JANUARY 2020

The Evolution of Technological Substitution in Low-Wage Labor Markets

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Abstract

This paper documents how the susceptibility of low-wage occupational employment to technological substitution has changed over the first two decades of the century. We find that low-wage automation has accelerated and spread to a broader set of jobs since the Financial Crisis – decreasing employment at both cognitively routine and manually routine jobs. However, we also find that low-wage automation is associated with increases in the demand for jobs requiring interpersonal tasks. That said, the growth in jobs requiring interpersonal tasks does not appear to be enough – as it was prior to the Financial Crisis - to fully offset the negative effects of automation on low-wage routine jobs. We also show that low-wage automation is occurring at a much higher rate outside of the largest U.S. cities and disproportionately impacts less-educated workers who are young, male, and especially minority.

JEL Codes: J20, J30

Keywords: Low-wage automation, routine tasks, minimum wages

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 done 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). A certain unease about technology is warranted when job loss arises 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 that it has been associated 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 how this change, to the extent it is taking place, is affecting individual workers. 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, a handful of recent studies explicitly examine this question by exploiting minimum wage hikes as a shock to the relative price of low-skill labor to help identify whether low-wage automation is taking place.

Broadly, these studies follow two strategies. First, a growing number of papers directly examine capital expenditures of firms following minimum wage hikes (Chen, 2019; Cho, 2018; Geng et al., 2018; Gustafson and Kotter, 2018; Hau et al., 2018; Qiu and Dai, 2019). Although the accumulated evidence to date is still somewhat mixed and concentrated in countries, especially China, where firm data on detailed capital expenditures exist, the majority of these studies find that minimum wage hikes expedite the adoption of labor-saving capital, consistent with the objective of automation. A second, smaller set of papers explore changes in the composition of low-wage employment and infer automation using a job's required tasks (Aaronson and Phelan 2017; Lordan and Neumark, 2018).[1] These papers follow a long, influential literature that assumes that automation technology is more likely to replace jobs with a larger share of tasks that are routine in nature (e.g. Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney 2006). The evidence from Aaronson and Phelan (2017) and Lordan and Neumark (2018), while somewhat differing in detail, largely suggest that jobs intensive in routine tasks are lost after minimum wage hikes and therefore low-wage automation is indeed taking place. An additional benefit of this employment-based approach is that it allows one to assess the impact of automation on the overall low-wage labor market and individual workers.

This paper extends the empirical analysis in Aaronson and Phelan (2017), which ends in 2009 in the midst of the Financial Crisis. Since then, the price of technology has continued to fall and many localities have enacted sharp increases in their minimum wage.[2] On its face, these developments might suggest that automation has spread over time. Our main contribution is to document the extent to which the susceptibility of low-wage occupational employment to technological substitution has indeed changed over the first two decades of the century (i.e. pre- vs. post-Financial Crisis). Along the way, we expand our previous empirical analysis by (a) taking advantage of the growing prevalence of city-level minimum wage legislation to show how results vary as we use move to local measures of labor markets and (b) exploring heterogeneity across demographic groups using the American Community Survey (ACS). The ACS also solves some practical measurement problems that arise with the main occupational dataset we focus on – the Occupational Employment Statistics (OES).

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, cognitively routine job loss has grown larger since the Financial Crisis and job loss has spread to jobs 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. As in Aaronson and Phelan (2017), 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

[1] A paper that is a little harder to categorize is Downey (2019), which posits that minimum wage hikes could reduce the automation of middle-skill jobs. He argues that automation technology that replaces middle-skill workers also increases the demand for low-skilled workers to operate the new technology. Therefore, minimum wage hikes will slow the adoption of automation technology that replaces middle-skill jobs.

[2] 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.

prior to the Financial Crisis – to offset the negative effects of automation on low-wage routine jobs.

We further document evidence of notable heterogeneous effects in both the OES and ACS. In particular, using the OES, we show that the impact of automation on low-wage employment loss is larger in rural and smaller metropolitan areas. Additionally, when we limit our ACS sample to those workers with a high school diploma or less, i.e. those who are most likely to be affected by minimum wage hikes, the estimated employment response across both routine and interpersonal jobs is about twice as large as the estimates using the full sample of workers in the ACS and OES. This estimated employment realignment notably arises among less educated workers who are young (under age 30), minority, or male and translates into especially large total job losses among less-educated minority workers.

In sum, low-wage automation is continuing to take place and quite likely has accelerated over the last decade. Minimum wage hikes continue to cause declines in occupations that are intensive in routine tasks. While this job loss has been accompanied by employment 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.

Theoretical Framework[3]

In a standard competitive model, higher costs arising from a minimum wage hike unambiguously lead to less local low-skill employment through both the elasticity of substitution between labor and other factors of production, i.e. the substitution effect, and the elasticity of demand for the output good, i.e. the scale effect (Hamermesh, 1996; Aaronson and French, 2007). Other inputs, for example capital and high-skill labor, may go up (gross substitute) or down (gross complement) depending on whether the substitution or scale effect dominates.

Yet even within low-wage labor markets, there may be heterogeneous effects of higher labor costs on employment. A series of influential papers show that technology is particularly suitable to displacing labor that performs routine tasks (e.g. Autor, Levy, and Murnane 2003; Acemoglu and Autor, 2011; Goos, Manning, and Salomons 2014). Thus, low-wage routine labor may experience disproportionate employment declines via the substitution effect. On the other hand, non-routine low-wage labor may be, at least in part, complementary to technological adoption, making the impact of capital investments on low-wage non-routine employment ambiguous.

One reason for this ambiguity is that often the introduction of new technologies involve moving some tasks that were previously performed by an employee onto the customer, such as scanning items with self-scanners. As firms introduce these new labor-saving technologies, they simultaneously create jobs requiring new skills, such as maintaining the new machinery or overseeing customer interaction with the technology. Consequently, in the short-run, employment growth in jobs that, say, require interpersonal skills could help offset the decline in

[3] This section borrows heavily from Aaronson and Phelan (2017). See it for a complete derivation of the model.

routine jobs that are eliminated by automation. However, 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.

However, two other potential explanations are consistent with offsetting non-routine employment growth that could persist over longer time horizons. First, automation technology could ease a fixed input in production problem. For example, the introduction of ordering kiosks or a smartphone based ordering app could eliminate the need for cashiers, freeing up precious space behind, say, a restaurant counter, which could be repurposed to increase meal production (Aaronson and Phelan, 2019). As wait times fall, fewer people skip their purchase and the restaurant can profitably hire more employees to prepare orders – offsetting the decline in cashiers. Second, long-lasting and offsetting non-routine employment growth could arise from changes to the composition of firms. Aaronson, French, Sorkin, and To (2018) suggest that minimum wage hikes cause labor-intensive firms to disproportionately fail since the cost of a minimum wage hike 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. Even still, these dynamics may take time to work out, especially if the firm is making large investments in equipment, technology, or processes. In our empirical work, data limitations only allow us to examine employment responses up to two years after a minimum wage change, but we acknowledge it would be ideal to study beyond that (Sorkin, 2015).

This simple framework implies that technological substitution stemming from a minimum wage hike will be characterized by falling routine employment among low-wage jobs. However, the short-run employment effects on non-routine labor are ambiguous and depend on whether workers complement the new technology. As such, the overall employment effects of minimum wage hikes may be negligible even if technological substitution is taking place. The model also implies that this employment realignment from routine to non-routine tasks can be caused by either labor-labor or technological substitution. Thus, the empirical analysis will need to compare employment at similarly paid occupations to distinguish between the two.

Data

The data used in this analysis come from four sources: employment and wage data 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 the occupational task data developed by Acemoglu and Autor (2011) based on the US Department of Labor's Occupation Information Network (O*NET). We discuss each in turn.

