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PEOPLE VERSUS MACHINES:
THE IMPACT OF MINIMUM WAGES ON AUTOMATABLE JOBS

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ABSTRACT

We study the effect of minimum wage increases on employment in automatable jobs – jobs in which employers may find it easier to substitute machines for people – focusing on low-skilled workers from whom such substitution may be spurred by minimum wage increases. Based on CPS data from 1980-2015, we find that increasing the minimum wage decreases significantly the share of automatable employment held by low-skilled workers, and increases the likelihood that low-skilled workers in automatable jobs become unemployed. The average effects mask significant heterogeneity by industry and demographic group, including substantive adverse effects for older, low-skilled workers in manufacturing. The findings imply that groups often ignored in the minimum wage literature are in fact quite vulnerable to employment changes and job loss because of automation following a minimum wage increase.

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Introduction

For decades, economists have studied the effects of the minimum wage on employees in the United States. These studies have largely focused on the employment effects for low-skilled workers – with the principal focus on teenagers. Overall, there is some controversy regarding whether disemployment effects exist, with some studies finding no effects,[1] although with more – and more diverse kinds of studies – finding evidence of disemployment effects.[2]

In this study, we explore the extent to which minimum wages induce substitution away from workers whose jobs are more easily automated. For instance, employers may substitute away from labor with technological innovations – such as supermarkets substituting self-service checkout for cashiers, and assembly lines in manufacturing plants substituting robotic arms for workers. At the same time, firms may hire other workers who perform new tasks that are complementary with the new technology. For example, a firm using more robots may hire individuals to service, troubleshoot, and maintain these new machines. It seems reasonable to expect that the workers more likely to be replaced following minimum wage increases are those who are low skilled, earning wages affected by increases in the minimum wage, while workers who "tend" the machines are higher skilled. This suggests that there is a potential for labor reallocation away from jobs that are automatable following increases in the minimum wage, that low-skilled workers in automatable jobs are particularly vulnerable to minimum wage increases, and that the net disemployment effects

[1] See, for example, Card and Kruger, 1994; Card and Kruger, 2000; Dube, Lester, and Reich, 2010; Allegretto et al., 2011; and Addison, Blackburn and Cotti, 2012.
[2] See for example Neumark and Wascher, 1996; Neumark, 2001; Singell and Terborg, 2007; Neumark and Wascher, 2007; Thompson, 2009; Sabia, Burkhauser, and Hansen, 2012; Neumark, Salas, and Wascher, 2014a, 2014b; Clemens and Wither, 2016; Meer and West, 2015; Powell, 2016. Neumark (2017) reviews the very recent literature, pointing out the kinds of studies that find disemployment effects and the kinds that do not.

may be smaller than the gross effects that workers in automatable tasks experience.[3]

We choose to focus on automation as it has been one of the dominant forces that has threatened low-skilled jobs in the United States in recent decades (Autor and Dorn, 2013; Autor, Dorn, and Hanson, 2015), presumably because of both technological advances and reductions in the cost of technology that can substitute for low-skilled labor. Minimum wages can exacerbate these changes, when they raise price of low-skilled labor in automatable jobs, for which machines can be substituted.

The main aim of this paper is to provide a richer understanding of how minimum wage policies have been shaping the type of employment held in the United States, within industries and for particular demographic groups. Specifically, we empirically assess whether the share of employment that is automatable declines in response to minimum wage increases. We focus on jobs that tend to be held by low-skilled workers, given that these are the jobs for which labor costs increase the most in relative terms following a minimum wage increase, which can prompt firms to substitute from people (low-skilled ones, in particular) towards machines. We complement our analyses of how the share of employment in automatable jobs responds to minimum wage increases with analyses of employment impacts for individual workers, estimating whether the probability that a low-skilled individual working in an automatable loses their job is larger following a minimum wage increase.

