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Abstract: This paper uses minimum wage hikes to evaluate the susceptibility of low-wage employment to technological substitution. We find that automation is accelerating and supplanting a broader set of low-wage routine jobs in the decade since the Financial Crisis. Simultaneously, low-wage interpersonal jobs are increasing and offsetting routine job loss. However, interpersonal job growth does not appear to be enough – as it was previous to the Financial Crisis – to fully offset the negative effects of automation on low-wage routine jobs. Employment losses are most evident among minority workers who experience outsized losses at routine-intensive jobs and smaller gains at interpersonal jobs.

JEL Codes: J15, J21, J24, J38, O33
Keywords: Low-wage automation, routine-biased technical change, minimum wage

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Introduction

The fear of automation technology and its potential to displace a large portion of the global labor force is nearly ubiquitous. A 2018 survey from the Pew Research Center reports that almost 80 percent of respondents across 10 countries believe that robots and computers are likely to take over much of the work currently performed by humans sometime in the next 50 years and this change will cause much more harm than good, including job loss and rising inequality (Pew 2018). Some argue that the Covid-19 pandemic could accelerate the adoption of automation technology, especially among jobs that require physical interaction (Leduc and Liu 2020; Barrero, Bloom, and Davis 2020).

A certain unease about technology is warranted when accompanied by job loss, as there is robust evidence that workers who are displaced from their jobs tend to experience large declines in lifetime earnings and consequently may face material hardship (e.g. Ruhm 1991; Jacobson, LaLonde, and Sullivan 1993; Sullivan and Von Wachter 2009; Davis and Von Wachter 2011; Jolly and Phelan 2015; Aaronson et al 2019). Indeed, the literature examining the impact of automation technology on middle-skill workers has found an association with both falling employment at middle-skill jobs (Goos, Manning, and Salomons, 2014) and falling earnings of affected workers (Autor and Dorn, 2013; Autor, 2019). Thus, it is well-accepted that the automation of middle-skill jobs has contributed to the rise in earnings inequality over at least the past 30 years.

Much less is known about the extent to which low-skill jobs are being automated and, if so, how it is impacting the low-wage workforce. Our reading is that, for many years, the literature more or less assumed it was too costly for firms to automate the lowest-wage jobs (Bresnahan, Brynjolfsson, and Hitt, 2002; Manning, 2004; and Autor, Katz, and Kearney, 2008). However, Muro, Maxim, and Whiton (2019) argue that it is now the lowest wage occupations that are most susceptible to automation. Consistent with that conclusion, a handful of recent studies exploit minimum wage hikes as a shock to the relative price of low-skill labor and often find evidence of capital adoption or labor substitution patterns consistent with low-wage automation.[1]

This paper extends previous work in Aaronson and Phelan (2017), which uses minimum wage changes between 1999 and 2009 to infer automation from changes in the task content of low-skill jobs.[2] Since 2009, the price of technology has continued to fall and many localities have enacted sharp increases in their minimum wage.[3] On its face, these developments might suggest that low-wage job automation has accelerated and spread over time. Thus, our first contribution is to document how the labor market realignment associated with the automation of low-wage employment has changed over the first two decades of the century (i.e. pre- vs. post-Financial Crisis). Along the way, we expand upon our previous empirical analysis by taking advantage of the growing prevalence of city-level minimum wage legislation to show how results vary as we move to local measures of labor markets. Our second contribution is to examine which demographic groups are most affected by low-wage automation.

Using both the Occupational Employment Statistics (OES) and American Community Survey (ACS), we show that the low-wage labor market implications of automation have widened since the Financial Crisis. Higher labor costs continue to be associated with falling employment at jobs intensive in cognitively routine tasks, as in Aaronson and Phelan (2017). However, the rate of job loss at cognitively routine occupations has increased since the Financial Crisis and job loss has spread to those intensive in manually routine tasks as well. Consequently, the total employment loss associated with an occupation's routineness – whether manual or cognitive – is twice as large now as it was in the decade prior to the Financial Crisis.

[1] Chen, 2019; Cho, 2018; Geng et al., 2018; Gustafson and Kotter, 2018; Hau et al., 2018; and Qiu and Dai, 2019 directly examine firm capital expenditures following minimum wage hikes. The majority, but not all, of these studies find that minimum wage hikes expedite the adoption of labor-saving capital.

[2] See also Lordan and Neumark (2018). Our strategy is in the spirit of Autor, Levy, and Murnane (2003) and Autor, Katz, and Kearney (2006).

[3] For example, the price of information technology hardware and services fell more than 20 percent between January 2010 and January 2018, as measured by the Consumer Price Index.

This decline in routine task employment has been offset by an increase in the demand for jobs requiring interpersonal tasks. While the positive impact on interpersonal tasks has also grown larger over time, there is some evidence to suggest that it does not seem to be enough – as it was prior to the Financial Crisis – to fully offset the negative effect of automation on low-wage routine jobs. These results are further supported by our analysis at the city-level, which additionally highlights a larger impact of automation on low-wage employment in rural and smaller metropolitan areas.

The basic employment realignment pattern we uncover – declining employment at routine-intensive occupations and increasing employment at interpersonal-intensive occupations – is evident across education, age, race, and gender sub-populations of low-wage workers. Among White and Asian-American workers, who comprise more than 75 percent of those employed in the lowest wage jobs, these two effects roughly offset, leading to no overall job loss following minimum wage hikes. However, non-Asian American minority workers experience larger employment declines from routine-intensive jobs and much smaller employment gains at interpersonal-intensive jobs. Consequently, minority workers experience notable job loss associated with automation. This finding is consistent with Bailey, DiNardo, and Stuart (2020), who find that the disemployment effect of minimum wage hikes disproportionately harm African Americans. We conclude by arguing that this disproportionate impact is unlikely to be related to occupational racial segregation (as in Del Rio and Alonso-Villar 2015) but there may be some suggestive evidence that it is partly driven by discriminatory practices (as in Holzer and Ihlanfeldt 1998 and Bar and Zussman 2017).

In sum, large minimum wage hikes encourage the automation of jobs intensive in routine tasks. This process has accelerated during the 2010s, and broadened into manually-intensive jobs as well. While the loss of routine jobs has been accompanied by growth in interpersonal-tasked jobs, it may no longer be enough to avoid a net decline in low-wage employment, as appeared to be the case prior to the Financial Crisis. These employment declines are especially evident among non-Asian minority workers who experience larger declines in employment at routine-intensive jobs but much smaller employment gains at interpersonal-intensive jobs.

I. Conceptual Framework

This section briefly discusses the differential impact that a minimum wage hike may have on the demand for low-wage workers within a standard competitive model. Consider a firm with a low-wage workforce that faces a legislated minimum wage hike. If the new minimum wage level is expected to exceed workers' marginal product, the firm has a few choices. They may try to improve the productivity of the workforce, either through training of incumbents or upgrading, as in Phelan (2019) and Clemens, Kahn, and Meer (2020). If the wage increase is large enough, an alternative path may be through labor-saving automation technology.

Automation need not lead to overall job loss, however. Ultimately, the extent of disemployment depends on whether worker skills are complements or substitutes to the emerging technology. A large, influential literature has shown that automation is especially likely to displace jobs with a heavy bent towards routine tasks (e.g. Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney 2007; Goos, Manning, and Salomons 2014), a finding consistent with the long secular decline in routine tasks in the U.S. (e.g Jaimovich, Eksten, Siu, and Yedid-Levi 2020). Conversely, new production processes may require complementary job tasks.

A canonical example is a new technology like a self-scanner that shifts a task from a worker to a customer. As firms introduce these new labor-saving technologies, they simultaneously create jobs requiring new skills, such as maintaining the new machinery or overseeing customer interactions with it. Consequently, in the short-run, employment growth in jobs that require non-routine skills may help offset the decline in routine jobs that are eliminated by automation. However, in the self-scanner example, some of this offsetting employment growth may not necessarily persist over longer periods of time as customers gradually adapt to the new technology. This is analogous to the reversal in skilled labor demand described in

Beaudry, Green, and Sands (2016), where non-routine labor demand may increase in the short-run but ultimately fall in the longer-run.

In some circumstances, the adoption of automation technology can lead to a permanently higher level of non-routine employment. One familiar example occurs when automation technology eases a capacity constraint that otherwise limits production. Take the introduction of ordering kiosks or a smartphone-based ordering app that eliminates the need for cashiers at a café. Limited space behind the counter can be repurposed to increase coffee production (Aaronson and Phelan 2019). As wait times fall, fewer people skip their purchase and the café can profitably hire more employees to prepare orders – offsetting the decline in cashiers.

Offsetting non-routine employment growth could also arise from the composition of firms. In Aaronson, French, Sorkin, and To (2018), minimum wage hikes cause labor-intensive firms to fail at a higher rate since the increase in labor cost falls disproportionately on them. As production shifts to more capital-intensive incumbent and entrant firms, the tasks associated with their newly expanded employment would reflect their higher-tech production processes. This across-firm labor supply response is also documented in Dustmann, Lindner, Schonberg, Umkehrer, and von Berge (2020), who find that minimum wages hikes cause workers to move from smaller less-productive firms to larger more-productive firms. Lastly, if the low-wage labor market is better characterized by monopsony, as some recent studies suggest (Krueger and Posner, 2018; Manning, 2020), minimum wage hikes would reduce employment at substitutable (i.e. routine) jobs but increase employment at all other types of low-wage employment.

Taken together, the adoption of automation technology due to a minimum wage hike is likely to be characterized by falling low-wage employment at routine jobs. However, the employment effects on non-routine tasks are ambiguous. Thus, our empirical analysis focuses on how the composition of employment changes after significant increases to the cost of low-wage labor.

II. Data

Our data come from four sources: employment and wages from the Bureau of Labor Statistics' Occupation Employment Statistics (OES) and the Census Bureau's American Community Survey (ACS), state and local minimum wage levels from Vaghul and Zipperer (2019), and occupational tasks developed by Acemoglu and Autor (2011) based on the US Department of Labor's Occupation Information Network (O*NET). We discuss each in turn.

A. Occupation Employment Statistics (OES)

The OES contains data on employment levels and average wages for each detailed Standard Occupational Classification (SOC) occupation by state and metropolitan area. Each annual release of the OES is based on surveys of 1.2 million establishments. An establishment's participation in the survey takes place at one of six survey dates over the previous three years and therefore the data in a given year reflect a three-year moving average of occupational employment and wages. Our primary analysis uses state-level occupational data from 2010 to 2018. We also estimate our empirical specifications using analogous data from 1999 to 2009 in order to compare our new estimates to the pre-Crisis period used in Aaronson and Phelan (2017).

The OES data collection process underwent two changes between 2010 and 2018 that need to be accounted for. First, there were minor adjustments to the occupational coding systems in both 2012 and 2017.[4] To address these changes, we create consistent occupations over the full 2010 to 2018 period whenever possible. We also add occupation fixed effects to the empirical specifications to ensure that the variation used in estimation occurs within occupations and is not due to spurious SOC coding revisions. Second, the 2017 release of the OES began reporting occupational employment for an industry that was not previously surveyed, the "private household" industry.[5] This change led to an implausibly large increase, from 144 thousand in

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[4] The OES largely adopted the 2010 SOC codes in 2010 but a few occupations were not updated until 2012. For more details, see the reply to question F.8 at https://www.bls.gov/oes/oes_ques.htm#Ques41, last accessed 12/4/19. Moreover, the OES combined 21 occupations into 10 more-aggregated occupations beginning with the 2017 data. See https://www.bls.gov/oes/changes_2017.htm, last accessed 12/4/19, for more details.
[5] See https://www.bls.gov/oes/2017/may/oes_tec.htm, last accessed 12/4/19, for more details.

2016 to 521 thousand in 2017, among “Personal and Home Care Aides” in California. Other states did not react this way. For example, Personal and Home Care Aide employment in Texas only increased from 189 thousand in 2016 to 197 thousand in 2017. After performing some additional tests comparing the similarity of annual state-level occupational employment levels in the OES and the ACS, we opt to exclude this one occupation in California from the analysis.[6]

Because minimum wage policies have become increasingly localized over the last decade, we also analyze OES occupational data for 328 metropolitan areas. Metro areas present additional challenges, however. Some metro boundaries have changed since 2010 and many frequently cross state, city, and county boundaries.[7] We address these concerns by developing time-consistent metropolitan areas and show estimates on a subsample of metro areas contained within a single state. Since metro areas are smaller, non-exhaustive geographies than states, the metro area data are also necessarily based on fewer establishment surveys and therefore may generate noisier estimates.

Since minimum wage hikes are likely to have larger effects on occupational employment at jobs that pay closer to the minimum wage, we group occupations within states (or metro areas) into wage bins according to the average 2010-2018 ratio of an occupation-state’s average wage to the effective minimum wage.[8] This approach ensures that occupations within states remain in the same wage bin over the panel but occupations across states can be in different wage bins. The specific bins we use are average wage-to-minimum wage ratios between 1.0 to 1.5 (Wage Group 1), 1.5 to 2.0 (Wage Group 2), 2.0 to 2.5 (Wage Group 3), and 2.5 to 6.0 (Wage Group 4). These bins differ slightly from our analysis of the 1999-2009 period in Aaronson and Phelan (2017)

[6] The correlation coefficient between the total state-level occupational annual employment for specific occupations such as cashiers and child care workers in the OES and ACS is close to 0.9. However, the correlation coefficient for Personal and Home Care Aides is 0.6. When we exclude Personal and Home Care Aides in California, this correlation coefficient increases to 0.78. Our subsequent analysis, which uses the ACS to examine the employment response of minimum wage hikes, will not require any adjustments as the ACS is a nationally representative sample of individuals.

[7] For example, 51 of the 328 metropolitan areas cross state lines.

[8] That is, $\overline{w2mw}_{js} = \frac{1}{9}\sum_{t=2010}^{2018} \frac{\overline{wage}_{jst}}{MW_{st}}$, where $\overline{wage}_{jst}$ is the average wage for occupation *j* in state *s* and year *t* from the OES and MW_{st} is the minimum wage in state s and year t. For the metro analysis, we look at wages and minimum wages at that geography.

because the minimum wage has become more binding since the Financial Crisis [9] This is evident in Figure 1, which shows that a larger share of low-wage employment occurs at occupations with an average wage-to-minimum wage ratio closer to 1. Consequently, we change the bounds that make up our Wage Groups to ensure the *share* of employment in each of the new wage intervals is fairly similar to the share of employment in the broader wage intervals used previously. For example, the share of employment in Wage Group 1 – the lowest paid occupations – was 21 percent in our earlier paper and 18 percent here.

B. American Community Survey (ACS)

We use the 2010 to 2018 ACS to supplement our analysis for two main reasons. First, the OES has at least two practical problems; its employment count is a three year moving average and it excludes (at least until 2017) agriculture and private household services, two important low-wage industries. Neither is an issue in the ACS. Second, the ACS allows us to split the sample by education, age, sex, and race and test whether these subsamples are more prone to changes in employment after minimum wage hikes.