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 employment 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 had two changes between 2010 and 2018 that we account for in our analysis. First, the OES made minor changes to its occupational coding systems in both 2012 and 2017.[4] 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 we use 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] For some reason, this change led to implausibly large increases in employment among "Personal and Home Care Aides," the largest occupation in the private household industry, in California where the number of Personal and Home Care Aides increased from 144 thousand in 2016 to 521 thousand in 2017. 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]

Over the last decade, minimum wage policy has become increasingly localized. Consequently, we also analyze OES occupational employment and wages for the 328 metropolitan areas that are reported in the survey. The metro area data, however, present some additional challenges. Geographic boundaries of some metropolitan areas have changed since 2010 and, moreover, 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 less establishments and therefore generate noisier estimates.

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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.

[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.

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

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 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 those used in Aaronson and Phelan (2017), as 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 in Aaronson and Phelan (2017). 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.

American Community Survey (ACS)

We use the 2010 to 2017 ACS to supplement our analysis for two main reasons.[10] The OES has at least two practical problems; its employment count averages over the previous three years and excludes some important low-wage industries, namely agriculture and private household services (at least until 2017). Neither is an issue in the ACS. Second, we can use the ACS micro data to compute state-level employment totals for different subgroups, such as less educated workers. Since different types of workers are differentially affected by minimum wage hikes, this heterogeneity analysis allows us to better understand the response magnitudes of a more targeted population.

Practically, we transform the ACS into a panel of occupation-state-year employment totals to match the OES' structure. We then further mimic the OES analysis by grouping occupations into the same wage intervals using the average ratio of the wage-to-minimum wage over the 2010 to 2017 period. Relative to the OES, this process 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. We address these issues in two ways. First, we compute the mean and standard deviation of the wage-to-minimum wage ratio for each occupation, across all states and all years. We then exclude any individual when their wage-to-minimum wage ratio is more than two standard deviations away from the mean ratio for their reported occupation.[11] Second, since this

[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.

[9] The wage intervals used in Aaronson and Phelan (2017) were 1.00-1.75, 1.75-2.50, 2.50-3.00, and 3.00-6.00.

[10] We will add the 2018 ACS once it is released, as that will allow the OES and ACS estimates to cover the same time period.

[11] This means that if an individual reported that they worked one hour for one week but earned $20,000 as a cashier, then their wage to minimum wage ratio of about 2000 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 only a few observations for a given occupation, these outliers could have very large effects on the average wage-to-minimum wage that we compute.

measurement error will be more problematic in occupations with fewer observations, we limit our analysis to occupations within states that have, on average, at least 25 workers per year.[12] That said, for completeness we also present results that do not impose this second restriction.

Minimum Wage Data

Effective state, city, and county minimum wage levels come from Vaghul and Zipperer (2019).[13] 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 wages 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.[14] Following Aaronson and Phelan (2017), 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.

Task Data

Data on the tasks performed at occupations come from Acemoglu and Autor (2011), who develop these measures from the O*NET database.[15] 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 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 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.[16] 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).

[12] While this restriction decreases our sample of occupation-state-years by 61 percent, it decreases the total amount of employment by only eight percent, as the dropped occupations are, by definition, the smallest in size.
[13] The minimum wage data is available at https://github.com/benzipperer/historicalminwage/releases, last accessed 11/12/19. We are not currently population-weight-adjusting state minimum wage levels for city or county laws but plan to in future drafts.
[14] These states are Arizona, Colorado, Connecticut, Florida, Missouri, Montana, Ohio, Oregon, Vermont, and Washington.
[15] The task data is available on David Autor's website at https://economics.mit.edu/faculty/dautor/data/acemoglu, last accessed 11/12/19.
[16] The correlation coefficient between cognitive and manual interpersonal tasks in the Acemoglu and Autor (2011) metrics is 0.48.

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 low-wage routine occupation has nearly half of its tasks associated with routine cognitive or routine manual tasks and likewise the average low-wage interpersonal 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 among nearly all Wage Group 1 occupations.[17]

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 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 an escalation in these 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 during our period of analysis and states that did not.[18] 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.[19] 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 employment patterns between states that passed minimum wage legislation and states that did not.

[17] 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.

[18] 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 14).

[19] 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).

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 Aaronson and Phelan (2017) and 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). A minimum wage hike is associated with automation if it causes falling relative employment at low-wage routine jobs (see our earlier paper for a theoretical model).

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 outcome variable has been advocated in minimum wage studies interested in the longer-term effects of minimum wage hikes (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, will only reflect a time series of employment changes in long differences. Specifically, we estimate the following difference-in-differences regression model:

$$\begin{aligned}\Delta \ln Emp_{jst} &= \propto_s + \propto_t + \propto_j + \propto_k + \sum_{k=1}^{4}\sum_{z=-2}^{1} \beta_z^k \left(WG_{js}^k * \Delta lnMW_{s,t+z}\right) \\ &+ \sum_{k=1}^{4}\sum_{z=-2}^{1} \beta_{z,T}^k \left(WG_{js}^k * \Delta lnMW_{s,t+z} * TaskShare_j\right) \\ &+ \sum_{k=1}^{4} \gamma_1^k \left(WG_{js}^k * Year_t * TaskShare_j\right) \qquad (1) \\ &+ \sum_{k=1}^{4} \gamma_2^k \left(WG_{js}^k * Year_t * lnEmp_{js,t-4}\right) + \varepsilon_{jst}\end{aligned}$$

where $\Delta \ln Emp_{jst}$ 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, $\Delta \ln MW_{s,t+z}$, are a set of four one-year changes in the natural log of the minimum wage in state *s* from two years ago (t-2) to one year from now (t+1), where for example, $\Delta \ln MW_{s,t-2} = \ln MW_{s,t-2} - \ln MW_{s,t-3}$. Thus, we estimate the effects of these hikes from one year before the hike up until two years after the hike. 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 lagged responses may be particularly important in our setting since substitution effects tend to be longer-term phenomena. The empirical specification also controls for state (α_s) or metro area (depending on the data source), 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.

This specification ensures that the identification of our key β^k_{zT} coefficients, which describe how employment growth varies across jobs according to their task content when the minimum wage increases, 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.

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. 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.

Equation (1) is nearly identical to Aaronson and Phelan's (2017) long-difference distributed lag model, so named because it has a long difference in the outcome but one year changes in the minimum wages 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 reflect marginal changes in the outcome. We made two minor alterations relative to Aaronson and Phelan (2017). First, we added occupation fixed effects because the occupation coding in the OES changed slightly in 2012 and 2017 and we want to ensure that identification comes from within occupations. Second, we no longer winsorize the sample by excluding observations with very large changes in state-occupation employment.

Results

OES State-level Estimates

Table 2 presents estimates of the effects of minimum wage hikes on overall and cognitively routine 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 effects on the collection of occupations in each wage grouping. 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).[20] Overall employment at occupations in Wage Groups 2 to 4 (average wage to minimum wage ratio of 1.5 to 6) do not appear to be materially affected by the minimum wage hike.[21]

In columns (5) to (12), we add the interaction between the routine cognitive share of an occupation and the minimum wage change. 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 wage jobs (i.e. 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, i.e. 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 – 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 estimates of the coefficients on the *ΔlnMW*TaskShare* interaction terms for each of the different task shares that we analyze, where 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

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[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).

manual tasks and the magnitudes 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. Again, no changes are occurring at occupations in Wage Groups 2, 3, or 4 (we report the results for Wage Group 3 and Wage Group 4 in Appendix Table A2). 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 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 minimum wage. 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. Taken together, the increase in employment at jobs intensive in interpersonal tasks that also follows 1 and 2 years after a minimum wage hike partially offsets the loss in employment at occupations intensive in routine cognitive and manual tasks. The remainder of Table 3 comfortingly suggests that minimum wage hikes tend not to affect employment at non-routine cognitive or non-routine manual 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 in the two years following a hike. However, the magnitude of the responses have clearly accelerated this decade. To see this swing, 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).[22] For example, when we combine routine cognitive and manual tasks together, the estimated 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, -0.22 (0.06) versus -0.08 (0.04), two years after a minimum wage hike. Similarly, the offsetting employment growth associated with Wage Group 1 occupations intensive in interpersonal tasks also grew between the first two decades of the 21st century (Panel D of Figure 6). The estimated

[22] 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 we winsorize the largest employment changes.

interpersonal 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.[23]

We find two other notable differences across the decades (see Appendix Table A3). First, the adverse impact of minimum wage hikes on overall Wage Group 1 employment may 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.