Our analysis is related to concurrent research by Aaronson and Phelan (forthcoming), who, for the period 1999-2009, analyze the susceptibility of low-wage employment to technological substitution in the short run. Specifically, they focus on regressions that model the probability of being employed within the next two years against measures of the task

[3] Of course, employers can respond to an increase in the minimum wage in a number of ways besides culling jobs. Other channels of adjustment that have been explored in the literature include changes in hours – where the empirical evidence is mixed (see Neumark and Washer, 2008, p. 78), job amenities (see Simon and Kaestner, 2004), prices (see Aaronson, 2001; Aaronson, French, and MacDonald, 2008; Lemos, 2008; MaCurdy, 2015), and compression of wage differentials (see DiNardo, Fortin, and Lemieux, 1996; and Autor, Manning, and Smith, 2016).

content in an individual’s current job. They find that minimum wage increases lead to job losses for cognitively-routine jobs, but not manually-routine or non-routine jobs. Their study provides some evidence that firms may automate routine jobs in response to a minimum wage increase, reducing employment opportunities for workers in routine jobs.

Our study contributes beyond this analysis in a number of ways. First, while Aaronson and Phelan (2017) are concerned with an average individual’s job loss, we focus on quantifying how shares in the employment of automatable tasks change following a minimum wage change, to provide more evidence on how the task composition of the workforce is affected.

Second, we expect that automation is a viable and likely substitute for certain types of low-skilled jobs, and therefore also certain types of low-skilled labor, implying that average effects may mask significant heterogeneity. Therefore, our second contribution is to provide a full picture of labor market adjustments across industries and a variety of demographic groups, which can uncover these important differential responses. This may be of particular interest within the broader minimum wage literature. While that literature has largely focused on teenagers (and more recently restaurant workers), the perspective we adopt in this paper suggests there may be subgroups of workers among those groups not usually considered in the minimum wage literature who may be adversely affected by minimum wages, because they tend to be employed in automatable jobs.

Third, for those who lose their jobs to automation following a minimum wage increase, we expect that the risk of not being able to find a similar job is greater for some groups as compared to others, and that an inability to do so has longer-term adverse consequences for earnings (and re-employment). Hence, we also analyze the effects of minimum wage increases on whether particular types of low-skilled individuals working in automatable jobs are more or less likely to stay in the same occupation following a minimum wage increase.

Together, our analyses provide the first evidence on how the shares of automatable jobs change following a minimum wage increase, and on the effects of minimum wages on groups that are very often ignored in the minimum wage literature, such as effects on older less-skilled workers who are in jobs where it is easier to replace people with machines.

Our work is timely given that many U.S. states have continued to regularly raise their minimum wages, and a large number of additional states have newly implemented minimum wage laws (all higher than the federal minimum wage), with a number of states now indexing their minimum wages. As of January 7, 2017, 30 states (including the District of Columbia) had a minimum wage higher than the federal minimum wage of $7.25, ranging as high as $11 in Washington State, and $11.50 in the District of Columbia.[4] Moreover, many U.S. cities have implemented minimum wages, with the minimum wage in Seattle (and nearby Sea-Tac) reaching $15. Policy debate regarding these increases frequently references the literature on disemployment effects discussed above (a literature from which advocates on either side can pick evidence to support their view). But this literature largely focuses on teenagers, for whom employment effects are either irrelevant, or at best very tangentially related, to the more important policy question of whether higher minimum wages help low-income families. If employment changes in response to higher minimum wages mask larger gross effects for subgroups of low-skilled workers in automatable tasks – and in particular subgroups ignored in the existing minimum wage literature – then the reliance of policymakers on evidence for teenagers may be ignoring potentially adverse effects for older workers more likely to be major contributors to their families' incomes.

Our empirical analysis draws on CPS data from 1980-2015. We distinguish between occupations that are intensive in automatable tasks by drawing on definitions provided in Autor and Dorn (2013) and Autor et al. (2015). We calculate for each industry within each

[4] See https://www.dol.gov/whd/minwage/america.htm (viewed February 1, 2017).

state-year cell an automatable employment share.[5] The core of our analysis links these measures to changes in the relevant minimum wage.