Practically, we transform the ACS into a panel of occupation-state-year employment counts to match the OES' structure. However, in a separate analysis, we go one step further and disaggregate these totals into industry as well.[10] We then mimic the OES analysis by grouping occupations within states into the same wage intervals using the average ratio of the wage-to-minimum wage over the 2010 to 2018 period. Relative to the OES, this process of grouping occupations to wage intervals is likely to be less precise, as some occupations have very few observations in a given state and an individual wage must be computed from an individual's reported annual earnings, weeks worked, and hours worked. Solely for the purpose of computing these average occupational wage calculations, we address this issue by excluding any individual

[9] The wage intervals used in Aaronson and Phelan (2017) are, 1.00-1.75, 1.75-2.50, 2.50-3.00, and 3.00-6.00.
[10] For industry, we use the detailed Census Industry Codes (CIC). However, since our emphasis is on low-wage employment, we classify only the 67 industries that employ at least 0.5 percent of workers paid less than 150 percent of the minimum wage and combine the remaining 203 CIC industries into a single industry. The results are not sensitive to reasonable perturbations of the 0.5 percent cutoff.

whose wage-to-minimum wage ratio is more than two standard deviations away from the mean ratio for their reported occupation.[11]

C. Minimum Wage Data

Effective state, city, and county minimum wage levels come from Vaghul and Zipperer (2019).[12] As shown in Appendix Table A1, 29 out of the 51 states (including the District of Columbia) increased their minimum wage between 2010 and 2018. Moreover, many of these hikes were quite large and implemented over several years. For example, both Massachusetts and California raised their minimum wage by 38 percent, from $8.00 to $11.00, over a period of three and four years, respectively. At the same time, ten states had predictable and small inflation-based increases in their minimum wage over the entire period.[13] We exclude these inflation-based adjustment states because they are unlikely to have the same effect as unanticipated and larger increases in the minimum wage.

D. Task Data

Data on the tasks performed at occupations come from Acemoglu and Autor (2011), who develop these measures from the O*NET database.[14] We transform their six measures – the extent to which an occupation is routine cognitive, routine manual, non-routine cognitive interpersonal, non-routine manual interpersonal, non-routine cognitive analytical, and non-routine manual physical – into six task shares following the approach described in Aaronson and Phelan (2017). To compute these shares, each z-score value for each occupation is rescaled relative to the minimum value across all occupations. The six rescaled values are then summed

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[11] This means that if an individual reported a single hour of work but earned $20,000 as a cashier, their wage to minimum wage ratio of about 2,000 would not influence our computation of a cashier's wage to minimum wage, which tends to be closer to 1.5. Since some states have a small handful of observations for a given occupation, these outliers could otherwise have a very large influence on the state-occupation average wage-to-minimum wage.

[12] The minimum wage data is available at https://github.com/benzipperer/historicalminwage/releases, last accessed 11/12/19. We do not population-weight-adjust state minimum wage levels for city or county laws.

[13] These states are Arizona, Colorado, Connecticut, Florida, Missouri, Montana, Ohio, Oregon, Vermont, and Washington.

[14] The task data is available on David Autor's website at https://economics.mit.edu/faculty/dautor/data/acemoglu, last accessed 11/12/19.

up for each occupation separately and a task share is defined as the ratio of the rescaled value to the sum of all rescaled values.

We often further combine the six tasks into more aggregated measures. For example, we always combine non-routine cognitive interpersonal and non-routine manual interpersonal into a single interpersonal task share.[15] For these combined task metrics, the task share is simply the sum of the two rescaled task measures divided by the sum of all six rescaled task measures. We also will show results based on the overall routineness of an occupation by combining routine cognitive and routine manual tasks into a single measure of routineness, paralleling the approach taken in many studies looking at middle-skill automation (e.g. Autor, Katz, and Kearney 2008).

Table 1 presents the 25 occupations with the largest share of routine tasks and interpersonal tasks among occupations that land in Wage Group 1 (those occupations with an average wage-to-minimum wage ratio less than 1.5) for at least one state. Motion Picture Projectionists, Sewing Machine Operators, and Meat and Poultry Trimmers tend to have a disproportionately high share of routine tasks while Personal and Home Care Aides, Recreation Workers, and Child Care Workers tend to have a disproportionately high share of interpersonal tasks. The average routine-intensive low-wage occupation has nearly half of its tasks associated with routine cognitive or routine manual tasks and likewise the average interpersonal-intensive low-wage occupation has nearly half of its tasks associated with interpersonal tasks. Therefore, naturally the importance of either routine or interpersonal tasks dwarfs non-routine tasks (either non-routine cognitive analytics or non-routine manual physical) among nearly all Wage Group 1 occupations.[16]

For each occupation, Table 1 also presents the cross-state average wage-to-minimum wage ratio, national employment in 2010, and the percent change in employment between 2010 and 2018. Between 2010 and 2018, employment grew by 21 percent among occupations

[15] The correlation coefficient between cognitive and manual interpersonal tasks is 0.48.
[16] The low-wage occupation with the largest share of non-routine tasks (34 percent) is bicycle repairman. The average share of non-routine tasks among the 25 low-wage occupations with the highest share of non-routine tasks is 27.5 percent.

intensive in interpersonal tasks but only four percent among occupations intensive in routine tasks. These divergent trends are even more pronounced among occupations where routine or interpersonal task share exceeds 50 percent (Figure 2). This shift in employment in the low-wage labor market mirrors the same secular patterns in routine and interpersonal tasks taking place among middle-skill jobs (Deming 2017; Autor 2019).

An increase in the relative price of labor vis-a-vis capital should be associated with elevated declines in routine employment and possibly elevated growth in non-routine employment, escalating these secular employment trends. While our empirical analysis will directly estimate these effects using minimum wage hikes, it is instructive to simply examine employment trends separately for states that increased their minimum wage and states that did not during our period of analysis.[17] Figures 3 to 5 present this comparison separately for occupations that are especially heavy in routine, interpersonal, and all other tasks, respectively. These figures highlight that employment trends were nearly identical in minimum wage and non-minimum wage hike states from 2010 until 2014, when states began introducing sizable hikes after a pause following the Financial Crisis.[18] After 2014, relative employment in minimum wage states declined markedly in routine occupations (Figure 3) and increased, although with a bit more delay, in interpersonal occupations (Figure 4). Interestingly, there appears to be no difference in employment growth at all other non-routine, non-interpersonal occupations (Figure 5), suggesting there are not clear secular differences in the employment patterns of low-wage jobs between states that passed minimum wage legislation and states that did not. Thus, the raw data seem to suggest that minimum wage hikes are associated with declining employment in routine-intensive low-wage jobs but growing employment in low-wage interpersonal-intensive jobs.

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[17] Between 2010 and 2018, there are 19 states that raised their minimum wage (see Table A1 for list) other than through CPI adjustments and 22 that did not. Again, we exclude the 10 states that have CPI adjustments (see footnote 13).

[18] The only non-CPI adjustment hikes introduced between 2010 and 2013 were in Illinois ($0.25 in 2011), Nevada ($0.70 in 2011), and Rhode Island ($0.35 in 2013).

III. Empirical Methodology

Our empirical methodology examines how minimum wage hikes affect occupational employment growth at jobs that differ in the extent to which they are associated with routine tasks. This approach follows an earlier academic literature which assumes that automation technology is more likely to replace jobs with a larger share of tasks that are routine in nature (Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney 2006), often referred to as "routine-biased technological change" (Goos, Manning, and Salomons 2014). Under this framework, a minimum wage hike is associated with automation if it causes falling relative employment at low-wage routine jobs.

Our primary empirical specification regresses long differences in occupational employment on changes in the minimum wage and interactions between the change in the minimum wage and the routineness of a job. An emphasis on long-differences in the outcome variable has been advocated by many researchers in the minimum wage literature interested in the longer-term effects of minimum wage hikes (e.g. Baker, Benjamin, and Stanger 1999; Meer and West 2016; and Sorkin 2015). It is especially appropriate for this analysis because the capital adoption necessary to automate certain jobs may take time to occur. Moreover, the structure of the OES data, which are based on surveys taking place over the past three years, means that employment changes will only reflect a time series from independent surveys in long differences. Specifically, we estimate the following difference-in-differences regression model:

$$\Delta \ln Emp_{jst} = \propto_s + \propto_t + \propto_j + \propto_k + \sum_{k=1}^{4} \sum_{z=-2}^{1} \beta_z^k \left(WG_{js}^k * \Delta lnMW_{s,t+z}\right)$$

$$+ \sum_{k=1}^{4} \sum_{z=-2}^{1} \beta_{z,T}^k \left(WG_{js}^k * \Delta lnMW_{s,t+z} * TaskShare_j\right)$$

$$+ \sum_{k=1}^{4} \gamma_1^k \left(WG_{js}^k * Year_t * TaskShare_j\right) \tag{1}$$

$$+ \sum_{k=1}^{4} \gamma_2^k \left(WG_{js}^k * Year_t * lnEmp_{js,t-4}\right) + \varepsilon_{jst}$$

where $\Delta lnEmp_{jst}$ is the change in the natural log of employment for occupation *j* in state *s* and year *t* from four years earlier. The minimum wage variables in the regression specification, $\Delta lnMW_{s,t+z}$, are a set of four one-year changes in the natural log of the minimum wage in state *s* from two years prior (t-2) to one year post year t (t+1), where for example, $\Delta lnMW_{s,t-2} = lnMW_{s,t-2} - lnMW_{s,t-3}$. Thus, we estimate the effects of these hikes from one year before the hike until two years after the hike.[19] This lead and lag structure allows us to test the parallel trends assumption (associated with the lead coefficient) implicit in this difference-in-differences empirical specification and to examine the effects of a minimum wage several years after a hike. The empirical specification also controls for state or metro area (α_s), year (α_t), occupation (α_j), and wage group (α_k) fixed effects; the task content of an occupation, $TaskShare_j$, where we allow this effect to vary over time ($Year_t$) by wage group (WG^k_{js}); and the lagged natural log of the employment level from four years prior ($lnEmp_{js,t-4}$), where we also allow this effect to vary over time by group. Observations are weighted using the base year employment levels ($Emp_{js,t-4}$) and standard errors are clustered at the state or metro area level.

Our key coefficients of interest, β^k_{zT}, describe the impact of a minimum wage hike on the cumulative change in employment of a particular task content *T*. Equation (1) ensures that the identification of β^k_{zT} takes place within occupations while still controlling for time trends in employment across tasks – such as the ongoing decline in routine jobs, which we document in Figure 2. To ease the interpretation of the β^k_{zT} coefficients, the $TaskShare_j$ variables are standardized to be z-scores. Thus, the β^k_{zT} coefficients represent the employment elasticity for a standard deviation increase in the specific task share *T*. We then estimate separate regressions for each task share, such as the extent to which an occupation is routine cognitive or routine manual.

[19] Equation (1) is a long-difference distributed lag model, so named because it has a long difference in the outcome but one year changes in the minimum wage like a distributed lag model. In this framework, the β coefficients reflect cumulative changes in the outcome up until a point in time – whereas a traditional distributed lag model reflects marginal changes in the outcome.

The β^{k}_{zT} coefficients will be unbiased so long as state-level minimum wage changes are unrelated to unobserved employment trends associated with task T in state *s*. This seems like a reasonable assumption. However, we also present estimates of Equation (1) that include state-by-year fixed effects (but exclude the non-interacted $\Delta lnMW_{s,t-z}$ variables due to multicollinearity). The β^{k}_{zT} coefficients in that specification will be unbiased so long as the state-level minimum wage changes are unrelated to unobserved employment trends associated with task *T* in state *s* and year *t*. This is even more likely to hold.

Our ACS analysis estimates Equation (1) with an occupation-industry-state-year panel that includes industry fixed effects. We also present an OES-comparable version of the ACS estimates without industry.

IV. Results

A. OES State-level Estimates

Table 2 presents our basic estimates of the effect of a minimum wage hike on overall employment over the period 2010 to 2018. In the first four columns, grouped under Specification 1, we show how overall cumulative employment changed in the year before, year of, year after, and two years after a minimum wage hike – where each column represents the estimated effect on the collection of occupations in each wage grouping (e.g. Wage Group 1). The estimates provide some evidence that minimum wage hikes over the last decade have been associated with employment declines at the lowest wage occupations. While none of the coefficients in any of the years after the hike are negative, the estimates for Wage Group 1 – those occupations with an average wage-to-minimum wage ratio less than 1.5 – imply that there was a positive leading effect. That is, employment in these occupations had been growing in states that increased their minimum wage prior to the hike. Thereafter, this relative employment advantage disappeared after the minimum wage increased and the change in employment growth, i.e. the difference in the coefficients from two years after the hike to the year prior to the hike, is -0.18 (0.10), which is statistically significant at the 10 percent level and economically on the higher side of the literature that has examined the overall employment effects of minimum wage hikes (Neumark and Wascher 2008; Dube, Lester, and Reich 2010; Neumark, Salas, and Wascher 2014; Allegreto, Dube, Reich, and Zipperer 2017; Cengiz, Dube, Lindner, and Zipperer, 2019).[20] Overall employment at occupations in Wage Groups 2 to 4 (average wage to minimum wage ratio of 1.5 to 6) are not materially affected by the minimum wage hike.[21]

In columns (5) to (12), we begin to explore different job tasks by adding the interaction between the routine cognitive share of an occupation and the minimum wage change (i.e. in Equation (1), $TaskShare_j$ is based on routine cognitive tasks). The first four of these columns (Specification 2) include state and year fixed effects and the latter four (Specification 3) include state-by-year fixed effects. The estimates strongly suggest that minimum wage hikes are associated with employment declines at the lowest paying jobs in Wage Group 1 that are intensive in routine cognitive tasks. This effect is evident one year after the hike, with an estimated elasticity of -0.10 (0.05), and more than doubles two years after the hike to -0.22 (0.06). In words, these estimates imply that an occupation with a routine cognitive share of tasks that is one standard deviation above average, such as Parking Enforcement Workers and Hotel Desk Clerks, experience relative employment declines of 2.2 percent for every 10 percent increase in the minimum wage. Occupations with routine cognitive tasks that are two standard deviations above average, such as Lobby Attendants and Gaming Dealers, would experience employment declines that are twice as large. Interestingly, there does not appear to be any impact of minimum wage hikes on routine cognitive employment at higher paying occupations in Wage Group 2, 3, or 4. Moreover, the results are not materially affected whether we use state and year fixed effects or state-by-year fixed effects. We also find that the overall employment effect – the difference in the coefficients between the leading effect and the change two years after the hike –

[20] The change in coefficients, like the coefficients themselves, should be interpreted as an elasticity.

[21] The coefficients for the second lowest wage occupation group (Wage Group 2) is positive between the lag and two year leading coefficients, i.e. the opposite direction, although the change is small and not statistically significant. Like with Wage Group 1, there appears to be a leading effect of minimum wage hikes on occupational employment in Wage Group 4 and the change between the leading and 2 year lag is negative although not statistically different from zero, -0.12 (0.09).

is more muted and statistically insignificant -0.12 (0.09) in this specification. Thus, while there is some evidence of overall employment declines, it is weakly statistically significant and not robust to the inclusion of routine task shares.

