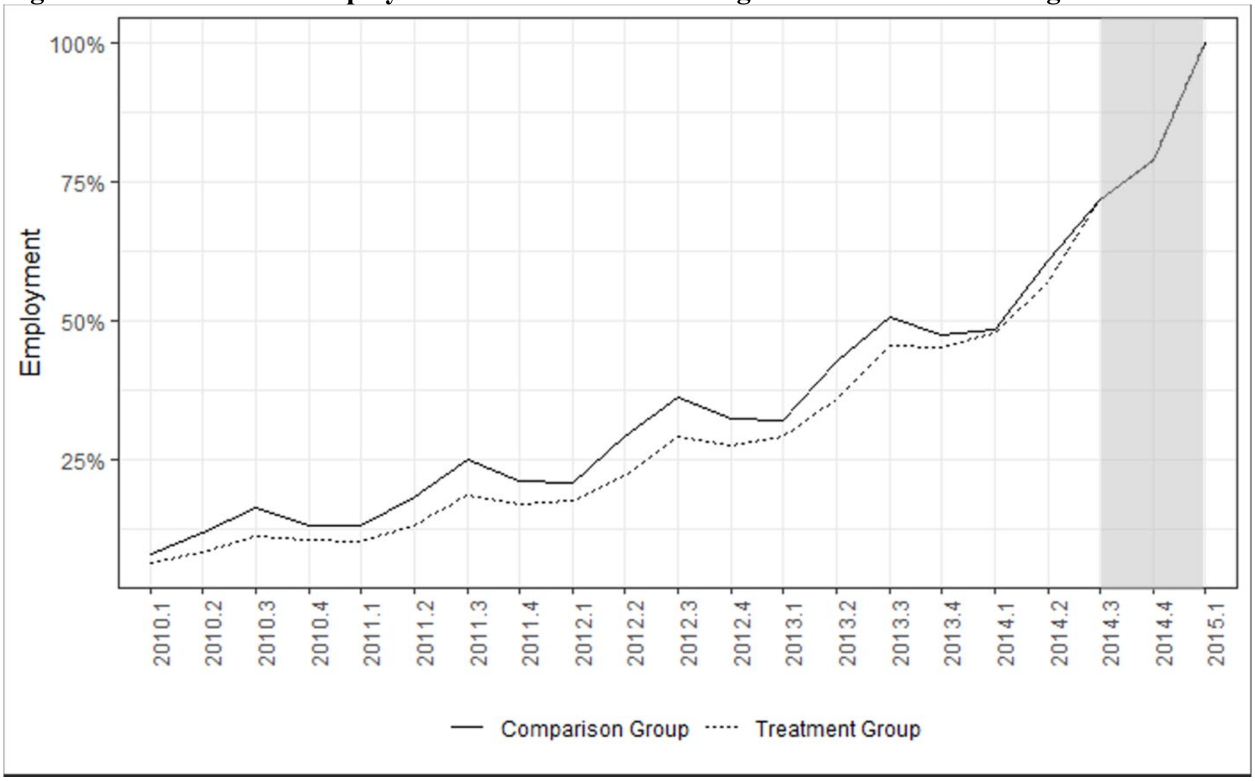
Notes. Each point estimate represents a separate linear regression model that includes controls for age at baseline, binary sex, race and ethnicity, and industry. For each outcome, the first row (shaded) represents the triple difference estimates from our main analytic approach, also shown in Tables 4 through 6. The second row excludes covariates from the triple difference model. The third row represents the triple difference estimates from the specification that uses the original earnings and hours worked instead of the ones censored at the top 99th percentile (top-coded). The fourth row are the triple different estimates using the main model specification, but with the full treatment and comparison pools prior to matching. Baseline quarter (pre-period) is 2015.1 for the main cohort and 2011.1 for the pseudo-cohort. The post-period is indicated as Q1 through Q7, which is 2015.2 through 2016.4 for the minimum wage cohort, and 2011.2 through 2012.4 for the pseudo-cohort. Standard errors are block-bootstrapped with 1000 replications. Earnings estimates in whole dollars adjusted for inflation using the CPI-W (2015.2).