OES Metropolitan-level Estimates

Next, we turn to using sizable variation in city and county minimum wage policy implemented during the 2010s and the OES metropolitan area data to estimate the effects of minimum wage hikes on occupational employment. 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 at higher paying jobs and therefore we move Wage Group 3 and 4 results to Appendix Table A4.

Overall, the MSA findings have a similar but more-muted flavor to the state-based ones. Among the specific tasks, the estimated effects are somewhat smaller but still suggest a comparable pattern of changes in occupational employment across the task space. 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) 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.

It is no surprise that precision declines once we switch to the MSA data which is composed of smaller samples of establishments. However, the smaller point estimates did surprise us. 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 (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

[23] 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 effects on manual interpersonal tasks look much more like cognitive interpersonal tasks in the 2010 to 2018 data.

largest metropolitan areas (Panel B of Table 4).[24] This restriction is economically important. 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, and strongly suggesting 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. 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. While the non-large city MSA estimates are not always statistically significant when one considers the pre-trends for Wage Group 2 occupations, the result that minimum wage hikes are also causing employment declines at higher-paying routine intensive jobs and employment gains at higher-paying interpersonal jobs is much more apparent on this sample.

ACS Estimates

Estimates of Equation (1) using a panel of state-occupation employment levels and average wages derived from the ACS are presented in Table 5.[25] Paralleling the OES, Panel A includes all respondents that work in Wage Group 1 occupations (other Wage Groups are reported in Appendix Table A6), and therefore unsurprisingly show very comparable results. The estimated elasticity on total employment of -0.20 (0.10) is nearly identical to the state-level OES results. Moreover, the ACS estimates likewise suggest that minimum wage hikes are associated with a reallocation of low-wage employment away from occupations intensive in routine cognitive and routine manual tasks and towards occupations intensive in interpersonal tasks. While there are large leading effects in each of these task-based interaction specifications (using all workers) that make the effects two years after the hike not statistically different from the leading effects, the estimates still imply a clear pattern that matches what we find in the OES. It is interesting to note that the timing of the employment response is also very similar, with most of the effects coming two years (instead of one year) after the hike. This implies that the delayed results that we observe in the OES are not an artifact of the moving average data, but likely reflect that the adoption of automation technology takes time to implement.

The primary reason to use the ACS is to explore heterogeneity by worker characteristics. Panel B in Table 5 restricts the workers in a Wage Group 1 occupation to those with a high school diploma or less. As expected, we find stronger evidence of employment changes after a minimum wage hike among lower-educated workers, as they are more likely impacted by minimum wage laws. In particular, we estimate the routine employment elasticity for HS or less workers is -0.43 (0.14) and the interpersonal employment elasticity for HS or less workers is

[24] 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.

[25] Recall that only state-occupations with at least 25 observations per year are included. The exclusion of especially small state-occupations decreases the noise in the estimates without materially altering the magnitudes of the key coefficients (see Appendix Table A7).

0.43 (0.19). Both estimates are nearly double the aggregate elasticity we found in both the OES and ACS, suggesting an even larger employment response to automation when we concentrate on a more targeted population of workers.

At the same time, there is little evidence that Wage Group 1 workers with at least some college experience are affected by minimum wage hikes in the same way (Panel C). These more-educated workers are not moving away from occupations intensive in routine tasks nor towards occupations intensive in interpersonal tasks when minimum wages increase. Surprisingly, however, it is the higher educated sample that are losing jobs when the minimum wage increases, with a two year post-hike total employment elasticity of -0.54 (0.17) for higher educated sample compared to 0.00 (0.20) for the less educated sample. We are unsure what to make of these findings so far; however, that there is little employment realignment consistent with automation may suggest that automation is probably not directly driving high-education employment loss. The next draft will explore this puzzling finding further.

Lastly, we further stratified the sample of high school graduates and dropouts to explore heterogeneity by age, race, and sex. Wage Group 1 results are presented in Table 6 and Wage Groups 2 to 4 are in Appendix Table A8. Panel A presents the overall employment effects and Panels B and C present the employment effects by routine and interpersonal task share.[26] While these estimates are noisy because of smaller sample sizes, they highlight some economically significant differences across demographic groups. First, the employment realignment away from routine jobs and towards interpersonal jobs is most evident among younger (under age 30) workers, minorities, and men. The elasticities associated with routine tasks two years after a minimum wage hike are -0.69 (0.10), -0.90 (0.31), and -0.58 (0.36), respectively, and the two year elasticities associated with interpersonal tasks are 0.82 (0.16), 0.92 (0.40), and 0.76 (0.37), respectively. This is not to say that older workers, non-minorities, and women (within the less-educated sample) are not being affected by minimum wage hikes, but the estimated effects on these less-affected groups are about half the size of their sample counterparts. Moreover, since younger workers are disproportionately impacted by minimum wage hikes, these results provide further evidence that the effects of minimum wage hikes on automation may be much larger than the estimates implied by the OES.

The overall employment effects appear to be especially large among less-educated minority workers, especially when we account for the leading (pre-hike) effects. The two-year overall employment effects net of the pre-trend is -1.32 (0.34). It is also negative and economically important for the young (-0.28 (0.23)) and men (-0.28 (0.27)) but these estimates are statistically imprecise. Nevertheless, they are suggestive that growth in interpersonal jobs is not able to fully offset the loss in routine jobs, especially among minorities. As such, the automation of low-wage jobs, at least in response to minimum wage hikes, may be causing some job loss among the most disadvantaged of the low-wage labor force.

[26] We continue to limit the sample to having at least 25 observations among individuals with less than a high school diploma. If we went further and, for example, required 25 observations among young, less educated workers, the samples fall dramatically and the geographic representation of the sample deteriorates. That said, the results – available by request – are similar even with this additional restriction.

Conclusion

An extensive empirical literature examines the economically important impact of technological substitution on middle-skill jobs (Autor, Levy, and Murnane 2003; Jaimovich and Sui 2012; Goos, Manning, and Salomons 2014). Our paper builds on the task-based occupational approach of these papers to examine the impact of automation on the low-wage labor market. Our approach uses exogenous variation in occupational wages, through changes in state and local minimum wage policy, to identify how automation alters the composition of occupational employment.

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. This 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. Additionally, the magnitude of the employment declines at low-wage routine jobs that we estimate over the period 2010-2018 is more than double the estimated effects that Aaronson and Phelan (2017) find during the first decade of the 21st century. Moreover, the decline in routine employment has spread to routine manual jobs, in addition to routine cognitive jobs. Like Aaronson and Phelan (2017), 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 magnitudes of this offsetting employment growth have 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 city size and demographics. Nearly all the realignment away from routine and toward interpersonal tasks after a minimum wage hike are occurring in rural areas and smaller cities. We also find that less-educated workers experience the brunt of this change – with employment declines at routine occupations and gains at interpersonal occupations almost twice the size of the overall sample. These results suggest that the extent of automation and its impact on the composition of tasks may actually be much more economically significant than we estimate in the OES, as the OES (and the "All Worker" ACS sample) includes many individuals working in low-paying occupation for whom the minimum wage is still not binding. Looking exclusively within the sample of less-educated workers, we find that our results are largely driven by the young, minorities, and men. Importantly, less educated minorities may be experiencing the largest damage to their job prospects, as the effect of automation on overall employment appears to be especially large for this group.