Table 3 presents the full set of β^k_{zT} coefficients for each of the T task categories. Each column reports the estimated elasticities from a different regression that includes state-by-year fixed effects (Specification 3 in Table 2). For ease of comparison, Column 1 repeats the cognitively routine estimates presented in Columns 9 and 10 of Table 2.

In Column 2, we show that minimum wage hikes are causing employment to decline at the lowest wage occupations intensive in routine *manual* tasks and the magnitude of the decline is quite similar to the observed decline at routine cognitive jobs. The point estimates imply that a 10 percent increase in the minimum wage causes employment to decline by 1.4 percent one year after the hike and 1.7 percent two years after the hike at occupations with a routine manual task share that is one standard deviation above average.[22] Again, no changes are occurring at occupations in Wage Groups 2, 3, or 4 (see Appendix Table A2 for Wage Groups 3 and 4 results). These patterns are consistent with minimum wage hikes expediting the adoption of automation technology, which, in turn, supplant employment at routine cognitive and routine manual jobs. Moreover, the timing of the changes in employment, one and two years after the hike, is consistent with longer-term substitution effects.

Although there is strong evidence of job loss among occupations intensive in routine tasks, minimum wage hikes also cause a significant offsetting increase in employment at jobs intensive in interpersonal tasks. Column 3 shows that a Wage Group 1 occupation with interpersonal tasks that are one standard deviation above average experiences employment growth of 1.9 percent and 2.4 percent one and two years after a 10 percent increase in the

[22] For a point of reference, low-wage routine manual jobs that are about one standard deviation above average include Meat/Poultry Trimmers and Farmworkers while low-wage routine manual jobs that are about two standard deviations above average include Laundry/Dry Cleaning Workers and Garment Pressers.

minimum wage.[23] While these coefficients are only statistically significant at the 8 and 6 percent level, respectively, the pattern of estimates and the timing relative to the change in employment at routine jobs is notable. And once again, no such effect shows up in Wage Groups 2, 3, or 4. Moreover, the remainder of Table 3 comfortingly suggests that minimum wage hikes tend not to affect employment at non-routine cognitive analytical or non-routine manual physical occupations, which are likely less automatable.

Figure 6 (and Appendix Table A3) compares our results from 2010 to 2018 with identical regression specifications estimated on the 1999 to 2009 OES data. We find that minimum wage hikes have led to declining routine employment in both decades and the secular pattern of the effects are similar in that the estimated realignment away from routine, as well as towards interpersonal tasks, grows in magnitude over the two years following a hike. However, the magnitude of the responses have clearly accelerated over time. To see this change, note that the rate of employment decline at routine jobs two years after the hike is larger in the post-Crisis period than in the pre-Crisis period, whether routine is defined by cognitive tasks (Panel A), manual tasks (Panel B), or both (Panel C).[24] For example, when we combine routine cognitive and manual tasks together, the estimated two-year elasticities for Wage Group 1 in the post-Crisis period are two and a half times the size of the estimated effects in the pre-Crisis period: i.e. -0.22 (0.06) versus -0.08 (0.04), respectively. Similarly, the offsetting employment growth associated with Wage Group 1 occupations intensive in interpersonal tasks grew between the first two decades of the 21st century (Panel D of Figure 6). The estimated interpersonal

[23] Occupations one standard deviation above average in interpersonal tasks include Manicurists and Restaurant/Cafe Hosts. Two standard deviation above average occupations include Recreation Workers and Personal/Home Care Workers.

[24] This remains the case even after we account for any pre-trend that may be taking place. Over the pre-Crisis period the estimated Wage Group 1 elasticity two years after a minimum wage hike relative to the leading effect is -0.12 (0.05). This is smaller in magnitude than a comparable estimate of -0.22 (0.14) for the post-Crisis period. Notably, this combined effect for the pre-Crisis period is quite similar to the results in Aaronson and Phelan (2017), who estimate an elasticity of -0.13 (0.05). The small -0.01 differences between our current and past point estimates are due to the addition of occupation fixed effects and whether to winsorize the largest employment changes.

elasticities two years after the hike are 0.24 (0.12) in the 2010-2018 period compared to -0.01 (0.07) in the 1999-2009 period.[25]

We find two other notable differences across the decades (see Appendix Table A3 for earlier decade details). First, the adverse impact of minimum wage hikes on overall Wage Group 1 employment appears to be larger post-Financial Crisis. Second, increases in the minimum wage in the 1999-2009 period affected the employment levels of routine and interpersonal occupations in Wage Group 2, whereas we find no such effects in the post-Crisis period. Thus, it is possible that some of the acceleration in the rate of automation that is apparent in Wage Group 1 occupations in the post-Crisis period may reflect a better "targeting" of occupations likely to be affected by minimum wage hikes than is the case in the earlier decade.

B. OES Metropolitan-level Estimates

Next, we turn to using sizable variation in city and county minimum wage policy implemented during the 2010s to estimate the effects of minimum wage hikes on occupational employment at the MSA level. Panel A of Table 4 presents the results when we use all MSAs available in the OES and reports results on overall (Column 1) and task share-specific (Columns 2 to 5) employment. Like with the state-based results discussed above, there is no discernable impact on employment at higher paying jobs and therefore we move the estimated Wage Group 3 and 4 coefficients to Appendix Table A4.

The MSA findings have a similar but muted flavor to the state-based ones. For example, the MSA estimates imply a two-year post-hike elasticity of -0.12 (0.07) when both routine cognitive and routine manual tasks are combined to form an overall routine share of tasks, compared to -0.22 (0.06) at the state level. Likewise, the interactive task elasticity is 0.16 (0.08)

[25] The estimated effect on interpersonal tasks over the period 1999-2009 is less evident here than in Aaronson and Phelan (2017) because much of the offsetting employment growth in the pre-Crisis period was in cognitive interpersonal jobs but not manually interpersonal jobs. In this study, we combine cognitive and manual interpersonal tasks for simplicity and because the distinction between cognitive and manual interpersonal tasks looks less important in the 2010 to 2018 data.

at the MSA-level and 0.24 (0.12) at the state-level. This attenuation also impacts the overall employment response in Wage Group 1, which becomes essentially zero at the MSA-level.

We expected that the precision of the estimates would decline once we switch to the MSA data, which is composed of smaller samples of establishments. However, the smaller point estimates are surprising. They could reflect measurement error introduced by MSA areas that cross state or city lines. However, when we limit our data to only those OES metropolitan areas that are wholly contained in a state, the point estimates, while more precise, do not increase materially (see Appendix Table A5).

Alternatively, the smaller MSA results could reflect heterogeneity. A metro area analysis will necessarily place a greater emphasis on urban areas than a state-level analysis, and perhaps the realignment in employment that we observe is more likely to take place in rural locations and smaller cities. To test this hypothesis, we re-estimate our statistical models excluding the 25 largest metropolitan areas (Panel B of Table 4).[26] When the largest cities are excluded, the estimated elasticity at low-wage routine cognitive occupations increases to -0.23 (0.09) two years after the hike (inclusive of the leading effect) and the estimated elasticity at low-wage interactive occupations increases to 0.23 (0.08), nearly the same as the state-level estimates.

These results strongly suggest that low-wage automation that is spurred on by minimum wage hikes is especially pertinent outside of the largest cities. This heterogeneity could arise because the minimum wage is less binding in large cities.[27] Consistent with that possibility, when we exclude the largest cities, we start to see some evidence that minimum wage hikes may be affecting employment at slightly higher paid occupations in Wage Group 2.[28] While these Wage

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[26] The 25 largest metropolitan areas in the OES are Atlanta, Baltimore, Boston, Chicago, Dallas, Denver, Detroit, Houston, Los Angeles, Miami, Minneapolis, Nassau County Long Island, New York City, Orlando, Portland OR, Philadelphia, Phoenix, Pittsburgh, Riverside California, San Diego, San Francisco, Seattle, St. Louis, Tampa, and Washington, DC.

[27] An alternative explanation that we cannot rule out is that the differing geographic boundaries – with many minimum wage hikes restricted to city limits but MSAs comprising much larger geographic areas – work to attenuate the estimated impact of the hike, even if the impact is actually taking place.

[28] The logic here is that if the minimum wage is more binding, it is more likely to spill over into wages at higher paying jobs. In turn, as wages rise at Wage Group 2 occupations, evidence of automation should also be more evident there.

Group 2 estimates are not always statistically significant when one considers pre-trends, it is more apparent among these somewhat higher wage jobs that minimum wage hikes are causing employment declines at routine intensive jobs and employment gains at interpersonal jobs.

C. ACS Estimates

Estimates of Equation (1) derived from the ACS, presented in Table 5, are consistent with those from the OES.[29] We find the estimated two-year-after employment elasticity among Wage Group 1 occupations is -0.16 (0.09), similar to the state-level OES results (Panel A). Moreover, we see a notable reallocation of low-wage employment away from occupations intensive in routine cognitive and routine manual tasks and towards occupations intensive in interpersonal tasks. The estimated two-year-after task-based point estimates are about 40 percent larger in the ACS than the state-based estimated using the OES.[30] The difference in magnitudes, while not statistically different, is likely due to being able to account for industry in the ACS. The ACS and OES estimates are remarkably similar when industry is not accounted for (see Appendix Table A6), suggesting, if anything, the OES estimates understate the employment realignment taking place in the low-wage labor market. Moreover, the timing of the employment response in the ACS estimates is also very similar to the OES estimates, with most of the effect coming two years, rather than one year, after the hike. This timing gives us greater confidence that the delayed results observed in the OES are not an artifact of the moving average data but instead reflects the time to implement new technology. In Panels B and C and Appendix Table A7, we show larger employment responses outside the 25 largest MSAs and no significant effect at higher wage occupations, again mimicking the results from the OES.[31]

[29] Table 5 is based on a state-industry-occupation panel. In Appendix Tables A6, we use a state-occupation panel more directly comparable to the OES. We prefer the version that controls for industry because it improves precision and addresses a potential concern with our OES estimates – that some of our effects could be due to differences in the scale effect across industries.

[30] The ACS all routine tasks elasticity is -0.31 (0.08) instead of -0.22 (0.06) in the OES. The ACS interpersonal tasks elasticity is 0.35 (0.08) versus 0.24 (0.12) in the OES.

[31] While the two year-after coefficient for the overall employment effect on the non-top 25 cities is a statistically insignificant and economically small -0.05 (0.09), there is a clear pre-trend. The two-year-after effect net of the pre-trend is -0.20 (0.15).

The key advantage of the ACS is it allows us to explore heterogeneity by worker characteristics. Specifically, we stratify the ACS by education (high school diploma or less versus some college or more), age (under age 30 versus 30 or older), race (non-Asian minorities vs. Whites and Asian Americans), and sex. Table 6 presents the results for Wage Group 1 (see Appendix Table A8 for other Wage Groups). Somewhat surprisingly, the employment realignment associated with minimum wage hikes – decreasing employment at routine-intensive jobs (Panel B) and increasing employment at interpersonal-intensive jobs (Panel C) – is evident in each of the different subsamples. Moreover, while the prevalence of low-wage employment is much larger for less-education and younger workers, the estimated employment elasticities at routine and interpersonal jobs (two years after a minimum wage hike) are only slightly larger than their subgroup counterpart and none are statistically different than the estimates on the overall sample. Likewise, the estimated overall employment effect is fairly similar by age, education, and gender (Panel A).[32]

<u>By Minority Status</u>

However, we find significant heterogeneity by race. The overall estimated employment effect among non-Asian minorities ("minority") is a strikingly large -0.56 (0.16) two-years after a minimum wage hike. By comparison, the overall employment elasticities for the Asian American and White samples ("non-minority") are essentially zero. This sharp distinction suggests that all of the employment losses associated with automation are borne by non-Asian minority workers, of which African Americans compose the majority.

The large negative employment loss is somewhat surprising since our estimate of the minority employment elasticity at routine-intensive jobs of -0.47 (0.19) is perfectly balanced by the estimated employment elasticity at interpersonal jobs of 0.49 (0.22). However, these employment responses need not be linear. A negative (positive) coefficient could represent either

[32] While the two-year after coefficient for men and women for the overall employment effects of minimum wages appear to be quite different, when one accounts for the leading effect, the change in estimates are quite similar.

large employment losses (gains) at jobs with a high level of a particular task, large employment gains (losses) at jobs with a low level of a particular task, or both.

Figure 7 explores this possible asymmetric employment response among Wage Group 1 occupations separately for minority and non-minority workers. In particular, the four panels plot the relative change in log routine or interpersonal employment between minimum wage hike states and non-minimum wage hike states for the minority (blue) and non-minority (red) sample employed at either "high" or "low" routine or interpersonal occupations. We define a high (low) occupation as having a task share among the highest (lowest) three deciles.[33] Among occupations especially high in routine tasks and low in interpersonal tasks (Panels A and D), both minority and nonminority workers experience the secular decline in those types of jobs roughly equally.

The striking dichotomy between minority and non-minority workers arises at low-routine and high-interpersonal jobs (Panels B and C). Beginning around 2014 when minimum wages legislation is revitalized, non-minority workers shift to low-routine and high-interpersonal jobs, whereas minorities do not. The minority/non-minority difference in the employment response at interpersonal-intensive (and routine-deficient) jobs is highly statistically significant and robust to alternative specifications such as limiting the sample to occupations with above average interpersonal tasks. Therefore, we find that minority workers are experiencing outsized job loss from low-wage automation because they are suffering larger employment losses at routine-intensive jobs while essentially missing out on the offsetting employment growth at interpersonal-intensive jobs.

One potential explanation for this differential employment effect by race relates to the occupational allocation of low-wage minority workers, as in Del Rio and Alonso-Villar (2015). Indeed, minority workers in the ACS are both more-likely to be employed in disappearing routine-intensive occupations and less-likely to be employed in growing interpersonal-intensive occupations. However, even when we look within high interpersonal (or low routine)

[33] The specific task share cutoffs for high/low routine jobs are above 45 percent and below 35 percent and the cutoffs for high/low interpersonal jobs are above 45 percent and below 37.5 percent.

occupations in Figure 7, the estimated employment effects vary significantly by race. Still, there may be racial differences in the occupation distribution even within those task groupings that affect the employment elasticities.