Figure 1. Timeline



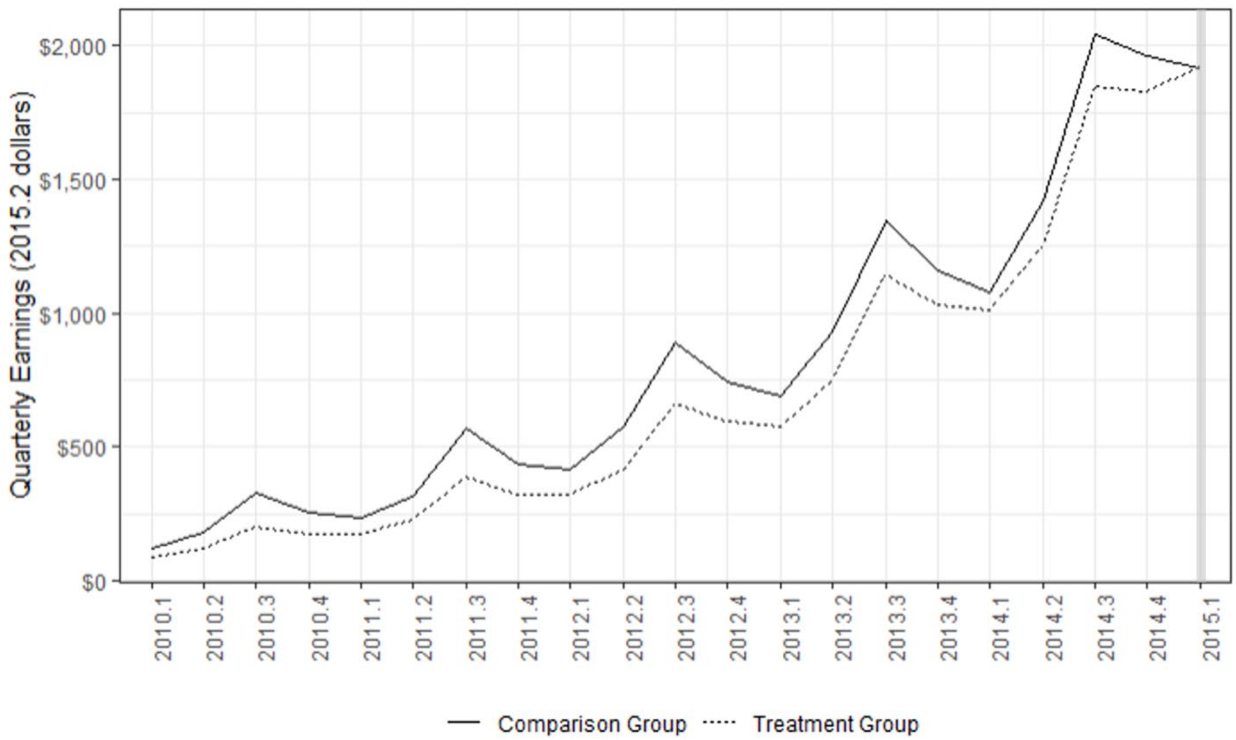
Notes. Authors' timeline of minimum wage increases in Seattle (city-level) and Washington state (statewide), from 2014 through 2017.