Overall, we find that increasing the minimum wage decreases significantly the share of automatable employment held by low-skilled workers. Our estimates suggest that an increase of the minimum wage by $1 (based on 2015 dollars) decreases the share of low-skilled automatable jobs by 0.43 percentage point (an elasticity of −0.11). However, these average effects mask significant heterogeneity by industry and by demographic group. In particular, there are large effects on the shares of automatable employment in manufacturing, where we estimate that a $1 increase in the minimum wage decreases the share of automatable employment among low-skilled workers by 0.99 percentage point (elasticity of −0.17). Within manufacturing, the share of older workers in automatable employment declines most sharply, and the share of workers in automatable employment also declines sharply for women and blacks.

Our analysis at the individual level draws many similar conclusions. We find that a significant number of individuals who were previously in automatable employment are unemployed in the period following a minimum wage increase. These effects are among the largest for individuals employed in the manufacturing industry, and are larger for the oldest and youngest workers, for females and for blacks. Overall, our analysis points to important heterogeneity in the employment effects of minimum wages, and highlights potentially adverse consequences of higher minimum wages for groups of workers that have not typically been considered in the extensive research literature on the employment effects of minimum wages. That is, the main message from our work is that groups often ignored in the minimum wage literature are in fact quite vulnerable to employment changes and job loss because of automation following a minimum wage increase.

[5] We actually distinguish between urban and non-urban areas within each state.

Analysis of Shares of Employment in Automatable Jobs

Methods

Our analysis focuses on low-skilled individuals, who we define as having a high school diploma equivalent or less. The data we analyze cover this group only, for almost all of our analyses.

We use data from Autor and Dorn (2013) and Autor et al. (2015) to measure routine task intensity. In particular, routine task intensity in each three-digit occupation is defined as follows:

$$RTI_k = \ln(T_k^R) - \ln(T_k^M) - \ln(T_k^A) \quad (1)$$

where T_k^R, T_k^M, and T_k^A are the levels of routine, manual, and abstract task inputs for occupation *k*.[6] Routine tasks involve a repeated sequence of actions, are easily codifiable, and therefore substitutable with technology. In contrast, manual tasks require actions that are not generally predictable in sequence, so substitution with technology is limited. To provide some examples, blue-collar jobs that are highly routine include machinists and typesetters. Jobs with low routine task intensity include bus driving and service station occupations. Blue-collar jobs that are classified as high on manual task intensity include taxi drivers, operating agents of construction equipment, and drivers of heavy vehicles, while meat cutters and upholsterers are low on this domain. Abstract tasks require high-level thinking that is more complementary with technology (Autor, 2013). Examples of low-skilled jobs that are high on abstract task intensity include supervisors of motor vehicle transportation, railroad conductors, and production foremen. Jobs that are low on abstract task intensity are garbage collectors, parking lot attendants, and packers. Thus, equation (1) is increasing in the absolute and relative quantity of tasks that are automatable within occupation *k*.

[6] These levels are defined using variables from versions of the *Dictionary of Occupation Titles*, where incumbents are asked to grade the level of their occupation with respect to particular attributes,

We further calculate for each industry *i*, within each area *a* (defined as state crossed by a metro dummy), in year *t*, a routine employment share, as follows:

$$RSH_{iat} = (\sum_{k=1}^{K}(L_{iat}) \cdot 1[RTI_k > RTI^{P66}])(\sum_{k=1}^{K}(L_{iat}))^{-1} \ , \qquad (2)$$

In equation (2), L_{iat} is equal to total employment in industry *i* in area *a* at time *t*. 1[.] is an indicator function taking the value of one if an occupation is in the top third of the employment-weighted distribution of *RTI* across occupations, using only low-skilled workers. The numerator is then the share of automatable low-skill employment in a particular industry, area, and year, and the denominator is total low-skilled employment in that industry, location, and year.