Therefore, we perform the following additional check. Instead of weighting the minority sample observations using the (four year lagged) occupational employment level of minorities, we use the sample weights that reflect the occupational distribution of the non-minority sample (DiNardo, Fortin, and Lemieux 1996). The minority-only estimates will then reflect the unique experience of minorities rather than racial differences in the distribution of occupational employment. Indeed, this adjustment has no impact; the estimated two-year-after employment elasticity barely changes: -0.56 (0.17) to -0.50 (0.32). While precision declines, this arises from increasing the sample weights on a few occupations where the base-year employment levels of minority workers are very small (and thus, the log employment changes are relatively large and volatile).[34] Therefore, the unique employment experience of the minority sample following automation is not due to differences in the initial occupational distribution of minority workers.[35]

Another potential explanation for the large employment losses experienced by minority workers is racial discrimination. If customers have discriminatory preferences (Holzer and Ihlanfeldt 1998; Bar and Zussman 2017), the creation of new interpersonal-intensive jobs associated with automation could harm the employment opportunities of minority workers. While a full analysis of this mechanism is beyond the scope of this paper, we see some suggestive evidence it could be a factor. In particular, the overall employment effect of minimum wage hikes on minority workers increases as the non-minority share of a state's population increases; the estimated employment elasticity two-years after a minimum wage hikes on low-wage minority employment is -0.41 (0.21) in states where the population is more than 20 percent

[34] When we exclude observations where the base-year occupational employment level for minority workers was 3 or less, the point estimate (and standard error) of the two-year-after employment elasticity are nearly alike: -0.50 (0.15) versus -0.56 (0.20).

[35] Moreover, there are no economically large racial differences in the education, age, and gender of our low-wage occupation sample, which might imply differential exposure to minimum wage hikes. Indeed, the average wage between minorities and non-minorities differs by a statistically insignificant $0.11.

minority, -0.65 (0.16) in states that are 15 to 20 percent minority, and -1.01 (0.47) in states that are less than 15 percent minority.[36] Alternatively, Small and Pager (2020) review research suggesting that standard corporate HR practices can lead to systematic racial differences in layoff decisions.

V. Conclusion

An extensive empirical literature examines the economically important impact of technological substitution on middle-skill jobs. Our paper builds on the task-based occupational approach of these papers to examine the impact of automation on the low-wage labor market. Using exogenous variation in occupational wages, through changes in state and local minimum wage policy, we examine how the effect of automation on the low-wage labor market has changed over the first two decades of the 21st century and whether specific demographic groups are more susceptible to the changing composition of occupational employment that is taking place.

We find strong evidence that minimum wage hikes are changing the composition of jobs in the low-wage labor market – decreasing employment at both routine cognitive and routine manual jobs and increasing employment at jobs intensive in interpersonal tasks. The decline at routine occupations, evident in two large, nationally representative datasets -- the OES and ACS – is consistent with the ways in which automation technology has changed the composition of middle-skill jobs and thus, strongly suggests that automation technology is also supplanting occupations intensive in routine tasks in the low-wage labor market. Interestingly, employment changes associated with minimum wage hikes are also evident in the overall low-wage labor market, suggesting that this trend is not simply due to the minimum wage but reflects a broader trend in low-wage job automation. Moreover, these dynamics are accelerating; the estimated decline from automation at low-wage routine jobs over the period 2010-2018 is more than

[36] The non-Asian minority share is 18 percent in the U.S., according to the unweighted ACS for 2010-2018.

double the estimated decline from the first decade of the 21st century and is spreading to a broader range of routine jobs. At the same time, we also find that the decline in routine employment is being offset by employment growth in jobs that are intensive in interpersonal tasks. While the magnitude of this offsetting employment growth has also grown since the pre-Financial Crisis period, there is some evidence to suggest that the growth in interpersonal occupations is not fully offsetting the decline in routine employment.

We also explore heterogeneity in this employment realignment across demographic groups including by age, education, sex, and race. While all groups experience a movement away from jobs intensive in routine tasks and towards jobs that are intensive in interpersonal tasks, the overall job loss associated with low-wage automation appears to be concentrated among racial minorities who experience larger declines in employment at routine jobs and much smaller employment gains at interpersonal jobs. Occupational segregation cannot explain the magnitudes of these job losses. Understanding the barriers or policies limiting the ability of low-wage minority workers to transition to interpersonal jobs strikes us as an especially important area of future research.

References

Aaronson, D., Agarwal, S., Hotchkiss, J.L. and Kelley, T., 2019. "Job displacement and financial outcomes." *Economics Letters, 177,* 18-21.

Aaronson, D., French, E., Sorkin, I. and To, T. 2018. "Industry dynamics and the minimum wage: a putty-clay approach." *International Economic Review*, *59*(1), 51-84.

Aaronson, D. and Phelan, B.J., 2017. "Wage Shocks and the Technological Substitution of Low-wage Jobs." *The Economic Journal*, *129*(617), 1-34.

Aaronson, D. and Phelan, B.J, 2019. "Does automation always lead to a decline in low-wage jobs?," *Chicago Fed Letter*.

Acemoglu, D. and Autor, D, 2011, "Skills, Tasks and Technologies: Implications for Employment and Earnings," *Handbook of Labor Economics*, 4, 1043-1171.

Allegretto, S., Dube, A., Reich, M. and Zipperer, B., 2017. "Credible research designs for minimum wage studies: A response to Neumark, Salas, and Wascher." *ILR Review, 70*(3), 559-592.

Autor, D., 2019. "*Work of the past, work of the future*." NBER Working Paper.

Autor, D. and Dorn, D., 2013. "The growth of low-skill service jobs and the polarization of the US labor market." *American Economic Review, 103*(5), 1553-97.

Autor, D. H., Katz, L.F. and Kearney, M.S., 2006. "The polarization of the US labor market." *American Economic Review*, *96*(2), 189-194.

Autor, D.H., Katz, L.F. and Kearney, M.S., 2008. "Trends in us wage inequality: revising the revisionists." *Review of Economics and Statistics*, 90(2), 300–23.

Autor, D.H., Levy, F. and Murnane, R.J., 2003. "The skill content of recent technological change: An empirical exploration." *The Quarterly Journal of Economics*, *118*(4), 1279-1333.

Bailey, M.J., DiNardo, J. and Stuart, B.A., 2020. "The Economic Impact of a High National Minimum Wage: Evidence from the 1966 Fair Labor Standards Act." National Bureau of Economic Research Working Paper No. 26926.

Bar, R. and Zussman, A., 2017. "Customer discrimination: evidence from Israel." *Journal of Labor Economics*, *35*(4), 1031-1059.

Barrero, Jose Maria, Nick Bloom, and Steven Davis, 2020, "Covid-19 is Also a Reallocation Shock," Working paper.

Beaudry, P., Green, D. and Sand, B. 2016, "The Great Reversal in the Demand for Skill and Cognitive Tasks," *Journal of Labor Economics*, 34(S1), S199-S247.

Bresnahan, T.F., Brynjolfsson, E. and Hitt, L.M., 2002. "Information technology, workplace organization and the demand for skilled labor: firm-level evidence." *Quarterly Journal of Economics*, 117(1), 339–76.

Cengiz, D., Dube, A., Lindner, A. and Zipperer, B., 2019. "The effect of minimum wages on low-wage jobs." *The Quarterly Journal of Economics*, *134*(3), 1405-1454.

Chen, Y., 2019, "What Do Establishments Do When Wages Increase? Evidence from Minimum Wages in the United States," Working Paper.

Cho, D., 2018. "Downward Wage Rigidity, Corporate Investment, and Firm Value." Working Paper.

Clemens, Jeffrey, Lisa Kahn, and Jonathan Meer, 2020, "Dropouts Need Not Apply: The Minimum Wage and Skill Upgrading," Working paper.

Davis, Steven and Till von Wachter, 2011, "Recessions and the Cost of Job Loss," *Brookings Papers on Economic Activity*.

Del Río, C. and Alonso-Villar, O., 2015. "The evolution of occupational segregation in the United States, 1940–2010: Gains and losses of gender–race/ethnicity groups." *Demography*, 52(3), 967-988.

Deming, D.J., 2017. "The growing importance of social skills in the labor market." *The Quarterly Journal of Economics*, *132*(4), 1593-1640.

DiNardo, J., Fortin, N.M. and Lemieux, T., 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." *Econometrica*, *64*(5), 1001-1044.

Dube, A., Lester, T.W. and Reich, M., 2010. "Minimum wage effects across state borders: Estimates using contiguous counties." *The Review of Economics and Statistics*, *92*(4), 945-964.

Dustmann, C., Lindner, A., Schönberg, U., Umkehrer, M. and Vom Berge, P., 2020. "Reallocation Effects of the Minimum Wage." *CReAM Discussion Paper*.

Geng, H. G., Huang, Y., Lin, C., & Liu, S., 2018. "Minimum Wage and Corporate Investment." Working Paper.

Goos, M., Manning, A. and Salomons, A., 2014. "Explaining job polarization: Routine-biased technological change and offshoring." *American Economic Review*, *104*(8), 2509-26.

Gustafson, M. and Kotter, J.D., 2018. "Minimum wage and corporate policy." Working Paper.

Hau, H., Huang, Y., & Wang, G., 2018. “Firm Response to Competitive Shocks: Evidence from China’s Minimum Wage Policy.” *Review of Economic Studies*, Forthcoming.

Holzer, H.J. and Ihlanfeldt, K.R., 1998. “Customer discrimination and employment outcomes for minority workers.” *The Quarterly Journal of Economics*, *113*(3), 835-867.

Jaimovich, Nir, Itay Eksten, Henry Siu, and Yaniv Yedid-Levi, 2020, “The Macroeconomics of Automation: Data, Theory, and Policy Analysis,” Working paper.

Jolly, N.A. and Phelan, B.J., 2015. “Job Displacement’s long-run effect on access to employer-provided health insurance and other fringe benefits.” *Economics Letters*, *130*, 100-104.

Jacobson, L.S., LaLonde, R.J. and Sullivan, D.G., 1993. “Earnings losses of displaced workers.” *American Economic Review*, 685-709.

Krueger, A.B. and Posner, E., 2018. “A Proposal for Protecting Low-Income Workers from Monopsony and Collusion.” *The Hamilton Project Policy Proposal*, *5*.

Leduc, S. and Liu, Z., 2020, May. “Can Pandemic-Induced Job Uncertainty Stimulate Automation?” Federal Reserve Bank of San Francisco Working Paper No. 2020-19.

Lordan, G. and Neumark, D., 2018. “People versus machines: The impact of minimum wages on automatable jobs.” *Labour Economics*, *52*, 40-53.

Manning, A., 2004. “We can work it out: the impact of technological change on the demand for low-skill Workers.” *Scottish Journal of Political Economy*, 51(5), 581–608.

Manning, A., 2020. “Monopsony in labor markets: a review.” *ILR Review*, Forthcoming.

Muro, M., Maxim, R. and Whiton, J., 2019. “Automation and artificial intelligence: How machines are affecting people and places.” Brookings Institution Report, available online at: https://www.brookings.edu/wp-content/uploads/2019/01/2019.01_BrookingsMetro_Automation-AI_Report_Muro-Maxim-Whiton-FINAL-version.pdf#page=29

Neumark, D. and Wascher, W.L., 2008. *Minimum wages*. MIT press.

Neumark, D., Salas, J.I. and Wascher, W., 2014. “Revisiting the Minimum Wage—Employment Debate: Throwing Out the Baby with the Bathwater?” *ILR Review*, 67(3 Suppl), 608-648.

Qiu, Y. and Dai, X., 2019. “Do Increases in State Minimum Wages Accelerate Technology Adoption?” Working Paper.

Pew Research Center, 2018. “In Advanced and Emerging Economies Alike, Worries about Job Automation.” Available at https://www.pewresearch.org/global/2018/09/13/in-advanced-and-emerging-economies-alike-worries-about-job-automation/, last accessed 11/13/19.

Phelan, Brian, 2019, "Hedonic-Based Labor Supply Substitution and the Ripple Effect of Minimum Wages," *Journal of Labor Economics* 37(3), 905-948.

Ruhm, Christopher, 1991, "Are Workers Permanently Scarred by Job Displacements?" *American Economic Review*, 81, 319–24.

Small, Mario and Devah Pager, 2020, "Sociological Perspectives on Racial Discrimation," Journal of Economic Perspectives 34(2), 49-67.

Sorkin, I. 2015. "Are There Long-Run Effects of the Minimum Wage?," *Review of Economic Dynamics*, 18(2), 306-333.

Sullivan, Daniel and Till von Wachter, 2009, "Job Displacement and Mortality: An Analysis Using Administrative Data," *The Quarterly Journal of Economics*, 124(3), 1265-1306.

Table 1: Routine and Interpersonal Intensive Low-Wage Occupations

Occupation	Average Wage-to-Minimum Wage	Share Routine	Share Inter-personal	2010 National Employment Levels	Employment Growth 2010-2018
Panel A: Routine Intensive Low-Wage Occupations					
Graders and Sorters, Agricultural Products	1.35	57%	25%	32,470	7%
Cutters and Trimmers, Hand	1.74	56%	25%	17,120	-40%
Motion Picture Projectionists	1.45	52%	27%	8,690	-58%
Textile and Garment Pressers	1.32	51%	23%	56,480	-32%
Sewing Machine Operators	1.49	51%	28%	147,040	-7%
Shoe Machine Operators and Tenders	1.63	51%	29%	890	-20%
Gaming and Sports Book Writers and Runners	1.54	51%	31%	12,230	-27%
Textile Weaving Machine Operators	1.81	50%	31%	20,940	-1%
Meat, Poultry, and Fish Cutters and Trimmers	1.56	49%	33%	160,330	-5%
Shoe and Leather Workers and Repairers	1.60	49%	27%	4,820	25%
Cashiers	1.29	48%	38%	3,354,170	8%
Slaughterers and Meat Packers	1.64	48%	31%	86,020	-27%
Gaming Cage Workers	1.63	47%	35%	12,780	17%
Laundry and Dry-Cleaning Workers	1.38	47%	37%	204,790	4%
Maids and Housekeeping Cleaners	1.39	46%	40%	865,980	7%
Gaming Dealers	1.30	46%	35%	73,830	15%
Service Station Attendants	1.41	45%	32%	86,070	30%
Textile Winding Machine Setters	1.79	44%	33%	26,700	12%
Cooks, Institution and Cafeteria	1.58	44%	39%	387,700	3%
Tellers	1.67	44%	39%	556,300	-16%
Gaming Change Persons and Booth Cashiers	1.53	43%	38%	13,910	46%
Painter and Plasterers Helpers	1.67	43%	28%	11,090	-24%
Farmworkers and Laborers	1.23	43%	32%	222,820	28%
Textile Dyeing Machine Operators	1.68	43%	34%	11,580	-27%
Switchboard Operators	1.73	42%	40%	138,180	-49%
Average Routine Intensive Occupation	**1.39**	**47%**	**37%**	**260,517**	**4%**
Panel B: Interpersonal Intensive Low-Wage Occupations					
Door-to-Door Salespeople	1.69	1%	79%	5,600	-2%
Residential Advisors	1.69	13%	68%	65,140	66%
Personal and Home Care Aides	1.33	24%	66%	681,430	225%
Recreation Workers	1.59	17%	64%	293,440	21%
Locker Room and Coatroom Attendants	1.41	30%	59%	15,930	10%
Child Care Workers	1.37	18%	58%	611,260	-8%
Tour Guides and Escorts	1.66	17%	55%	28,930	34%
Recreational Protective Service Workers	1.33	31%	54%	117,530	17%
Amusement and Recreation Attendants	1.28	21%	53%	254,670	23%
Bartenders	1.42	27%	52%	495,350	27%
Hosts and Hostesses	1.26	29%	52%	329,030	27%
Manicurists and Pedicurists	1.35	31%	51%	47,430	125%
Funeral Attendants	1.60	26%	50%	29,590	18%
Nonfarm Animal Caretakers	1.43	25%	49%	135,070	48%
Retail Salespersons	1.61	30%	46%	4,155,210	7%
Floral Designers	1.64	25%	46%	47,860	-10%
Bakers	1.59	30%	46%	140,800	28%
Waiters and Waitresses	1.38	35%	46%	2,244,470	15%
Physical Therapist Aides	1.63	34%	45%	45,910	3%
Receptionists and Information Clerks	1.71	36%	44%	997,110	5%
Transportation Attendants, Except Air	1.60	34%	44%	24,030	-6%
Food Concession Attendants	1.24	36%	44%	446,630	6%
Hotel, Motel, and Resort Desk Clerks	1.40	37%	43%	222,550	17%
Food Preparation Workers	1.34	35%	42%	802,630	1%
Nursing Aides and Attendants	1.65	35%	42%	1,473,990	2%
Average Interpersonal Intensive Occupation	**1.50**	**31%**	**48%**	**548,464**	**21%**

Notes: This table presents the 25 occupations with the highest routine share of tasks and highest interpersonal share of tasks. The table is limited to the lowest paying occupations, which are defined to be the occupations that are classified as Wage Group 1 for at least one state. The 2010 employment levels come from the OES and represent national totals in the U.S., except Personal Home Care Aides, which excludes California (see text for more details).