Figure 2. Pre-Trends in Employment for the Minimum Wage Cohort After Matching



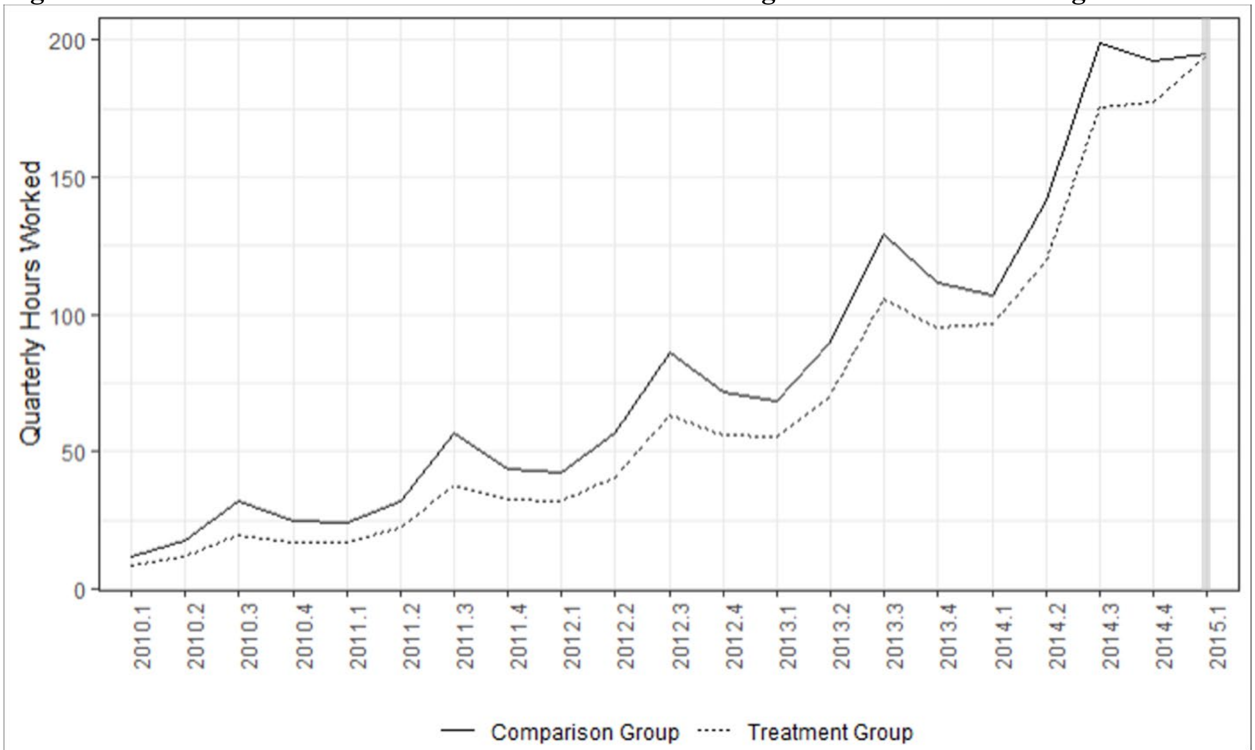
Notes. Shading indicates matching period. Treatment and comparison cohorts are Unemployment Insurance-covered workers in Washington earning less than $11 per hour (2015.2 dollars) in the first quarter of 2015 (2015.1). Treated workers are those whose highest-hour job in 2015.1 was located within the city of Seattle. Comparison workers are those whose highest-hour job in 2015.1 was located in Washington state outside of Seattle and its surrounding counties (King, Snohomish, Kitsap, and Pierce). Comparison group selected through matching baseline and pre-period employment, earnings, hours worked, age and industry.

Figure 3. Pre-Trends in Earnings for the Minimum Wage Cohort After Matching



Notes. Shading indicates matching period. Treatment and comparison cohorts are Unemployment Insurance-covered workers in Washington earning less than $11 per hour (2015.2 dollars) in the first quarter of 2015 (2015.1). Treated workers are those whose highest-hour job in 2015.1 was located within the city of Seattle. Comparison workers are those whose highest-hour job in 2015.1 was located in Washington state outside of Seattle and its surrounding counties (King, Snohomish, Kitsap, and Pierce). Comparison group selected through matching baseline and pre-period employment, earnings, hours worked, age and industry. Earnings estimates in whole dollars adjusted for inflation using the CPI-W (2015.2).

Figure 4. Pre-Trends in Hours Worked for the Minimum Wage Cohort After Matching



Notes. Shading indicates matching period. Treatment and comparison cohorts are Unemployment Insurance-covered workers in Washington earning less than $11 per hour (2015.2 dollars) in the first quarter of 2015 (2015.1). Treated workers are those whose highest-hour job in 2015.1 was located within the city of Seattle. Comparison workers are those whose highest-hour job in 2015.1 was located in Washington state outside of Seattle and its surrounding counties (King, Snohomish, Kitsap, and Pierce). Comparison group selected through matching baseline and pre-period employment, earnings, hours worked, age and industry.