Our analysis initially focuses on the following specification:

$$RSH_{iat} = b_1 MW_{st} + A_a \gamma + T_t \lambda + I_i \varphi + \varepsilon_{iat} \ , \qquad (3)$$

where MW_{st} denotes the minimum wage in state *s* at time *t*. Equation (3) also includes area (A_a), year (T_t), and industry (I_i) fixed effects. Area is defined as state-specific dummy variables interacted with whether the individual lives in a metro area or not. Negative and significant estimates of b_1 would imply that the share of employment that is automatable declines in response to minimum wage increases.[7]

We next turn to disaggregating these effects across industries and demographic groups, in part to see whether there are sectors or groups particularly vulnerable to automation in response to minimum wage increases. In other work, differential patterns of task reallocation have been documented for various demographic groups. For example, less-

[7] We also augment equation (3) adding up to three lags of our minimum wage variable. The inclusion of lags allows for a period of adjustment to re-organize the factors of production away from labor and towards capital investments in technology. We note that in all models the lags are not significant, suggesting that investment in technology is relatively fast. As we discuss later, however, the minimum wage is defined based on the average minimum wage in the current and past 11 months, itself averaged over the year, so that the absence of lagged effects still allows effects that can arise over nearly two years.

educated, male, and young workers have been the most susceptible to reductions in employment that is intensive in routine tasks (Autor and Dorn, 2013; Autor and Dorn, 2009). And other evidence indicates that less-educated individuals working in manufacturing are most vulnerable to employment loss caused by global trade (Bound and Holzer, 2000; Malamud and Wozniak, 2012). We therefore focus on differences in effects by age and sex, and we also examine differences by race.[8] Specifically, for race we look at whites and blacks (we do not look at other categories given small cell sizes), and for age we look at aged 40 and over, those aged 25 or younger, and the intermediate group aged 26-39.

To unpack the impact of minimum wage increases by age, sex, and race, we use measures of task intensity for each subgroup (indexed by *c*), as follows:

$$RSH_{ciat} = (\sum_{k=1}^{K}(L_{ciat}) \cdot 1[RTI_k > RTI^{P66}])(\sum_{k=1}^{K}(L_{ciat}))^{-1} \quad .^{9} \tag{4}$$

In this case the numerator is the share of automatable employment held by a particular sub-group in a specific industry, area, and year, and the denominator is total employment of a particular subgroup by industry, area, and year. We estimate equation (3) for the separate subgroups, indexed by *c*, using *RSH* as defined in equation (4).

There are two main sources of tasks that are routine intensive. The first are tasks found in blue-collar manufacturing occupations that are also capital intensive. For example, automobiles are most often produced using conveyor belts. Workers perform tasks within this assembly line, which are routine and substitutable with robotic arms. The second is codifiable administrative-support tasks that are typical to the inputs required in the financial service industries, among others (Autor and Dorn, 2013; Autor et al., 2015). The variation across industries in the proportion of individuals that are working in automatable

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[8] The minimum wage literature also has many of examples of papers that consider variation in employment effects across subgroups. For example, gender (Dube, Lester, and Reich, 2016), age (Giuliano, 2012), and ethnicity (Allegretto, Dube, and Reich, 2011).

[9] RTI_k and RTI^{P66} are computed as before, for all low-skilled workers.

employment, among low-skilled workers, is reported in Table 1. Finance, retail, manufacturing, and public administration have particularly high shares of low-skilled workers doing automatable tasks.

We expect the minimum wage to change the share of employment in automatable tasks in differing degrees for particular industries. The impact directly relates to how dominant an automatable task type is in the industry in question, and the ease and cost of automating a task. To uncover whether there are differential effects by industry we estimate equation (3) separately by one-digit industry, in the aggregate (using *RSH* as defined in equation (2)), and by demographic group (using *RSH* as defined in equation (4)).