Table 2: Employment Effect of a Minimum Wage Hike, by Routine Cognitive Share of Tasks
Occupation Employment Statistics, 2010-2018

	Specification 1:				**Specification 2:**				**Specification 3:**			
	Wage Group1	**Wage Group2**	**Wage Group3**	**Wage Group4**	**Wage Group1**	**Wage Group2**	**Wage Group3**	**Wage Group4**	**Wage Group1**	**Wage Group2**	**Wage Group3**	**Wage Group4**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔMW Next Year	0.19***	-0.09	-0.02	0.13**	0.18***	-0.10	0.01	0.13**				
	(0.07)	(0.06)	(0.12)	(0.05)	(0.06)	(0.06)	(0.11)	(0.05)				
ΔMW This Year	0.06	0.05	-0.04	0.04	0.07	0.05	-0.05	0.04				
	(0.08)	(0.06)	(0.06)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)				
ΔMW Last Year	0.09*	-0.04	-0.01	0.12**	0.10**	-0.05	-0.03	0.12**				
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)				
ΔMW 2Yrs Ago	0.01	0.02	-0.06	0.00	0.05	0.01	-0.05	-0.01				
	(0.08)	(0.05)	(0.08)	(0.08)	(0.07)	(0.05)	(0.06)	(0.08)				
ΔMW Next Year X RoutineSh					0.00	0.00	-0.07	-0.08	0.01	-0.03	-0.09	-0.07
					(0.08)	(0.08)	(0.10)	(0.04)	(0.08)	(0.09)	(0.11)	(0.04)
ΔMW This Year X RoutineSh					-0.03	0.01	-0.01	0.01	-0.03	0.02	-0.04	0.01
					(0.04)	(0.03)	(0.05)	(0.02)	(0.04)	(0.03)	(0.04)	(0.02)
ΔMW Last Year X RoutineSh					-0.10*	0.04	0.02	0.04	-0.09*	0.03	0.00	0.04
					(0.05)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)	(0.05)	(0.03)
ΔMW 2Yrs Ago X RoutineSh					-0.22***	0.03	-0.07	0.09	-0.21***	0.04	-0.09	0.08
					(0.06)	(0.05)	(0.08)	(0.05)	(0.07)	(0.05)	(0.08)	(0.06)
State FE and Year FE	**Yes**				**Yes**				**No**			
State-by-Year FE	**No**				**No**				**Yes**			

Notes: This table reports the β_z^k and $\beta_{z,T}^k$ coefficients and standard errors from Equation (1). Specification 1 excludes the ΔMW-X- TaskSh interaction term; Specification 2 is Equation (1); and Specification 3 includes state-by-year fixed effects and includes the non-interacted ΔMW variables. Wage groups 1, 2, 3, and 4 includes occupations with the ratio of the average wages to the minimum wage of 1.0-1.5, 1.5-2.0, 2.0-2.5, and 2.5-6.0, respectively The sample size is $N = 95,781$ for all specifications. * p<0.10, ** p<0.05, and *** p<0.01.

Table 3: Employment Effects by Task Shares
Occupation Employment Statistics, 2010-2018

	Routine Cognitive	Routine Manual	Interpersonal	Nonroutine Cognitive	Nonroutine Manual
	(1)	(2)	(3)	(4)	(5)
Wage Group 1					
ΔMW Next Year X Task Share	0.01	0.03	-0.10	0.02	0.14
	(0.08)	(0.21)	(0.13)	(0.14)	(0.09)
ΔMW This Year X Task Share	-0.03	-0.10	0.03	0.05	0.07
	(0.04)	(0.09)	(0.09)	(0.12)	(0.07)
ΔMW Last Year X Task Share	-0.09*	-0.14*	0.19*	-0.09	-0.02
	(0.05)	(0.07)	(0.10)	(0.09)	(0.08)
ΔMW 2Yrs Ago X Task Share	-0.21***	-0.17***	0.24*	0.01	0.05
	(0.07)	(0.06)	(0.12)	(0.14)	(0.10)
Wage Group 2					
ΔMW Next Year X Task Share	-0.03	0.03	-0.03	-0.07	0.11**
	(0.09)	(0.07)	(0.06)	(0.08)	(0.05)
ΔMW This Year X Task Share	0.02	-0.08	0.00	0.08	0.01
	(0.03)	(0.09)	(0.09)	(0.05)	(0.07)
ΔMW Last Year X Task Share	0.03	0.03	-0.10	0.00	0.07
	(0.05)	(0.06)	(0.08)	(0.06)	(0.07)
ΔMW 2Yrs Ago X Task Share	0.04	0.05	-0.12**	0.06	0.02
	(0.05)	(0.03)	(0.05)	(0.08)	(0.05)

Notes: Each column varies by the task share used in the interaction term, ΔMW-X-Task Share. All specifications are otherwise identical to Specification 3 in Table 2. Each column presents the results from a different regression. The results from Wage Group 3 and Wage Group 4 are presented in Appendix Table A2. See the notes to Table 2 for Wage Group definitions. The sample size is $N = 95,781$ for each regression. *p<0.10, **p<0.05, and ***p<0.01.

Table 4: MSA-Level Employment Effects by Task Share

Occupation Employment Statistics, 2010-2018

		Employment Effects by Task Content			
	Overall Employment Effect	Routine Cognitive Tasks	Routine Manual Tasks	All Routine Tasks	Inter-personal Tasks
	(1)	(2)	(3)	(4)	(5)
Panel A: All Observations					
Wage Group 1					
ΔMW Next Year	0.07	0.01	0.02	0.02	-0.19
	(0.14)	(0.07)	(0.07)	(0.07)	(0.12)
ΔMW This Year	0.09	-0.06	-0.04	-0.05*	-0.05
	(0.06)	(0.04)	(0.04)	(0.03)	(0.08)
ΔMW Last Year	0.02	-0.04	0.09	0.03	0.00
	(0.09)	(0.03)	(0.06)	(0.04)	(0.08)
ΔMW 2Yrs Ago	0.09	-0.12**	-0.08	-0.12*	0.16*
	(0.07)	(0.06)	(0.06)	(0.07)	(0.08)
Wage Group 2					
ΔMW Next Year	-0.04	0.00	0.00	0.01	-0.02
	(0.13)	(0.04)	(0.05)	(0.06)	(0.05)
ΔMW This Year	-0.05	0.02	-0.13**	-0.10*	0.09
	(0.10)	(0.03)	(0.05)	(0.05)	(0.06)
ΔMW Last Year	-0.05	0.06	-0.08	-0.01	0.01
	(0.10)	(0.04)	(0.05)	(0.05)	(0.06)
ΔMW 2Yrs Ago	0.05	-0.08	0.04	-0.05	-0.04
	(0.08)	(0.07)	(0.09)	(0.07)	(0.08)
Panel B: Exclude the 25 Largest Metropolitan Areas					
Wage Group 1					
ΔMW Next Year	0.07	0.03	0.12*	0.08	-0.16**
	(0.09)	(0.05)	(0.06)	(0.06)	(0.08)
ΔMW This Year	0.02	-0.08*	-0.02	-0.08	0.08
	(0.07)	(0.04)	(0.07)	(0.05)	(0.06)
ΔMW Last Year	0.05	-0.06	-0.04	-0.06	0.13
	(0.06)	(0.04)	(0.05)	(0.04)	(0.07)
ΔMW 2Yrs Ago	0.01	-0.18***	-0.09	-0.15***	0.23***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)
Wage Group 2					
ΔMW Next Year	-0.06	-0.11***	-0.02	-0.13*	0.08
	(0.06)	(0.04)	(0.06)	(0.07)	(0.07)
ΔMW This Year	-0.02	-0.03	-0.09*	-0.10*	0.06
	(0.10)	(0.04)	(0.05)	(0.05)	(0.06)
ΔMW Last Year	-0.11	-0.01	-0.10*	-0.10*	0.08
	(0.07)	(0.04)	(0.05)	(0.05)	(0.06)
ΔMW 2Yrs Ago	-0.01	-0.11**	-0.15***	-0.24***	0.14**
	(0.07)	(0.05)	(0.05)	(0.06)	(0.06)

Notes: This table reports results using a panel of MSA-occupations. Each column-panel is a separate regression. The results for Wage Group 3 and 4 are presented in Appendix Table A4. See the notes for Table 2 for Wage Group definitions. Panel A's results include all MSAs ($N = 324,808$). Panel B excludes the 25 largest MSAs ($N = 289,014$). *p<0.10, **p<0.05, and ***p<0.01.

Table 5: Employment Effects by Task Share
American Community Survey, 2010-2018

		Employment Effects by Task Content			
	Overall Employment Effect	Routine Cognitive Tasks	Routine Manual Tasks	All Routine Tasks	Inter-personal Tasks
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample					
ΔMW Next Year	0.09	-0.05	-0.04	-0.05	0.07
	(0.10)	(0.09)	(0.11)	(0.11)	(0.11)
ΔMW This Year	0.09	0.03	0.03	0.04	-0.02
	(0.10)	(0.08)	(0.11)	(0.08)	(0.11)
ΔMW Last Year	0.08	0.05	0.10	0.09	-0.10*
	(0.09)	(0.07)	(0.07)	(0.06)	(0.05)
ΔMW 2Yrs Ago	-0.16*	-0.25***	-0.29***	-0.31***	0.35***
	(0.09)	(0.07)	(0.09)	(0.08)	(0.08)
Panel B: Exclude the 25 Largest MSAs					
ΔMW Next Year	0.15	-0.02	0.03	0.00	-0.02
	(0.13)	(0.13)	(0.12)	(0.13)	(0.14)
ΔMW This Year	0.06	0.02	-0.04	0.00	0.06
	(0.13)	(0.09)	(0.12)	(0.10)	(0.14)
ΔMW Last Year	0.17	0.05	0.04	0.06	-0.08
	(0.17)	(0.08)	(0.10)	(0.07)	(0.07)
ΔMW 2Yrs Ago	-0.05	-0.29***	-0.31**	-0.34***	0.39***
	(0.09)	(0.10)	(0.12)	(0.11)	(0.10)
Panel C: 25 Largest MSAs Only					
ΔMW Next Year	-0.22	-0.14	-0.10	-0.15	0.12
	(0.22)	(0.21)	(0.15)	(0.18)	(0.16)
ΔMW This Year	-0.10	0.00	-0.01	0.03	0.02
	(0.27)	(0.17)	(0.08)	(0.11)	(0.07)
ΔMW Last Year	-0.13	0.10	0.22	0.18*	-0.17
	(0.24)	(0.08)	(0.17)	(0.10)	(0.19)
ΔMW 2Yrs Ago	0.01	-0.05	-0.07	-0.12	0.12
	(0.20)	(0.14)	(0.30)	(0.19)	(0.29)

Notes: This table is based on a panel of occupation-industry-state (Panels A and B) or occupation-industry-MSA (Panel C) employment levels computed from the American Community Survey. Each column-panel is a separate regression. The results for Wage Groups 2, 3, and 4 for Panel A and Panel B are presented in Appendix Table A7. See notes for Table 2 for Wage Group definitions. The Panel A, B, and C specifications use $N = 235,770$, $N = 216,904$, and $N = 59,006$ observations, respectively. *p<0.10, **p<0.05, and ***p<0.01.