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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 top 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 we define 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: These empirical specifications are very similar to the empirical specifications in Aaronson and Phelan (2019). The only difference is that the wage intervals are adjusted to reflect the compression in employment near the minimum and the empirical specification is expanded to include occupation fixed effects and all observations, regardless of the change in log employment. $N = 95,781$ for all three specifications. *p<0.10, **p<0.05, and ***p<0.01.

Table 3: Employment Effects at Occupations Based on Other 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: This table presents the results from five different regression specifications that include separate ΔMW-x-Task Share variables in each specification, one for each of the five task shares. All specifications include state-by-year fixed effects and are otherwise identical to Specification 3 in Table 1. $N = 95,781$ for each of the five specifications. The results from Wage Group 3 and Wage Group 4 are excluded from this table because these higher wage occupations, much like Wage Group 2, do not appear to be affected by the minimum wage hikes. *p<0.10, **p<0.05, and ***p<0.01.

Table 4: MSA-Level Estimates from the OES, 2010-2018

	Overall Employment Effect	Employment Effects by Task Content: Routine Cognitive Tasks	Routine Manual Tasks	Combined 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 presents the results from eight different regression specifications using the MSA-level data from the Occupation Employment Statistics, where state-by-year fixed effects are included in the task-interaction specifications. Panel A presents estimates when all MSAs are included in the specifications ($N = 324,808$). Panel B presents estimates when the 25 largest MSAs are excluded from the analysis ($N = 289,014$). The results from Wage Group 3 and 4 are excluded from this table because these higher wage occupations do not appear to be affected by the minimum wage hikes. *p<0.10, **p<0.05, and ***p<0.01.

Table 5: Employment Effects in the American Community Survey 2010-2017

	Overall Employment Effect	Employment Effects by Task Content: Routine Cognitive Tasks	Routine Manual Tasks	All Routine Tasks	Inter-personal Tasks
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample of Individuals					
ΔMW Next Year	0.06	-0.11	-0.12	-0.13	0.13
	(0.16)	(0.09)	(0.12)	(0.10)	(0.10)
ΔMW This Year	0.19	-0.02	0.06	0.02	0.00
	(0.11)	(0.07)	(0.09)	(0.07)	(0.09)
ΔMW Last Year	0.15	0.02	-0.04	-0.01	0.04
	(0.10)	(0.06)	(0.06)	(0.05)	(0.08)
ΔMW 2Yrs Ago	-0.20**	-0.21***	-0.21	-0.23**	0.26*
	(0.10)	(0.08)	(0.15)	(0.09)	(0.15)
Panel B: Individuals with a High School Degree or Less					
ΔMW Next Year	0.01	-0.14	-0.02	-0.09	0.01
	(0.17)	(0.11)	(0.13)	(0.10)	(0.13)
ΔMW This Year	0.18	0.13	0.07	0.12	-0.01
	(0.13)	(0.12)	(0.14)	(0.12)	(0.15)
ΔMW Last Year	0.07	-0.20	-0.15	-0.20**	0.23*
	(0.13)	(0.07)	(0.11)	(0.09)	(0.12)
ΔMW 2Yrs Ago	0.00	-0.38***	-0.36**	-0.43***	0.43**
	(0.20)	(0.14)	(0.16)	(0.14)	(0.19)
Panel C: Individuals with more than a High School Degree					
ΔMW Next Year	0.19	-0.09	-0.17	-0.13	0.18
	(0.24)	(0.12)	(0.16)	(0.13)	(0.14)
ΔMW This Year	0.27	-0.25***	-0.14	-0.20**	0.15
	(0.23)	(0.08)	(0.13)	(0.09)	(0.13)
ΔMW Last Year	0.27	0.15	0.03	0.10	-0.02
	(0.23)	(0.13)	(0.15)	(0.13)	(0.15)
ΔMW 2Yrs Ago	-0.54***	-0.01	0.05	0.02	0.05
	(0.17)	(0.13)	(0.22)	(0.14)	(0.21)

Notes: This table presents the results from fifteen different regression specifications, where each column represents the results from a different regression using aggregated annual state-level occupational employment data computed from the 2010-2017 American Community Survey. These employment levels are computed either using all individuals or individuals with varying degrees of educational attainment. All three samples are limited to occupations with state-year employment levels of at least 25 workers. $N = 22,009$ for the regressions that use all individuals, $N = 10,335$ for for the regressions that only include high school graduates, and $N = 16,522$ for the regressions using individuals with more than a high school degree. Estimates that include all occupation-state-year observations are included in Table A5 in the Appendix. The results from Wage Group 2-4 are excluded from this table because these higher wage occupations do not appear to be affected by the minimum wage hikes. *p<0.10, **p<0.05, and ***p<0.01.

Table 6: **Heterogeneity in Effects for Wage Group 1 of Less-Educated ACS Sample**

	By Age		By Race		By Sex	
	Under Age 30	**Aged 30+**	**Non-Asian Minorities**	**Whites & Asians**	**Women**	**Men**
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall Employment Effect						
ΔMW Next Year	0.39**	-0.15	0.80***	-0.14	0.05	0.37
	(0.17)	(0.19)	(0.29)	(0.17)	(0.20)	(0.25)
ΔMW This Year	-0.09	0.60***	0.43	0.21	0.23	0.35*
	(0.15)	(0.16)	(0.26)	(0.18)	(0.15)	(0.19)
ΔMW Last Year	0.02	0.27*	0.23	-0.03	0.09	0.15
	(0.14)	(0.14)	(0.23)	(0.12)	(0.11)	(0.20)
ΔMW 2Yrs Ago	0.10	0.02	-0.52	0.20	-0.09	0.09
	(0.19)	(0.28)	(0.36)	(0.17)	(0.21)	(0.21)
Panel B: Employment Effects by Routine Tasks						
ΔMW Next Year	-0.17	-0.13	-0.26	-0.17	-0.20*	0.06
	(0.18)	(0.12)	(0.20)	(0.12)	(0.11)	(0.24)
ΔMW This Year	-0.17	0.16*	-0.08	-0.01	0.01	-0.21
	(0.19)	(0.09)	(0.26)	(0.15)	(0.11)	(0.28)
ΔMW Last Year	-0.19	-0.32	-0.56**	-0.16	-0.26**	-0.43**
	(0.21)	(0.19)	(0.27)	(0.11)	(0.10)	(0.17)
ΔMW 2Yrs Ago	-0.69***	-0.26	-0.90***	-0.43***	-0.47***	-0.58
	(0.10)	(0.23)	(0.31)	(0.15)	(0.13)	(0.36)
Panel C: Employment Effects by Interpersonal Tasks						
ΔMW Next Year	0.22	0.02	0.16	0.14	0.19	-0.13
	(0.20)	(0.14)	(0.23)	(0.15)	(0.13)	(0.23)
ΔMW This Year	0.19	0.07	0.07	0.15	0.12	0.36
	(0.18)	(0.12)	(0.22)	(0.16)	(0.11)	(0.26)
ΔMW Last Year	0.36	0.33	0.62**	0.23*	0.37***	0.31*
	(0.24)	(0.20)	(0.28)	(0.13)	(0.12)	(0.18)
ΔMW 2Yrs Ago	0.82***	0.26	0.92**	0.46**	0.46**	0.76**
	(0.16)	(0.26)	(0.40)	(0.20)	(0.21)	(0.37)

Notes: This table presents the results from eighteen regression specifications, where the sample of less educated workers from the ACS is further by age, race, and sex. All samples are limited to observations where the average number of less educated workers in the state-occupation is at least 25. $N = 11,574$ for the under age 30 sample; $N = 15,277$ for the age 30+ sample; $N = 11,047$ for the non-Asian minority sample; $N = 15,307$ for the white and Asian sample; $N = 13,548$ for the female sample; and $N = 13,442$ for the male sample. The results from Wage Group 2-4 are excluded from this table because these higher wage occupations do not appear to be affected by the minimum wage hikes. *p<0.10, **p<0.05, and ***p<0.01.