Data

Our main data source for our analysis of employment shares is pooled monthly CPS samples from 1980-2015. These data are matched to monthly state-level data on the minimum wage that was gathered by the authors. We allow for a period of adjustment by defining the minimum wage as the average over the current month plus the last 11 months. In addition, we do not include agriculture and mining in our sub-group analysis by industry, as we cannot meaningfully or reliably calculate RSH_{iat} in many states or areas with a low representation of these industries. We then create our share of employment variable on a yearly basis, and similarly construct an annual average of the minimum wage variable.[10]

We rely on crosswalks provided by Autor and Dorn (2013) and Dorn (2009) to convert occupation codes in the CPS to a consistent coding system across years.[11] The measure of routine task intensity (*RTI*) described in equation (1) is provided by Autor and

[10] This choice is made for statistical reasons given that cell sizes are too small for accurate calculation of RSH_{iat} on a monthly basis. In particular, cell sizes are too small for specific industries and demographic groups at a monthly basis. This level of analysis is also more intuitive given that substituting to automation requires some period of adjustment.

[11] Specifically, we follow Lordan and Pischke (2016) and match the currently relevant Census occupation code system (1980, 1990, 2000 or 2010) to the relevant Autor and Dorn crosswalk. This gives us a consistent coding system that can be matched directly to our measure of automatable tasks.

Dorn (2013) and is matched to the CPS data using this coding system. As noted earlier, we use data on individuals with a high school diploma equivalent or less. The first column of Table 1 reports the means, by industry, of the shares in automatable jobs

Individual-Level Analysis

Methods

We also estimate regressions using individual-level data on low-skilled individuals. Specifically, we estimate the model:

$$Emp_{jiai+1}=b_1(RSH_{jiat}\cdot MW_{at})+ b_2RSH_{jiat} +T_t\cdot S_s\lambda + I_i\varphi + \varepsilon_{jiat} \quad , \tag{5}$$

where *Emp* is the probability that the j^{th} person is employed in industry i, area a, at time t+1. It is assigned zero if a person was unemployed in t+1. The sample consists of those employed in period t, and either employed or unemployed (i.e., in the labor force) in period t+1. We could include transitions to non-employment as well, but we exclude them to capture the non-employment most likely to be involuntary and hence related to the policy change (and the type of job in which one works). We can, we believe, more reliably interpret these transitions, for this sample, as reflecting job loss.

Equation (5) relates this job loss to workers having held a routine job in period t, and facing a minimum wage increase. The coefficient on the interaction $RSH_{jiat}\cdot MW_{at}$ – b_1 – is therefore informative as to whether a person in automatable work is more vulnerable to job loss following a minimum wage increase. We can only look at those initially employed because we need to classify the routine task intensity of jobs, so we are capturing only flows out of employment and into unemployment.

Note that equation (5) includes a full set of state-by-year interactions, to allow for differential time patterns across states; that is why S_s (for states) appears in the equation, rather than A_a (for areas), as in equation (3). Given the inclusion of the state-by-year interactions, the main effect MW_{st} drops out of the equation, and identification of the coefficient on the interaction comes from variation in the availability of automatable jobs within states across time.[12]

All other definitions are consistent with equations (1) through (4). Under the expectation that individuals working in automatable jobs at the time of a minimum wage increase are more likely to have lost jobs by the next period as compared to individuals that are in jobs that are not automatable, we expect the coefficient on b_1 to be negative and significant. We unpack heterogeneity in b_1 by estimating equation (5) separately by industry and demographic subgroup.

We complement these regressions with analyses that consider a dependent variable that equals one if an individual had the same occupation code in the interview year, and zero otherwise (including both the unemployed and job switchers, but again excluding those who leave the labor force). In these analyses, a negative and significant b_1 presumably captures, to some extent, movements of labor out of employment in automatable tasks following a minimum wage increase (either to alternate work in non-automatable tasks or to not working).