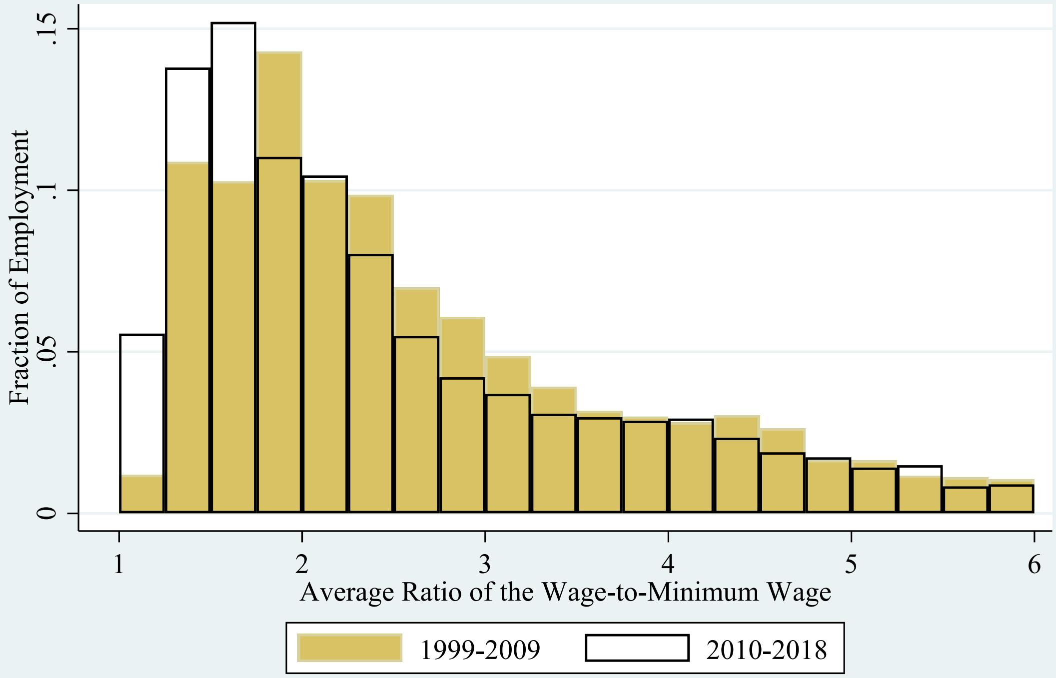
Table 6: Employment Effects by Background Characteristics

American Community Survey, 2010-2018

	By Education		By Age		By Race		By Sex	
	High School or Less	Some College or More	Under Age 30	Aged 30+	Non-Asian Minorities	Whites and Asians	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Overall Employment Effect								
ΔMW Next Year	0.06	0.25	0.23	-0.12	0.27	0.04	0.04	0.28**
	(0.15)	(0.18)	(0.18)	(0.13)	(0.21)	(0.11)	(0.13)	(0.13)
ΔMW This Year	0.18	-0.04	-0.15	0.31**	0.31	0.04	0.10	0.05
	(0.14)	(0.26)	(0.14)	(0.12)	(0.25)	(0.09)	(0.13)	(0.16)
ΔMW Last Year	0.05	0.21	-0.13	0.30**	0.28*	0.04	0.04	0.22
	(0.10)	(0.19)	(0.14)	(0.12)	(0.15)	(0.10)	(0.08)	(0.16)
ΔMW 2Yrs Ago	-0.05	-0.16	-0.13	-0.05	-0.56***	-0.04	-0.24**	-0.06
	(0.22)	(0.16)	(0.13)	(0.16)	(0.17)	(0.10)	(0.10)	(0.14)
Panel B: Employment Effects by Routine Tasks								
ΔMW Next Year	-0.06	-0.05	0.07	-0.15	0.08	-0.09	-0.06	-0.16
	(0.14)	(0.10)	(0.13)	(0.19)	(0.15)	(0.11)	(0.11)	(0.13)
ΔMW This Year	0.10	-0.06	-0.01	0.04	0.01	0.00	0.05	0.19
	(0.11)	(0.09)	(0.11)	(0.14)	(0.18)	(0.08)	(0.08)	(0.14)
ΔMW Last Year	-0.07	0.21	-0.04	0.19*	-0.11	0.12	0.05	0.05
	(0.10)	(0.13)	(0.11)	(0.11)	(0.16)	(0.08)	(0.07)	(0.12)
ΔMW 2Yrs Ago	-0.36***	-0.28**	-0.34***	-0.35***	-0.47**	-0.31***	-0.27***	-0.34*
	(0.11)	(0.13)	(0.10)	(0.13)	(0.19)	(0.09)	(0.08)	(0.17)
Panel C: Employment Effects by Interpersonal Tasks								
ΔMW Next Year	-0.02	0.15	-0.07	0.15	-0.17	0.11	0.09	0.20
	(0.15)	(0.12)	(0.13)	(0.16)	(0.14)	(0.14)	(0.11)	(0.20)
ΔMW This Year	0.01	0.04	-0.01	0.00	-0.03	0.04	-0.06	-0.05
	(0.11)	(0.14)	(0.11)	(0.14)	(0.19)	(0.12)	(0.11)	(0.21)
ΔMW Last Year	0.13	-0.23*	0.14	-0.20**	0.17	-0.15**	-0.07	-0.05
	(0.10)	(0.12)	(0.10)	(0.10)	(0.17)	(0.07)	(0.07)	(0.14)
ΔMW 2Yrs Ago	0.36***	0.36**	0.35***	0.43***	0.49**	0.37***	0.34***	0.36**
	(0.12)	(0.13)	(0.12)	(0.12)	(0.22)	(0.09)	(0.09)	(0.17)

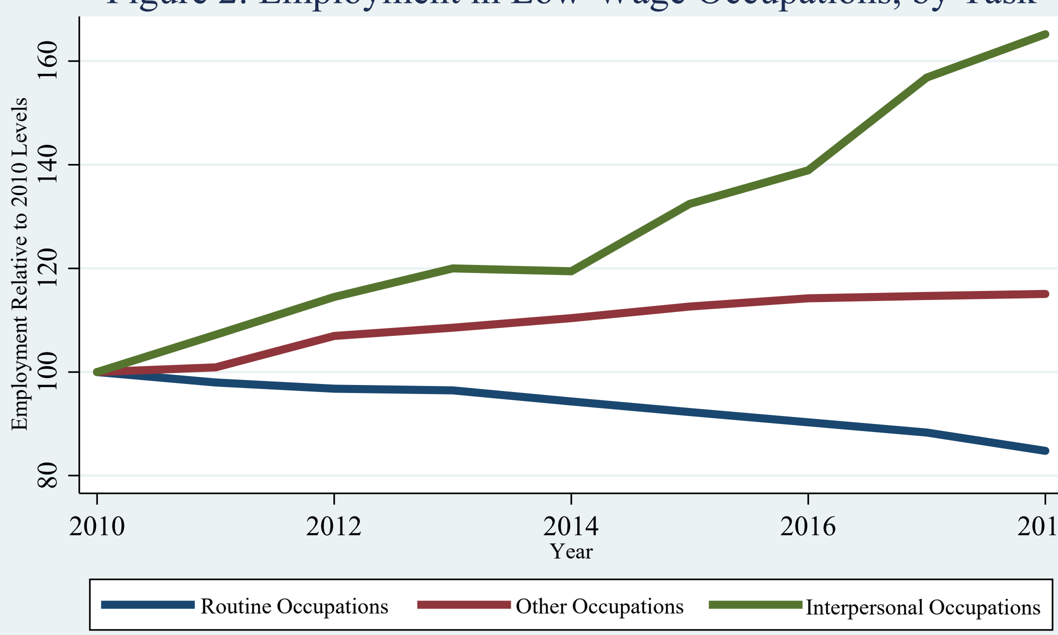
Notes: This table presents results stratified by education, age, race, and sex. Each column-panel is a separate regression. The results for Wage Groups 2 and 3 are presented in Appendix Table A8. See the notes of Table 2 for the Wage Group definitions. The occupation-industry-state-year employment levels for each subgroup are computed from the sample of individuals in the American Community Survey. The total number of observations in each regression includes: high school or less $N = 124, 409$; some college or more $N = 188, 359$; under aged 30 $N = 100, 569$; aged 30+ $N = 207, 197$; non-Asian minorities $N = 81, 3304$; white and Asian $N = 214, 905$; female $N = 155, 869$, and male $N = 147, 024$. * p<0.10, ** p<0.05, and *** p<0.01.

Figure 1: Distribution of the Occupation-State Average Wage to Minimum Wage Ratio



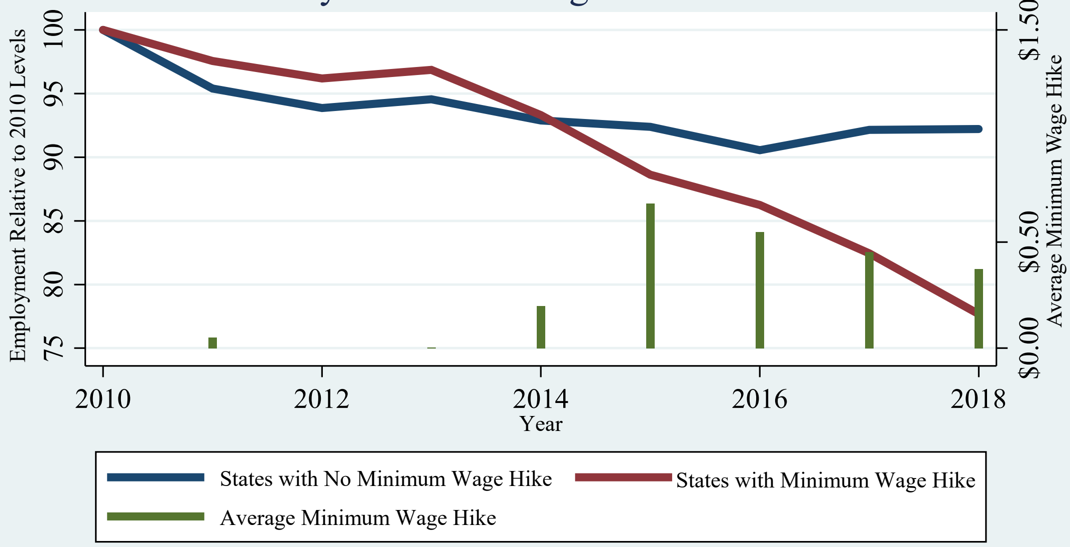
Notes: Wages and employment are from the 1999-2018 Occupation Employment Statistics.

Figure 2: Employment in Low-Wage Occupations, by Task



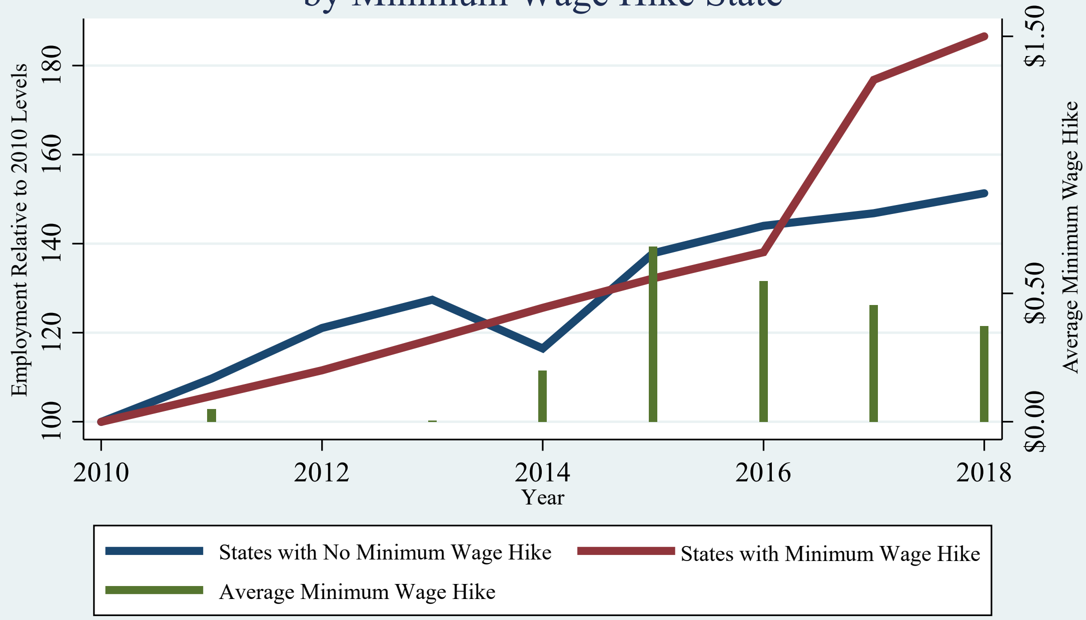
Notes: This figure is based on occupations that fall in Wage Group 1 in at least one state and uses data from the Occupation Employment Statistics. A routine (interpersonal) occupation has a routine (interpersonal) task share of at least 50 percent.

Figure 3: Employment in Low-Wage Routine Occupations by Minimum Wage Hike State



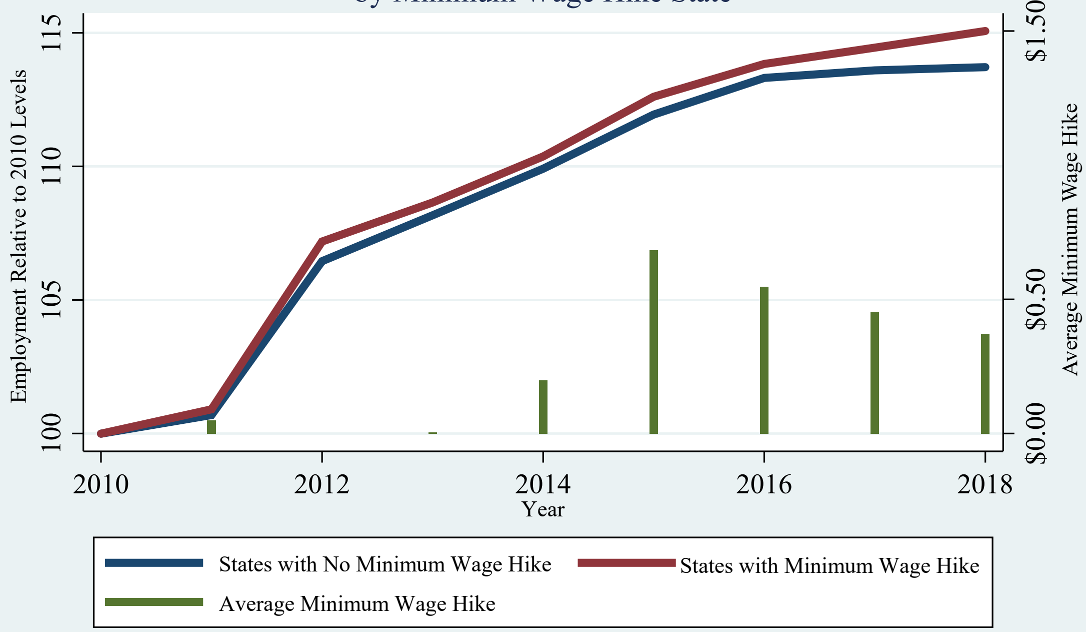
Notes: This figure is based on occupations that fall in Wage Group 1 in at least one state and uses data from the OES. The sample is further limited to occupations where routine tasks compose more than 50 percent of total tasks. The average minimum wage hike is an employment-based weighted average of the 19 states that increased their minimum wage at least once between 2010 and 2018. We exclude the 10 states with automatic annual inflation-based adjustments.

Figure 4: Employment in Low-Wage Interpersonal Occupations by Minimum Wage Hike State



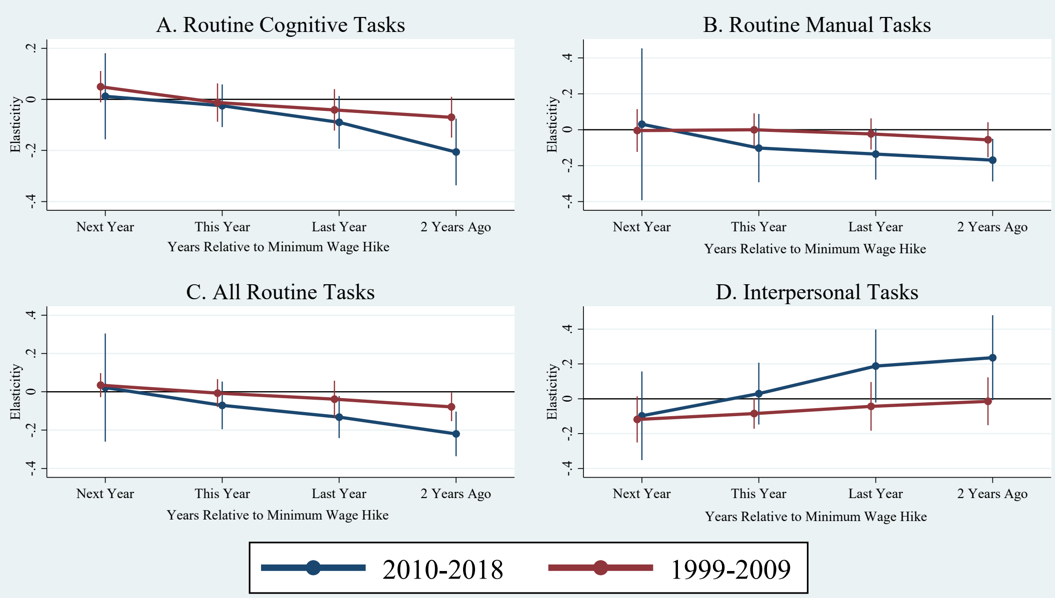
Notes: This figure is analogous to Figure 3 except it is limited to occupations where interpersonal tasks compose more than 50 percent of total tasks.