Figure 1: Wage Distribution of Occupations

by State-level Wage-to-Minimum Wage Ratio

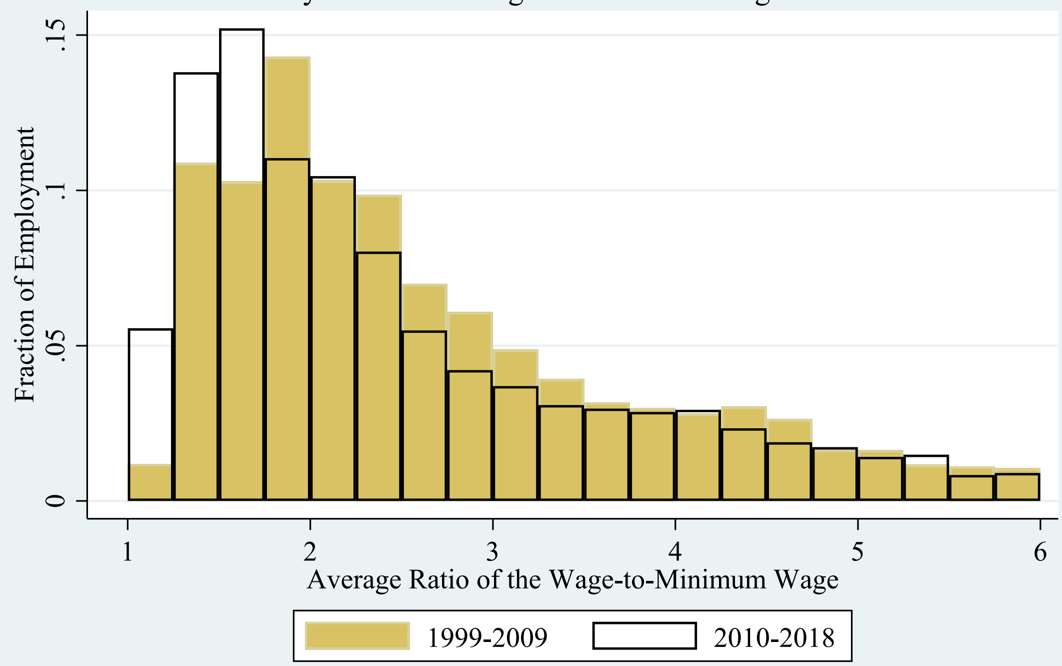
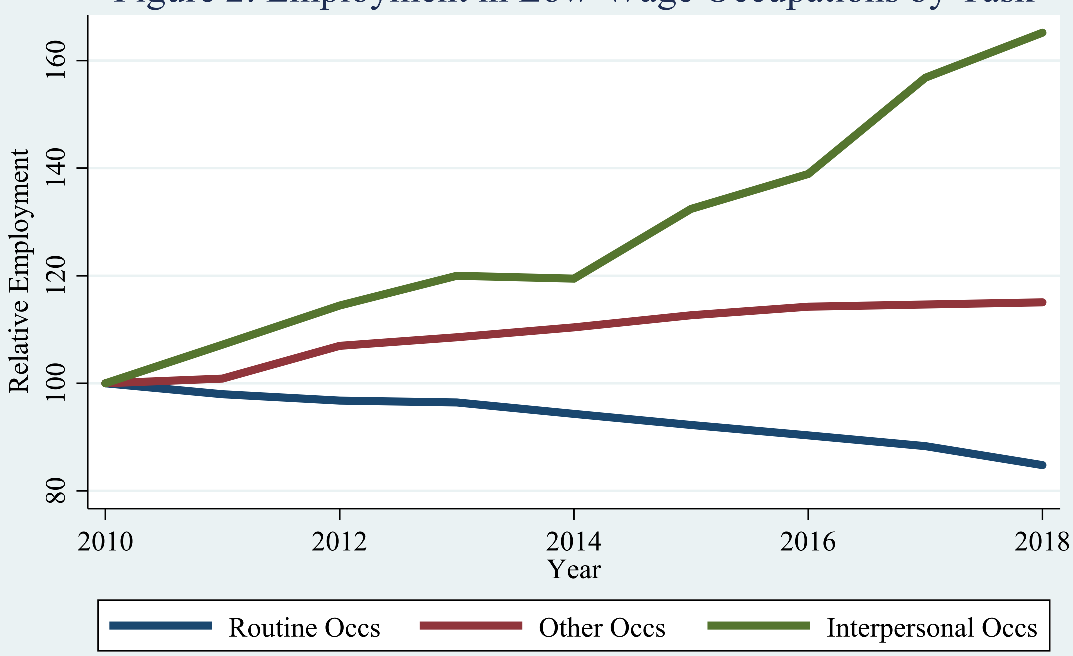
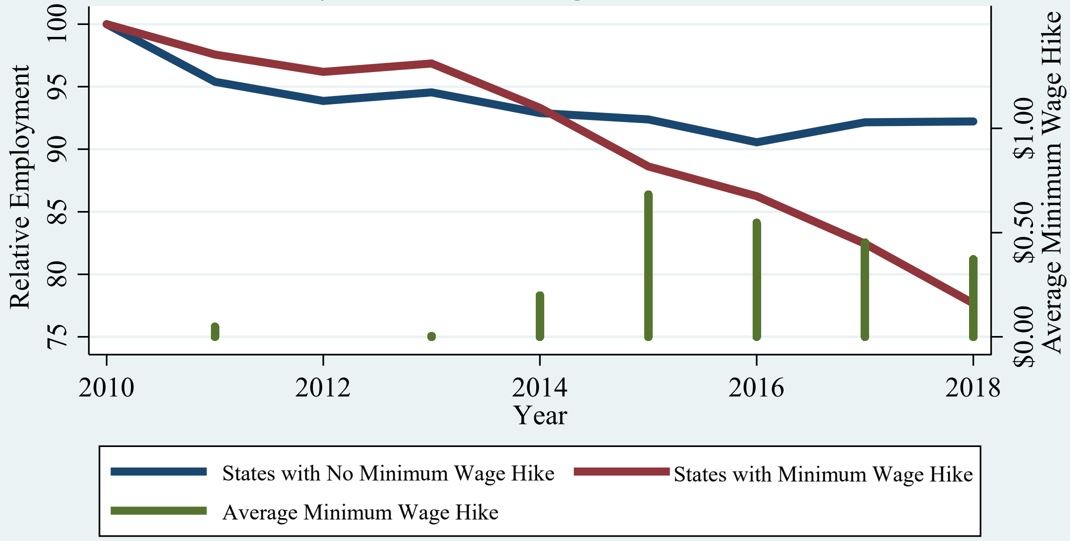