Data

We estimate equation (5) using data from the Annual Social and Economic Supplement (ASEC) of the CPS. We focus only on individuals with a high school diploma equivalent or less, as in our shares analysis. The ASEC files are useful for our purposes because they collect information on the job held by respondents in the previous year at the

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[12] We cannot meaningfully document an effect of minimum wages on wages of those in automatable work, since this would restrict us only to those who are employed in both periods, and because the main effect of the minimum wage is subsumed in the fixed effects. Moreover, we do not necessarily expect a larger wage effect for those in automatable work; the substitution response may simply be larger. We did verify that in models for wages, the estimate of b_1 is negative and significant. Assuming (as in past work) that minimum wages on average raise wages of low-skill workers, this suggests that the pay increase induced by a higher minimum wage for those in automatable work is not as high as for those in non-automatable work, which fits the story that automation reduces demand for those in automatable tasks and may increase demand for workers with different (and likely higher) skills.

three-digit occupation level. Thus, *RSH* is based on this occupation. The last two columns of Table 1 report the average probabilities that employed, low-skilled workers in automatable jobs remain employed, or in the same occupations (for those who remain in the labor force).

Results

Effects on Employment Shares

The results from our share of employment analyses (equation (3)) are reported in Table 2. In the aggregate across all industries, as indicated in column (1), we find that minimum wage increases cause a statistically significant reallocation of labour away from automatable tasks. We find that a $1 increase in the minimum wage leads to a 0.43 percentage point decrease in the share of automatable jobs done by low-skilled workers. The implied elasticity (computed across observations and then averaged) is −0.10. When we look separately at the construction, wholesale, retail, and finance industries, the estimates are centered around zero and are not significant. In contrast, the effects are significant and often substantive in other industries. Specifically, the estimates imply that a minimum wage increase of $1 causes a 0.99 percentage point decrease in the share of automatable jobs done by low-skilled workers in manufacturing (implied elasticity is −0.17). The estimates also suggest a substantive effect in public administration, although the estimate is not statistically significant.

Table 3 presents our analysis of the effects of the minimum wage on the share of employment in automatable jobs, broken down by demographic group. The table reveals that there is significant heterogeneity in these effects beyond the differences by industry documented in Table 2. For example, a higher minimum wage significantly reduces the shares of both younger (≤ 25) and older (> 40) workers in jobs that are automatable, by a larger magnitude compared to those aged 26-39. For the younger and older groups, the estimates imply that a $1 increase in the minimum wage reduces the shares in automatable work by 0.94 and 0.72 percentage points respectively (the corresponding elasticities are

−0.20 and −0.17. Looking by both age and industry, for older workers (≥ 40 years old) the negative effect mainly arises in the manufacturing and public administration sectors (a decrease of 1.68 and 3.50 percentage points for a $1 minimum wage increase respectively), while for younger workers (≤ 25 years old) the effects are large in many sectors but the estimate is close to zero for manufacturing. The middle age group, also, exhibits a decline in the share of workers in automatable jobs in manufacturing when the minimum wage increases – a 1.21 percentage point decline for a $1 increase. Thus, older workers appear more vulnerable to substitution away from automatable jobs when the minimum wage increases.

On average, females are affected more adversely than males: in the aggregate estimates in column (1), the negative estimate is significant only for females, and is almost ten times larger, indicating that, for females, a minimum wage increase of $1 causes a decrease of 1.01 percentage points in the share of automatable jobs (the elasticity is −0.14). Across industries, these negative effects for females are concentrated in manufacturing, services, and public administration; for example, a $1 minimum wage increase reduces the share of automatable jobs in public administration by 3.67 percentage points – an elasticity of −0.41). For males, only the estimate for manufacturing is statistically significant; the estimated effect implies that a $1 increase in the minimum wage causes a decrease of 0.62 percentage point (an elasticity of −0.13).

Table 3 also points to similar overall effects by race, with a $1 increase in the minimum wage reducing the share in automatable jobs by 0.57 percentage point for whites and 0.72 percentage point for blacks.[13] However, the effects are heterogeneous across industries. There are large estimated effects in manufacturing (1.19 percentage points) and public administration (1.53 percentage points) for whites, although only the first estimate is

[13] Implied elasticities evaluated at the mean are −0.13 and −0.16 respectively.

statistically significant. For blacks, there are large and statistically significant decreases in automatable shares in manufacturing and transport (declines of about 4.5 percentage point in both).