Figure 5: Employment in Low-Wage Non-Routine/Non-Interpersonal Occupations by Minimum Wage Hike State



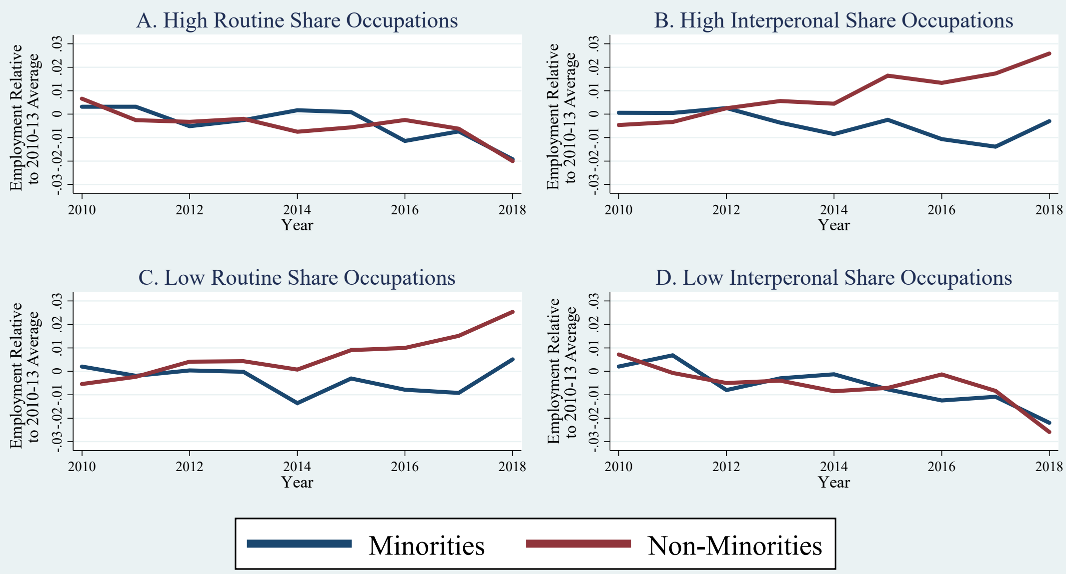
Notes: This figure is analogous to Figures 3 and 4 except it is limited to occupations where neither routine nor interpersonal tasks compose more than 50 percent of the total tasks.

Figure 6: Effect of Minimum Wage Hikes by Task Intensity 1999-2009 vs. 2010-2018



Notes: This figure presents the estimated elasticity prior to and following a minimum wage hike for Wage Group 1 occupations using 1999-2009 and 2010-2018 OES data. The standard error bars capture the 95% confidence interval for each estimated elasticity.

Figure 7: Wage Group 1 Employment Effects, by Race and Minimum Wage Hike Status



Notes: This figure plots the relative change in log routine or interpersonal employment between minimum wage hike and non-minimum wage hike states. Non-minorities include Whites and Asians. Minorities include all other races. High routine (interpersonal) share occupations include all occupations with an routine (interpersonal) share greater than 45 percent. Low routine (interpersonal) share occupations include all occupations with a routine (interpersonal) share less than 35 (37.5) percent. High (low) share occupations reflect occupations in the upper (lower) three declines of the distribution.

Table A1: State-Level Minimum Wage Changes, 2010-2018

	States														
Year	**AK**	**AZ**	**AR**	**CA**	**CO**	**CT**	**DE**	**DC**	**FL**	**HI**	**IL**	**ME**	**MD**	**MA**	**MI**
2010	\$7.75	\$7.25	\$7.25	\$8.00	\$7.25	\$8.25	\$7.25	\$8.25	\$7.25	\$7.25	\$8.00	\$7.50	\$7.25	\$8.00	\$7.40
2011		\$7.35			\$7.36				\$7.25		\$8.25				
2012		\$7.65			\$7.64				\$7.67						
2013		\$7.80			\$7.78				\$7.79						
2014		\$7.90			\$8.00	\$8.70			\$7.93						
2015	\$8.75	\$8.05	\$7.50	\$9.00	\$8.23	\$9.15	\$7.75	\$9.50	\$8.05	\$7.75			\$8.00	\$9.00	\$8.15
2016	\$9.75	\$8.05	\$8.00	\$10.00	\$8.31	\$9.60	\$8.25	\$10.50	\$8.05	\$8.50			\$8.25	\$10.00	\$8.50
2017	\$9.80	\$10.00	\$8.50	\$10.50	\$9.30			\$11.50	\$8.10	\$9.25		\$9.00	\$8.75	\$11.00	\$8.90
2018	\$9.84	\$10.50	\$8.50	\$11.00	\$10.20			\$12.50	\$8.25	\$10.10		\$10.00	\$9.25	\$11.00	\$9.25
2019	\$9.89	\$11.00	\$9.25	\$12.00	\$11.10	\$10.10	\$8.75	\$13.25	\$8.46			\$11.00	\$10.10	\$12.00	\$9.45

	MN	**MO**	**MT**	**NE**	**NV**	**NJ**	**NY**	**OH**	**OR**	**RI**	**SD**	**VT**	**WA**	**WV**
2010	\$7.25	\$7.25	\$7.25	\$7.25	\$7.55	\$7.25	\$7.25	\$7.30	\$8.40	\$7.40	\$7.25	\$8.06	\$8.55	\$7.25
2011			\$7.35		\$8.25			\$7.40	\$8.50			\$8.15	\$8.67	
2012			\$7.65					\$7.70	\$8.80			\$8.46	\$9.04	
2013		\$7.35	\$7.80					\$7.85	\$8.95	\$7.75		\$8.60	\$9.19	
2014		\$7.50	\$7.90			\$8.25	\$8.00	\$7.95	\$9.10	\$8.00		\$8.73	\$9.32	
2015	\$8.00	\$7.65	\$8.05	\$8.00		\$8.38	\$8.75	\$8.10	\$9.25	\$9.00	\$8.50	\$9.15	\$9.47	\$8.00
2016	\$9.00		\$8.05	\$9.00			\$9.00			\$9.60	\$8.55	\$9.60		\$8.75
2017	\$9.50	\$7.70	\$8.15			\$8.44	\$9.70	\$8.15	\$9.75		\$8.65	\$10.00	\$11.00	
2018	\$9.65	\$7.85	\$8.30			\$8.60	\$10.40	\$8.30	\$10.25	\$10.10	\$8.85	\$10.50	\$11.50	
2019	\$9.86	\$8.60	\$8.50		\$8.85	\$11.10	\$8.55	\$10.75	\$10.50	\$9.10	\$10.78	\$12.00		

Notes: This table excludes 22 states in which the minimum wage did not change between 2010-2019. The empirical analysis also excludes the following states that had automatic CPI adjustments over most of the period of analysis: Arizona, Colorado, Connecticut, Florida, Missouri, Montana, Ohio, Oregon, Vermont, and Washington.

Table A2: Employment Effects by Task Shares for Wage Group 3 and 4
Occupation Employment Statistics, 2010-2018

	Routine Cognitive	Routine Manual	Interpersonal	Nonroutine Cognitive	Nonroutine Manual
	(1)	(2)	(3)	(4)	(5)
Wage Group 3					
ΔMW Next Year X Task Share	-0.09	-0.05	0.14	0.09	-0.04
	(0.11)	(0.11)	(0.12)	(0.12)	(0.04)
ΔMW This Year X Task Share	-0.04	-0.05	0.03	0.13**	0.00
	(0.04)	(0.08)	(0.07)	(0.06)	(0.03)
ΔMW Last Year X Task Share	0.00	-0.04	0.04	0.15*	-0.06*
	(0.05)	(0.05)	(0.05)	(0.08)	(0.03)
ΔMW 2Yrs Ago X Task Share	-0.09	0.01	0.03	0.06	0.02
	(0.08)	(0.07)	(0.09)	(0.12)	(0.04)
Wage Group 4					
ΔMW Next Year X Task Share	-0.07	-0.20**	0.19***	0.17**	-0.18***
	(0.04)	(0.08)	(0.06)	(0.08)	(0.06)
ΔMW This Year X Task Share	0.01	0.01	0.00	-0.01	-0.01
	(0.02)	(0.08)	(0.07)	(0.06)	(0.07)
ΔMW Last Year X Task Share	0.04	0.02	0.00	-0.06*	-0.03
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
ΔMW 2Yrs Ago X Task Share	0.08	0.10*	-0.09**	-0.08	0.05
	(0.06)	(0.05)	(0.04)	(0.05)	(0.06)

Notes: This table shows the Wage Group 3 and 4 coefficients for the regressions presented in Table 3. See Table 3 for more details. *p<0.10, **p<0.05, and ***p<0.01.

Table A3: Employment Effects, by Task Share and Decade

Occupational Employment Statistics, 1999-2018

	Overall Employment Effect		**Employment Effects by Task Content: Routine Cognitive Tasks**		**Routine Manual Tasks**		**All Routine Tasks**		**Interpersonal Tasks**	
	1999-2009	**2010-2018**	**1999-2009**	**2010-2018**	**1999-2009**	**2010-2018**	**1999-2009**	**2010-2018**	**1999-2009**	**2010-2018**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Wage Group 1										
ΔMW Next Year	0.07	0.19***	0.05	0.01	0.00	0.03	0.04	0.02	-0.12*	-0.10
	(0.06)	(0.07)	(0.03)	(0.08)	(0.06)	(0.21)	(0.03)	(0.14)	(0.07)	(0.13)
ΔMW This Year	0.07	0.06	-0.01	-0.03	0.00	-0.10	-0.01	-0.07	-0.09*	0.03
	(0.06)	(0.08)	(0.04)	(0.04)	(0.05)	(0.09)	(0.04)	(0.06)	(0.04)	(0.09)
ΔMW Last Year	0.10	0.09*	-0.04	-0.09*	-0.02	-0.14*	-0.04	-0.13**	-0.04	0.19*
	(0.06)	(0.05)	(0.04)	(0.05)	(0.04)	(0.07)	(0.05)	(0.05)	(0.07)	(0.10)
ΔMW 2Yrs Ago	0.09	0.01	-0.07*	-0.21***	-0.06	-0.17***	-0.08**	-0.22***	-0.01	0.24*
	(0.05)	(0.08)	(0.04)	(0.07)	(0.05)	(0.06)	(0.04)	(0.06)	(0.07)	(0.12)
Wage Group 2										
ΔMW Next Year	0.06	-0.09	0.04*	-0.03	-0.05	0.03	-0.01	0.01	0.00	-0.03
	(0.05)	(0.06)	(0.03)	(0.09)	(0.03)	(0.07)	(0.04)	(0.08)	(0.05)	(0.06)
ΔMW This Year	0.03	0.05	0.04	0.02	-0.06*	-0.08	-0.02	-0.07	0.02	0.00
	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)	(0.09)	(0.04)	(0.08)	(0.04)	(0.09)
ΔMW Last Year	0.04	-0.04	0.01	0.03	-0.05	0.03	-0.04	0.06	0.02	-0.10
	(0.08)	(0.05)	(0.03)	(0.05)	(0.04)	(0.06)	(0.05)	(0.08)	(0.05)	(0.08)
ΔMW 2Yrs Ago	-0.01	0.02	-0.01	0.04	-0.11	0.05	-0.12	0.08	0.13*	-0.12**
	(0.09)	(0.05)	(0.05)	(0.05)	(0.07)	(0.03)	(0.07)	(0.07)	(0.07)	(0.05)

Notes: This table shows results by decade using the specifications from Table 3. See Table 3 for more details. N=151, 948 for the 1999-2009 period and N=95, 781 for the 2010-2018 period. *p<0.10, **p<0.05, and ***p<0.01.

Table A4: MSA-level Employment Effects, by Task Share for Wage Group 3 and 4

Occupation Employment Statistics, 2010-2018

	Overall Employment Effect		Employment Effects by Task Content: Routine Cognitive Tasks		Routine Manual Tasks		All Routine Tasks		Interpersonal Tasks	
	All MSAs	Exclude 25 Largest MSAs	All MSAs	Exclude 25 Largest MSAs	All MSAs	Exclude 25 Largest MSAs	All MSAs	Exclude 25 Largest MSAs	All MSAs	Exclude 25 Largest MSAs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Wage Group 3										
ΔMW Next Year	-0.02	-0.03	-0.13**	-0.11*	-0.11	-0.08	-0.24***	-0.20***	0.12	0.12**
	(0.12)	(0.08)	(0.05)	(0.07)	(0.08)	(0.08)	(0.07)	(0.06)	(0.08)	(0.06)
ΔMW This Year	-0.09	-0.01	-0.04	-0.05	0.00	-0.07	-0.04	-0.12**	-0.04	0.10**
	(0.07)	(0.07)	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
ΔMW Last Year	-0.04	-0.09	-0.04	-0.05	0.05	0.00	-0.01	-0.06	-0.02	0.04
	(0.12)	(0.07)	(0.04)	(0.04)	(0.06)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)
ΔMW 2Yrs Ago	-0.06	-0.13*	-0.08*	-0.06	0.00	-0.04	-0.09*	-0.12*	0.03	0.07
	(0.08)	(0.07)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
Wage Group 4										
ΔMW Next Year	0.02	0.10	0.00	-0.05	-0.16***	-0.07	-0.10***	-0.08**	0.13***	0.06
	(0.13)	(0.08)	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
ΔMW This Year	-0.12*	-0.10	-0.05**	-0.05	-0.07**	-0.12***	-0.08***	-0.12***	0.07***	0.11***
	(0.07)	(0.12)	(0.02)	(0.04)	(0.03)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)
ΔMW Last Year	0.02	-0.02	0.03	0.04	-0.04	-0.13**	-0.01	-0.05	0.03	0.09**
	(0.09)	(0.07)	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)
ΔMW 2Yrs Ago	0.07	-0.07	0.08**	0.09**	0.01	-0.14***	0.06	-0.02	-0.05	0.07
	(0.09)	(0.06)	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)

Notes: This table shows the Wage Group 3 and 4 coefficients for the regressions presented in Table 4. See Table 4 for more details. *p<0.10, **p<0.05, and ***p<0.01.