Figure 2: Employment in Low-Wage Occupations by Task



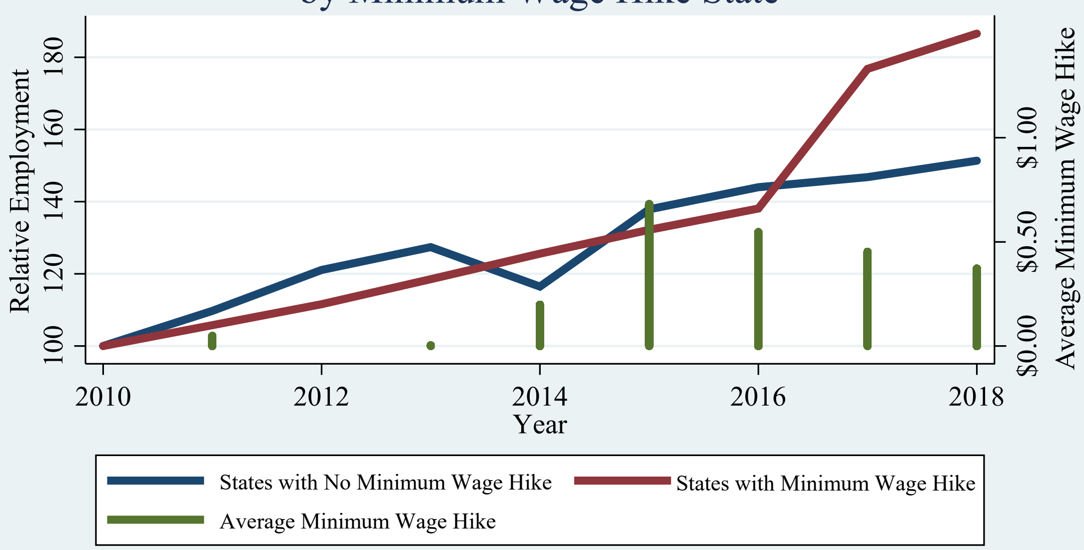
Note: A low-wage occupation is in Wage Group 1 for at least one state. A routine (interpersonal) occupation has a routine (interpersonal) task share of at least 50 percent.

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



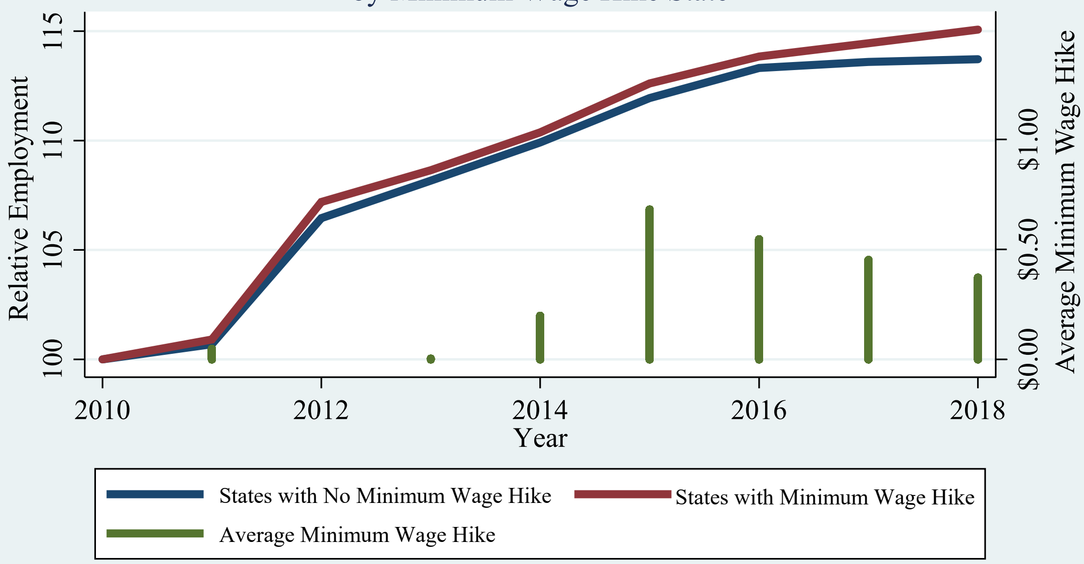
Note: This figure is limited to occupations where routine tasks compose more than 50 percent of the total tasks. The average minimum wage hike is a employment-based weighted average for those states that increased their minimum wage. 19 states increased their minimum wage, separate from automatic inflation-based adjustments, 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



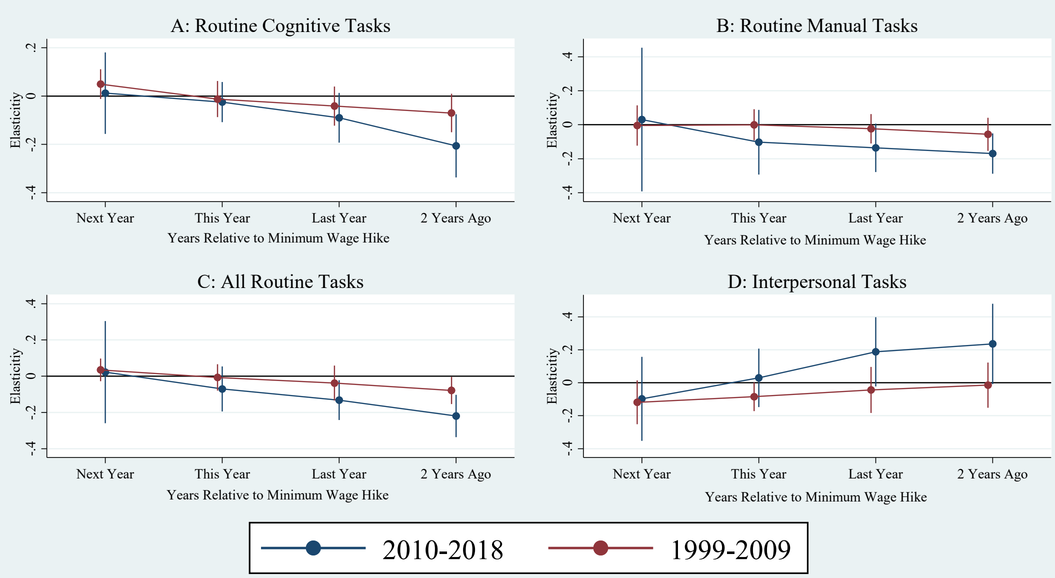
Note: This figure is limited to occupations where interpersonal tasks compose more than 50 percent of the total tasks. The average minimum wage hike is a employment-based weighted average for those states that increased their minimum wage. 19 states increased their minimum wage, separate from automatic inflation-based adjustments, between 2010 and 2018. We exclude 10 states with automatic annual inflation-based adjustments.

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



Note: This figure is limited to occupations where neither the routine tasks nor interpersonal tasks compose more than 50 percent of the total tasks. The average minimum wage hike is a employment-based weighted average for those states that increased their minimum wage. 19 states increased their minimum wage, separate from automatic inflation-based adjustments, between 2010 and 2018. We exclude 10 states with automatic annual inflation-based adjustments.

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



Note: This figure presents the estimated elasticity prior to and following a minimum wage hike for Wage Group 1 occupations using two samples from the OES. The standard error bars capture the 95% confidence interval for each estimated elasticity. The empirical specification for the 1999-2009 sample is identical to the 2010-2018 sample, except for the curoffs for the wage grouping.

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 the minimum wages from 22 states because their minimum wages did not change over the period 2010-2019. Twenty-One of these states followed the U.S. Federal minimum wage of $7.25, which also did not change over the period of analysis. These include: Alabama, Georgia, Idaho, Indiana, Iowa, Kansas, Kentucky, Louisiana, Mississippi, New Hampshire, North Carolina, North Dakota, Oklahoma, Pennsylvania, South Carolina, Tennessee, Texas, Utah, Virginia, Wisconsin, and Wyoming. New Mexico's minimum wage also did not change over the period of analysis, but its minimum wage was $7.50 over the period of analysis. The empirical analysis also excludes the minimum wage changes from the states that had inflation-based automatic adjustments in place over most of the period of analysis. These states include: Arizona, Colorado, Connecticut, Florida, Missouri, Montana, Ohio, Oregon, Vermont, and Washington

Table A2: Employment Effects at Occupations Based on 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 presents the results from Wage Group 3 and Wage Group 4 for the specifications presented in Table 3. See Table 3 for additional notes. *p<0.10, **p<0.05, and ***p<0.01.