Appendix

Appendix Table 1. Comparison of Pseudo-Cohort Characteristics Before and After Matching

	Before Matching					After Matching				
	Treatment		Comparison		Norm.	Treatment		Comparison		Norm.
	Mean	SD	Mean	SD	Diff.	Mean	SD	Mean	SD	Diff.
Employment History										
2010.3[a]	0.71	*(0.45)*	0.77	*(0.42)*	-0.14	0.71	*(0.45)*	0.71	*(0.45)*	0.00
2010.4[a]	0.80	*(0.40)*	0.84	*(0.36)*	-0.13	0.80	*(0.40)*	0.80	*(0.40)*	0.00
2011.1[a]	1.00	*(0.00)*	1.00	*(0.00)*	--	1.00	*(0.00)*	1.00	*(0.00)*	--
Industry at Baseline (2011.1)										
Accommodation and Food Service[a]	0.33	*(0.47)*	0.28	*(0.45)*	0.13	0.33	*(0.47)*	0.33	*(0.47)*	0.00
Characteristics at Baseline (2011.1)										
Quarterly Hours Worked[b]	192	*(163)*	225	*(166)*	-0.20	192	*(163)*	191	*(162)*	0.00
Quarterly Total Earnings[b,c]	1861	*(1557)*	2154	*(1581)*	-0.19	1861	*(1557)*	1858	*(1552)*	0.00
Age at Baseline (2011.1)[b]	21.03	*(2.04)*	20.62	*(2.07)*	0.20	21.03	*(2.04)*	21.03	*(2.04)*	0.00
N	6,607		51,248			6,607		6,607		

Notes. Pseudo-*t*reatment and comparison pools are Unemployment Insurance-covered workers in Washington earning less than $11 per hour in the first quarter of 2011 (2011.1) aged 16 to 24 at baseline. Pseudo-treated workers are those whose highest-hour job in 2011.1 was located within the city of Seattle. Comparison workers are those whose highest-hour job in 2011.1 was located in Washington state outside of Seattle and its surrounding counties (King, Snohomish, Kitsap, and Pierce). The normalized difference divides the mean difference by the square root of the average of the variance (Imbens, 2015).

[a] Variables matched exactly.

[b] Variables matched with one nearest neighbor using Mahalanobis distance.

[c] Dollars adjusted for inflation using the CPI-W (2015.2)

Appendix Table 2. Demographic Characteristics of Pseudo-Cohort After Matching

	Treatment		Comparison		Norm.
	Mean	SD	Mean	SD	Diff.
Female	0.55	*(0.50)*	0.53	*(0.50)*	0.03
Race and Ethnicity					
White alone	0.61	*(0.49)*	0.73	*(0.44)*	-0.27
Black alone	0.07	*(0.25)*	0.01	*(0.12)*	0.27
Asian or Pacific Islander alone	0.13	*(0.34)*	0.03	*(0.16)*	0.39
Native American alone	0.00	*(0.07)*	0.01	*(0.09)*	-0.04
Hispanic alone	0.11	*(0.31)*	0.17	*(0.37)*	-0.17
Multiracial and Other	0.04	*(0.19)*	0.03	*(0.18)*	0.03
Missing Race and Ethnicity	0.04	*(0.20)*	0.02	*(0.14)*	0.13
Industry at Baseline (2011.1)					
Accommodation and Food Services	0.33	*(0.47)*	0.33	*(0.47)*	0.00
Health Care and Social Assistance	0.13	*(0.33)*	0.12	*(0.33)*	0.01
Retail Trade	0.14	*(0.35)*	0.19	*(0.39)*	-0.13
Everything Else	0.40	*(0.49)*	0.35	*(0.48)*	0.09
N	6,607		6,607		

Notes. Pseudo-treatment and comparison pools are Unemployment Insurance-covered workers in Washington earning less than $11 per hour in the first quarter of 2011 (2011.1) aged 16 to 24 at baseline. Pseudo-treated workers are those whose highest-hour job in 2011.1 was located within the city of Seattle. Comparison workers are those whose highest-hour job in 2011.1 was located in Washington state outside of Seattle and its surrounding counties (King, Snohomish, Kitsap, and Pierce). The normalized difference divides the mean difference by the square root of the average of the variance (Imbens, 2015).