Table A5: MSA-level Employment Effects, Excluding MSAs that Cross State Borders
Occupation Employment Statistics, 2010-2018

		Employment Effects by Task Content			
	Overall Employment Effect	**Routine Cognitive Tasks**	**Routine Manual Tasks**	**All Routine Tasks**	**Inter-personal Tasks**
Wage Group 1					
ΔMW Next Year	-0.09	-0.03	0.07	0.02	-0.10
	(0.10)	(0.06)	(0.09)	(0.09)	(0.12)
ΔMW This Year	0.05	-0.09***	0.01	-0.06*	0.03
	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)
ΔMW Last Year	-0.03	-0.04	0.06*	0.01	0.03
	(0.08)	(0.03)	(0.04)	(0.03)	(0.05)
ΔMW 2Yrs Ago	0.01	-0.15**	-0.05	-0.13*	0.18**
	(0.05)	(0.06)	(0.07)	(0.07)	(0.08)
Wage Group 2					
ΔMW Next Year	-0.21***	-0.02	-0.03	-0.04	-0.01
	(0.08)	(0.06)	(0.06)	(0.07)	(0.06)
ΔMW This Year	-0.09	0.02	-0.12*	-0.09	0.07
	(0.10)	(0.04)	(0.07)	(0.07)	(0.07)
ΔMW Last Year	-0.15***	0.07*	-0.11**	-0.03	0.06
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
ΔMW 2Yrs Ago	-0.05	-0.10	0.04	-0.07	-0.03
	(0.06)	(0.08)	(0.10)	(0.08)	(0.08)

Notes: This table presents results analogous to Table 4 when 51 of the 328 metro areas that cross state boundaries are excluded. The sample size is $N = 270,622$ for all of these specifications. See Table 4 for more details. *p<0.10, **p<0.05, and ***p<0.01.

Table A6: Employment Effects Using an Occupation-State-Year Panel
American Community Survey, 2010-2018

	Overall Employment Effect	Routine Cognitive Tasks	Routine Manual Tasks	All Routine Tasks	Inter-personal Tasks
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample					
ΔMW Next Year	0.16	-0.05	-0.03	-0.04	0.06
	(0.10)	(0.06)	(0.09)	(0.07)	(0.09)
ΔMW This Year	0.17	-0.06	-0.11	-0.08	0.14
	(0.11)	(0.07)	(0.10)	(0.07)	(0.09)
ΔMW Last Year	0.08	-0.02	-0.03	-0.02	0.07
	(0.09)	(0.06)	(0.08)	(0.05)	(0.09)
ΔMW 2Yrs Ago	-0.04	-0.15*	-0.24**	-0.21**	0.25**
	(0.08)	(0.09)	(0.12)	(0.09)	(0.10)
Panel B: Exclude the 25 Largest MSAs					
ΔMW Next Year	0.15	-0.07	-0.05	-0.06	0.07
	(0.14)	(0.09)	(0.14)	(0.11)	(0.14)
ΔMW This Year	0.13	-0.03	-0.13	-0.07	0.16
	(0.12)	(0.09)	(0.12)	(0.09)	(0.13)
ΔMW Last Year	0.15	0.00	-0.03	-0.01	0.04
	(0.14)	(0.07)	(0.11)	(0.06)	(0.11)
ΔMW 2Yrs Ago	-0.02	-0.22*	-0.29**	-0.27**	0.33***
	(0.09)	(0.11)	(0.13)	(0.11)	(0.12)
Panel C: 25 Largest MSAs Only					
ΔMW Next Year	0.02	-0.01	-0.01	-0.02	-0.03
	(0.19)	(0.22)	(0.19)	(0.18)	(0.20)
ΔMW This Year	0.10	-0.18	-0.25**	-0.20*	0.31**
	(0.26)	(0.17)	(0.10)	(0.11)	(0.13)
ΔMW Last Year	-0.14	-0.01	0.05	0.03	0.02
	(0.26)	(0.06)	(0.14)	(0.07)	(0.15)
ΔMW 2Yrs Ago	0.14	0.06	0.08	0.04	0.02
	(0.21)	(0.12)	(0.28)	(0.16)	(0.22)

Notes: This table removes the industry component of the ACS panel used in Table 5 to be comparable to the OES analysis. See Table 5 for more details. The sample sizes are $N = 67,409$, $N = 66,150$, and $N = 18,798$ for Panel A, B, and C, respectively. *p<0.10, **p<0.05, and ***p<0.01.

Table A7: Employment Effects by Task Share for Wage Groups 2-4
American Community Survey, 2010-2018

	Overall Employment Effect	Routine Cognitive Tasks	Routine Manual Tasks	All Routine Tasks	Inter-personal Tasks
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample of Individuals					
Wage Group 2					
ΔMW Next Year	0.00	0.01	-0.02	-0.02	0.05
	(0.09)	(0.09)	(0.07)	(0.08)	(0.07)
ΔMW This Year	0.02	-0.04	-0.04	-0.05	0.05
	(0.09)	(0.07)	(0.09)	(0.08)	(0.08)
ΔMW Last Year	0.04	-0.05	-0.10*	-0.12*	0.14**
	(0.10)	(0.09)	(0.05)	(0.06)	(0.07)
ΔMW 2Yrs Ago	-0.15*	0.13	0.00	0.10	-0.06
	(0.08)	(0.10)	(0.09)	(0.09)	(0.09)
Wage Group 3					
ΔMW Next Year	0.11*	0.15**	-0.04	0.07	-0.01
	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)
ΔMW This Year	0.10	0.07	0.05	0.06	-0.06
	(0.10)	(0.08)	(0.06)	(0.05)	(0.04)
ΔMW Last Year	-0.06	0.02	-0.09*	-0.05	0.08
	(0.08)	(0.06)	(0.05)	(0.06)	(0.07)
ΔMW 2Yrs Ago	-0.14	-0.02	-0.09*	-0.04	0.05
	(0.10)	(0.05)	(0.05)	(0.06)	(0.07)
Wage Group 4					
ΔMW Next Year	0.07	-0.03	-0.06	-0.06	0.05
	(0.08)	(0.04)	(0.07)	(0.04)	(0.05)
ΔMW This Year	0.01	0.04	-0.04	0.00	0.01
	(0.06)	(0.05)	(0.05)	(0.03)	(0.04)
ΔMW Last Year	0.04	0.00	0.03	0.02	-0.02
	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)
ΔMW 2Yrs Ago	0.09*	-0.02	-0.01	-0.01	0.01
	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)
Panel B: Excluding Individuals from the 25 Largest MSAs					
Wage Group 2					
ΔMW Next Year	0.03	0.01	0.03	0.02	0.00
	(0.14)	(0.10)	(0.06)	(0.08)	(0.07)
ΔMW This Year	0.13	-0.09	-0.09	-0.12**	0.08
	(0.11)	(0.06)	(0.08)	(0.05)	(0.07)
ΔMW Last Year	0.12	-0.17**	-0.07	-0.17**	0.17**
	(0.13)	(0.08)	(0.06)	(0.07)	(0.07)
ΔMW 2Yrs Ago	-0.09	0.23**	0.07	0.21**	-0.14
	(0.10)	(0.11)	(0.09)	(0.10)	(0.09)
Wage Group 3					
ΔMW Next Year	0.16*	0.11	-0.04	0.03	0.01
	(0.08)	(0.08)	(0.07)	(0.07)	(0.06)
ΔMW This Year	0.13	0.04	0.04	0.03	-0.03
	(0.12)	(0.09)	(0.08)	(0.07)	(0.07)
ΔMW Last Year	0.00	-0.07	-0.05	-0.08	0.07
	(0.14)	(0.06)	(0.06)	(0.06)	(0.07)
ΔMW 2Yrs Ago	-0.05	-0.04	-0.10	-0.06	0.06
	(0.11)	(0.06)	(0.07)	(0.07)	(0.07)
Wage Group 4					
ΔMW Next Year	0.17	-0.05	-0.06	-0.07	0.06
	(0.11)	(0.06)	(0.08)	(0.07)	(0.06)
ΔMW This Year	0.06	0.07	-0.07	0.00	0.03
	(0.09)	(0.04)	(0.06)	(0.05)	(0.06)
ΔMW Last Year	0.02	-0.02	0.09*	0.04	-0.05
	(0.10)	(0.07)	(0.05)	(0.06)	(0.05)
ΔMW 2Yrs Ago	0.16*	0.03	-0.01	0.03	0.01
	(0.09)	(0.06)	(0.05)	(0.05)	(0.05)

Notes: Notes: This table shows the Wage Group 2, 3, and 4 coefficients for the regressions presented in Table 5. See Table 5 for more details. *p<0.10, **p<0.05, and ***p<0.01.

Table A8: Employment Effects by Background Characteristics for Wage Groups 2-3
American Community Survey, 2010-2018

	By Education		By Age		By Race		By Sex	
	High School or Less	Some College or More	Under Aged 30	Aged 30+	Non-Asian Minorities	Whites and Asians	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Overall Employment Effect								
Wage Group 2								
ΔMW Next Year	0.10	-0.05	-0.17	0.08	0.01	0.03	0.25	-0.05
	(0.14)	(0.14)	(0.16)	(0.10)	(0.13)	(0.11)	(0.22)	(0.10)
ΔMW This Year	0.12	-0.04	0.19	-0.03	-0.01	0.06	0.20	-0.04
	(0.13)	(0.10)	(0.13)	(0.09)	(0.14)	(0.07)	(0.21)	(0.09)
ΔMW Last Year	0.07	0.06	-0.12	0.13	0.13	-0.10	0.36**	-0.03
	(0.12)	(0.14)	(0.16)	(0.09)	(0.10)	(0.13)	(0.17)	(0.11)
ΔMW 2Yrs Ago	-0.08	-0.08	-0.19	-0.13	-0.14	-0.10	-0.20	-0.12
	(0.15)	(0.11)	(0.15)	(0.10)	(0.12)	(0.14)	(0.12)	(0.10)
Wage Group 3								
ΔMW Next Year	0.25	0.04	0.23	0.05	0.21**	-0.06	0.13	0.10
	(0.17)	(0.10)	(0.17)	(0.08)	(0.09)	(0.12)	(0.20)	(0.09)
ΔMW This Year	0.19	0.01	0.07	0.11	0.07	0.16	0.52**	0.03
	(0.12)	(0.14)	(0.25)	(0.09)	(0.10)	(0.12)	(0.24)	(0.09)
ΔMW Last Year	-0.11	0.05	-0.27	0.02	-0.11	-0.02	0.23	-0.08
	(0.10)	(0.11)	(0.22)	(0.08)	(0.10)	(0.07)	(0.28)	(0.08)
ΔMW 2Yrs Ago	-0.19	-0.23***	-0.03	-0.16	-0.08	-0.19**	-0.37	-0.12
	(0.17)	(0.07)	(0.17)	(0.11)	(0.14)	(0.08)	(0.33)	(0.08)
Panel B: Employment Effects by Routine Tasks								
Wage Group 2								
ΔMW Next Year	0.08	-0.11	-0.10	0.00	-0.01	-0.05	-0.03	-0.03
	(0.11)	(0.08)	(0.09)	(0.10)	(0.07)	(0.11)	(0.15)	(0.07)
ΔMW This Year	-0.16*	-0.04	-0.18**	-0.03	-0.04	-0.08	0.06	-0.10
	(0.08)	(0.14)	(0.08)	(0.11)	(0.11)	(0.11)	(0.11)	(0.08)
ΔMW Last Year	-0.14	-0.12	-0.14	-0.13	-0.12*	-0.10	-0.21*	-0.08
	(0.09)	(0.08)	(0.13)	(0.08)	(0.07)	(0.09)	(0.13)	(0.08)
ΔMW 2Yrs Ago	0.05	0.16*	0.11	0.07	0.14	-0.16	0.00	0.08
	(0.13)	(0.10)	(0.09)	(0.12)	(0.09)	(0.13)	(0.17)	(0.08)
Wage Group 3								
ΔMW Next Year	-0.05	0.10	-0.17	0.10*	0.09	0.05	0.12	0.06
	(0.12)	(0.08)	(0.23)	(0.05)	(0.08)	(0.12)	(0.17)	(0.06)
ΔMW This Year	0.05	0.06	0.05	0.06	-0.03	0.12	0.21	0.05
	(0.15)	(0.10)	(0.23)	(0.06)	(0.06)	(0.11)	(0.16)	(0.06)
ΔMW Last Year	0.04	-0.05	0.00	-0.08	0.05	-0.11	-0.14	-0.07
	(0.06)	(0.07)	(0.11)	(0.07)	(0.08)	(0.07)	(0.18)	(0.06)
ΔMW 2Yrs Ago	-0.17	0.01	-0.07	-0.03	-0.03	-0.09	-0.37**	0.00
	(0.14)	(0.06)	(0.21)	(0.09)	(0.07)	(0.07)	(0.17)	(0.07)
Panel C: Employment Effects by Interpersonal Tasks								
Wage Group 2								
ΔMW Next Year	0.06	0.08	0.26***	0.00	-0.06	0.24***	0.14	0.03
	(0.07)	(0.10)	(0.09)	(0.08)	(0.08)	(0.08)	(0.12)	(0.07)
ΔMW This Year	0.11	0.05	0.10	0.08	0.06	0.03	0.03	0.07
	(0.08)	(0.14)	(0.09)	(0.10)	(0.12)	(0.09)	(0.11)	(0.09)
ΔMW Last Year	0.12	0.15*	0.16	0.10	0.12*	0.13	0.20	0.09
	(0.10)	(0.08)	(0.14)	(0.08)	(0.07)	(0.08)	(0.14)	(0.09)
ΔMW 2Yrs Ago	0.01	-0.11	-0.04	0.00	-0.12	0.14	0.01	0.01
	(0.12)	(0.12)	(0.10)	(0.11)	(0.09)	(0.11)	(0.16)	(0.08)
Wage Group 3								
ΔMW Next Year	0.05	0.00	0.19	-0.04	-0.03	0.01	0.09	0.00
	(0.08)	(0.07)	(0.17)	(0.05)	(0.09)	(0.08)	(0.14)	(0.05)
ΔMW This Year	-0.04	-0.05	-0.04	-0.04	0.03	-0.13	-0.34	-0.02
	(0.09)	(0.10)	(0.13)	(0.06)	(0.07)	(0.09)	(0.21)	(0.06)
ΔMW Last Year	0.07	0.03	0.15	0.10	-0.14	0.23***	-0.07	0.13
	(0.07)	(0.07)	(0.10)	(0.09)	(0.09)	(0.07)	(0.13)	(0.08)
ΔMW 2Yrs Ago	0.16	-0.03	-0.08	0.07	0.06	0.10*	0.38***	0.01
	(0.12)	(0.07)	(0.14)	(0.09)	(0.12)	(0.06)	(0.12)	(0.08)

Notes: This table shows the Wage Group 2 and 3 coefficients for the regressions presented in Table 6. See Table 6 for more details. *p<0.10, **p<0.05, and ***p<0.01.