Table A3: Employment Effects of Minimum Wage Hikes Across Tasks Over Time

1999-2009 vs. 2010-2018

	Overall Employment Effect		Employment Effects by Task Content: Routine Cognitive Tasks		Routine Manual Tasks		Combined Routine Cog. & Man. 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 presents estimates from two periods using the state-level Occupation Employment Statistics, 1999-2009 (N=151,948) and 2010-2018 (N=95,781). The empirical specifications are identical except for time period used. The results from Wage Group 3 and 4 are excluded from this table because like in Table 2, there are no major effects taking place. *p<0.10, **p<0.05, and ***p<0.01.

Table A4: MSA-Level Estimates from the OES for Wage Group 3 and 4, 2010-2018

	Overall Employment Effect		Employment Effects by Task Content: Routine Cognitive Tasks		Routine Manual Tasks		Combined Routine Cognitive & Manual 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 presents the results for Wage Group 3 and Wage Group 4 from the MSA-level analysis presented in Table 5. $N = 324,808$ when all MSAs are included in the specifications. $N = 289,014$ when the 25 largest MSAs are excluded from the analysis. See Table 5 for the remaining notes.
*p<0.10, **p<0.05, and ***p<0.01.

Table A5: **MSA-Level Estimates, Excluding MSAs that Cross State Borders**

		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 the results from the metropolitan area analysis from the OES when we exclude metro areas that cross state boundaries. This includes 51 of the 328 metro areas in the OES. $N = 270,622$ for all of these specification. See Table 5 for the remaining notes. *p<0.10, **p<0.05, and ***p<0.01.

Table A6: Employment Effects in the ACS, Wage Group 2-4

	Overall Employment Effect	Employment Effects by Task Content: 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	0.14	0.03	-0.09	-0.05	0.08
	(0.13)	(0.07)	(0.09)	(0.09)	(0.08)
ΔMW This Year	0.07	-0.06	-0.12	-0.13	0.12
	(0.09)	(0.06)	(0.08)	(0.08)	(0.08)
ΔMW Last Year	-0.04	-0.13*	-0.13*	-0.18**	0.18***
	(0.09)	(0.08)	(0.07)	(0.07)	(0.05)
ΔMW 2Yrs Ago	-0.03	0.13**	-0.07	0.03	-0.05
	(0.06)	(0.06)	(0.18)	(0.14)	(0.13)
Wage Group 3					
ΔMW Next Year	0.15	0.16**	-0.03	0.09	0.01
	(0.11)	(0.06)	(0.08)	(0.06)	(0.07)
ΔMW This Year	0.07	-0.04	0.06	0.01	-0.07
	(0.11)	(0.07)	(0.08)	(0.06)	(0.05)
ΔMW Last Year	-0.02	0.01	-0.13*	-0.08	0.10
	(0.08)	(0.04)	(0.07)	(0.05)	(0.07)
ΔMW 2Yrs Ago	-0.02	0.00	-0.10	-0.06	0.09*
	(0.10)	(0.06)	(0.06)	(0.06)	(0.05)
Wage Group 4					
ΔMW Next Year	0.14	-0.06	-0.05	-0.07	0.04
	(0.12)	(0.05)	(0.08)	(0.06)	(0.06)
ΔMW This Year	0.06	0.03	-0.11**	-0.04	0.03
	(0.08)	(0.05)	(0.04)	(0.03)	(0.03)
ΔMW Last Year	-0.02	-0.02	-0.01	-0.02	0.03
	(0.07)	(0.06)	(0.04)	(0.04)	(0.03)
ΔMW 2Yrs Ago	0.06	-0.03	-0.05	-0.03	0.03
	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)
Panel B: Individuals with a High School Degree or Less					
Wage Group 2					
ΔMW Next Year	0.20	0.09	-0.15	-0.10	0.13
	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)
ΔMW This Year	0.15	-0.12	-0.13*	-0.19**	0.15*
	(0.15)	(0.09)	(0.07)	(0.09)	(0.09)
ΔMW Last Year	-0.07	-0.19*	-0.05	-0.17*	0.12
	(0.08)	(0.09)	(0.10)	(0.10)	(0.09)
ΔMW 2Yrs Ago	0.03	0.18	-0.10	0.02	0.01
	(0.14)	(0.11)	(0.21)	(0.18)	(0.16)
Wage Group 3					
ΔMW Next Year	0.24	0.17*	-0.11	0.08	0.03
	(0.16)	(0.09)	(0.17)	(0.16)	(0.15)
ΔMW This Year	0.05	-0.13	0.11	-0.02	-0.07
	(0.13)	(0.13)	(0.10)	(0.15)	(0.10)
ΔMW Last Year	-0.14	0.09	-0.16**	-0.09	0.17**
	(0.12)	(0.12)	(0.07)	(0.09)	(0.07)
ΔMW 2Yrs Ago	0.03	0.03	-0.21	-0.21	0.15
	(0.17)	(0.10)	(0.13)	(0.12)	(0.13)
Wage Group 4					
ΔMW Next Year	0.11	-0.09	-0.15	-0.16	0.12
	(0.20)	(0.18)	(0.09)	(0.14)	(0.10)
ΔMW This Year	-0.10	0.04	-0.15	-0.10	0.07
	(0.13)	(0.15)	(0.10)	(0.10)	(0.09)
ΔMW Last Year	-0.05	0.18**	0.00	0.11	-0.02
	(0.13)	(0.08)	(0.10)	(0.07)	(0.09)
ΔMW 2Yrs Ago	0.06	-0.06	-0.07	-0.08	0.08
	(0.10)	(0.14)	(0.09)	(0.14)	(0.11)

Notes: See the notes to Table 5. *p<0.10, **p<0.05, and ***p<0.01.

Table A6: Employment Effects in the ACS, All Observations

		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 of Individuals					
Wage Group 1					
ΔMW Next Year	0.07	-0.11	-0.14	-0.14	0.14
	(0.11)	(0.07)	(0.10)	(0.09)	(0.09)
ΔMW This Year	0.16	-0.03	0.02	0.00	0.02
	(0.11)	(0.07)	(0.08)	(0.06)	(0.08)
ΔMW Last Year	0.12	0.01	-0.02	0.00	0.03
	(0.09)	(0.06)	(0.07)	(0.05)	(0.08)
ΔMW 2Yrs Ago	-0.21**	-0.17**	-0.19	-0.20**	0.21
	(0.10)	(0.07)	(0.14)	(0.09)	(0.15)
Wage Group 2					
ΔMW Next Year	0.08	-0.02	-0.05	-0.06	0.09
	(0.13)	(0.07)	(0.09)	(0.08)	(0.08)
ΔMW This Year	0.05	-0.06	-0.15*	-0.14*	0.13*
	(0.09)	(0.05)	(0.08)	(0.07)	(0.08)
ΔMW Last Year	-0.01	-0.12*	-0.15**	-0.19***	0.18***
	(0.08)	(0.06)	(0.06)	(0.06)	(0.05)
ΔMW 2Yrs Ago	-0.08	0.12***	-0.10	0.01	-0.02
	(0.06)	(0.04)	(0.18)	(0.13)	(0.12)
Panel B: Individuals with a High School Degree or Less					
Wage Group 1					
ΔMW Next Year	0.13	-0.15	-0.05	-0.11	0.07
	(0.13)	(0.11)	(0.13)	(0.11)	(0.12)
ΔMW This Year	0.21*	0.03	0.02	0.03	0.01
	(0.12)	(0.09)	(0.11)	(0.11)	(0.11)
ΔMW Last Year	0.10	-0.18**	-0.12	-0.17**	0.20**
	(0.13)	(0.08)	(0.09)	(0.08)	(0.10)
ΔMW 2Yrs Ago	0.03	-0.31**	-0.39**	-0.41***	0.43**
	(0.19)	(0.13)	(0.17)	(0.15)	(0.19)
Wage Group 2					
ΔMW Next Year	0.26***	0.12	-0.10	-0.02	0.09
	(0.08)	(0.10)	(0.10)	(0.12)	(0.11)
ΔMW This Year	0.19	-0.17**	-0.17*	-0.25***	0.18*
	(0.13)	(0.08)	(0.09)	(0.09)	(0.09)
ΔMW Last Year	-0.03	-0.24**	-0.09	-0.24**	0.19**
	(0.08)	(0.09)	(0.09)	(0.10)	(0.09)
ΔMW 2Yrs Ago	0.02	0.07	-0.17	-0.09	0.09
	(0.11)	(0.08)	(0.22)	(0.18)	(0.15)
Panel C: Individuals with more than a High School Degree					
Wage Group 1					
ΔMW Next Year	0.21	-0.12	-0.25*	-0.19*	0.27**
	(0.17)	(0.10)	(0.13)	(0.11)	(0.10)
ΔMW This Year	0.17	-0.17**	-0.08	-0.13*	0.12
	(0.21)	(0.08)	(0.11)	(0.07)	(0.10)
ΔMW Last Year	0.27	0.10	0.01	0.06	0.00
	(0.19)	(0.11)	(0.13)	(0.11)	(0.13)
ΔMW 2Yrs Ago	-0.48***	-0.02	0.03	0.01	0.01
	(0.17)	(0.11)	(0.18)	(0.13)	(0.16)
Wage Group 2					
ΔMW Next Year	-0.05	-0.20**	0.00	-0.14*	0.13
	(0.18)	(0.08)	(0.12)	(0.08)	(0.10)
ΔMW This Year	-0.03	-0.01	-0.22	-0.13	0.16
	(0.08)	(0.09)	(0.13)	(0.10)	(0.11)
ΔMW Last Year	0.04	-0.09	-0.22**	-0.20***	0.22***
	(0.14)	(0.09)	(0.10)	(0.07)	(0.08)
ΔMW 2Yrs Ago	-0.12	0.13**	-0.07	0.05	-0.08
	(0.14)	(0.07)	(0.19)	(0.13)	(0.15)

Notes: This presents the ACS estimate similar to Table 5, except we all include all observations, not just those with a minimum average employment level of 25. See Table 6 for more details. $N = 55,390$ all individual sample, $N = 41,441$ for high school only sample, and $N = 50,818$ more than high school sample *p<0.10, **p<0.05, and ***p<0.01.

Table A8: Heterogeneity in Effects of Less-Educated ACS Sample, Wage Group 2-3

	By Age		By Race		By Sex	
	Under Age 30	Aged 30+	Non-Asian Minorities	Whites & Asians	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall Employment Effect						
Wage Group 2						
ΔMW Next Year	0.21	0.26	0.54	0.11	0.29**	0.25
	(0.15)	(0.16)	(0.33)	(0.12)	(0.11)	(0.16)
ΔMW This Year	0.57***	0.12	0.78**	0.07	0.20	0.26**
	(0.16)	(0.17)	(0.29)	(0.11)	(0.25)	(0.12)
ΔMW Last Year	-0.03	0.08	0.40	-0.15	0.11	-0.03
	(0.16)	(0.08)	(0.28)	(0.12)	(0.09)	(0.12)
ΔMW 2Yrs Ago	0.08	-0.02	-0.08	0.03	-0.06	0.14
	(0.21)	(0.11)	(0.19)	(0.12)	(0.12)	(0.21)
Wage Group 3						
ΔMW Next Year	0.95***	0.04	0.98***	0.08	0.31	0.24
	(0.32)	(0.17)	(0.25)	(0.18)	(0.24)	(0.17)
ΔMW This Year	0.07	0.14	0.66**	-0.11	-0.20	0.33**
	(0.28)	(0.14)	(0.32)	(0.11)	(0.12)	(0.15)
ΔMW Last Year	-0.12	-0.04	0.29	-0.12	0.03	-0.08
	(0.26)	(0.10)	(0.28)	(0.11)	(0.14)	(0.13)
ΔMW 2Yrs Ago	0.13	0.08	0.53	-0.11	0.15	0.02
	(0.31)	(0.15)	(0.37)	(0.15)	(0.27)	(0.18)
Panel B: Employment Effects by Routine Tasks						
Wage Group 2						
ΔMW Next Year	-0.07	-0.18	-0.31	-0.13	-0.16	-0.16
	(0.24)	(0.12)	(0.19)	(0.13)	(0.15)	(0.15)
ΔMW This Year	-0.49***	-0.18	-0.48**	-0.24***	-0.26**	-0.29*
	(0.16)	(0.13)	(0.19)	(0.09)	(0.12)	(0.16)
ΔMW Last Year	-0.34	-0.26***	-0.65***	-0.16	-0.29*	-0.23
	(0.28)	(0.08)	(0.14)	(0.12)	(0.16)	(0.15)
ΔMW 2Yrs Ago	-0.29	-0.13	-0.05	-0.22	-0.01	-0.43*
	(0.23)	(0.20)	(0.30)	(0.15)	(0.17)	(0.24)
Wage Group 3						
ΔMW Next Year	-0.34	0.26*	0.16	0.04	-0.06	0.21
	(0.51)	(0.13)	(0.40)	(0.12)	(0.18)	(0.26)
ΔMW This Year	0.15	-0.08	0.01	0.10	0.03	0.06
	(0.30)	(0.12)	(0.30)	(0.12)	(0.20)	(0.11)
ΔMW Last Year	-0.02	-0.03	-0.18	-0.03	0.14	-0.21*
	(0.17)	(0.10)	(0.21)	(0.10)	(0.12)	(0.09)
ΔMW 2Yrs Ago	-0.16	-0.26**	-0.17	-0.26	-0.24	-0.14
	(0.32)	(0.11)	(0.39)	(0.15)	(0.11)	(0.15)
Panel C: Employment Effects by Interpersonal Tasks						
Wage Group 2						
ΔMW Next Year	0.24	0.10	0.30	0.11	0.07	0.33**
	(0.18)	(0.11)	(0.21)	(0.11)	(0.13)	(0.13)
ΔMW This Year	0.34**	0.22*	0.39**	0.23**	0.27**	0.14
	(0.16)	(0.12)	(0.17)	(0.11)	(0.13)	(0.11)
ΔMW Last Year	0.33	0.12	0.53***	0.07	0.21	0.11
	(0.21)	(0.10)	(0.18)	(0.11)	(0.15)	(0.18)
ΔMW 2Yrs Ago	0.23	0.18	0.16	0.24**	0.02	0.48**
	(0.24)	(0.15)	(0.38)	(0.11)	(0.16)	(0.21)
Wage Group 3						
ΔMW Next Year	0.39	0.03	0.11	0.14	0.00	0.17
	(0.47)	(0.12)	(0.33)	(0.16)	(0.18)	(0.18)
ΔMW This Year	-0.05	-0.07	-0.01	-0.19*	-0.20	-0.07
	(0.20)	(0.09)	(0.19)	(0.11)	(0.14)	(0.13)
ΔMW Last Year	0.22	0.12	0.12	0.17**	-0.01	0.23**
	(0.17)	(0.10)	(0.16)	(0.06)	(0.13)	(0.09)
ΔMW 2Yrs Ago	0.16	0.19	0.09	0.21	0.13	0.18
	(0.37)	(0.11)	(0.42)	(0.11)	(0.19)	(0.14)

Notes: See the notes for Table 6. *p<0.10, **p<0.05, and ***p<0.01.