Effects on Remaining Employed

The estimates in Table 3 are consistent with substitution away from labor doing routine tasks in response to minimum wage increases, in a number of industries (depending on the demographic group). However, this evidence does not necessarily imply that those previously in automatable jobs become unemployed. It is possible that the decline in the share of employment in automatable tasks comes about from a reduction in employment in automatable tasks and an increase in employment in less routine tasks, although this seems unlikely if the latter jobs are higher skilled, except perhaps for some subgroups.

To study directly whether a higher minimum wage increases unemployment among low-skilled workers who were in jobs with routine tasks, Table 4 reports estimates of equation (5), which models the effects of minimum wage increases on the probability a particular individual who holds an automatable job is still employed in the next period, as opposed to unemployed. Overall, we find evidence indicating that the negative effects on employment shares in automatable jobs reported in Tables 2 and 3 are associated with job loss and transitions to unemployment among workers initially doing automatable jobs.

First, looking across industries in the pooled estimates in column (1), we find evidence of significant declines in the probability of remaining employed – and hence transitioning to unemployed – for those who were previously in automatable employment. Second, there is some correspondence in the estimated effects by industry, with a strong decline for the pooled data evident for manufacturing, and a large point estimate for public administration (although significant). Third, the pattern of heterogeneity in estimated effects by demographic group is also similar in some respects to the estimated effects on shares reported in Table 3, with the youngest and oldest workers adversely affected, and females more adversely affected than males.

In terms of magnitudes, the pooled estimates imply that a $1 minimum wage increase lowers the probability that a worker in automatable employment remains employed by 0.12 percentage point;[14] the percentage point effect on the probability of unemployment is of course then an increase of 0.12 percentage point. The effect in manufacturing is about 50 percent larger, consistent with the large effect for manufacturing reported in Table 2. The services estimate implies that a $1 minimum wage increase lowers the probability of remaining in employment by 0.15 percentage point. None of the other full sample estimates by industry are statistically significant, although the estimate for finance is sizable – of roughly the same magnitude as the effect for manufacturing.

Looking at effects for manufacturing by age, there are adverse employment effects for both the oldest and youngest groups, with an implied decline in the probability of employment, from a $1 minimum wage increase, of 0.28 percentage point and 0.78 percentage point, respectively. Similarly, there is evidence of declining employment (increased job loss) in services for those aged 25 or younger (0.42 percentage point), and for those over 40 years old (0.33 percentage point).

Looking at males and females separately, the estimates parallel those for the share in automatable employment in Table 3, indicating sharper employment declines for women than for men (a decline of 0.19 versus 0.13 percentage point), with the effect more strongly statistically significant for women. However, for men there is statistically significant evidence of a decline in employment in manufacturing (0.20 percentage point), and a marginally significant decline in services. For females, there is also evidence of heterogeneity, with sharp negative effects in manufacturing (0.67 percentage point) and retail (0.39 percentage point).

[14] Given that all observations in the individual-level analysis are initially employed, the estimated coefficients are easily interpreted as percent declines as well, so we do not report elasticities.

Finally, looking at the estimated effects by race, for low-skilled whites there is evidence (significant at the 10-percent level) of increased job loss in manufacturing, with a $1 increase in the minimum wage reducing by 0.17 percentage point the probability of remaining employed in the next period. For low-skilled blacks, the evidence of negative employment effects is statistically significant only for transportation, although there are large (but insignificant) negative estimates for many industries; note that the standard errors for blacks are much larger.

Effects on Occupational Switching

Table 5 reports similar estimates, but now the dependent variable is equal to one if an individual stayed in the same occupation in the subsequent period, and zero otherwise. As in Table 4, the sample includes those employed in period *t* and in the labor force in period *t*+1; in addition, those employed have to have valid occupation codes. Thus, the estimated effect of the minimum wage-routine interaction captures the change in job opportunities in the worker's initial occupation, with a "decline" captured in either non-employment *or* a change of occupations.

Overall, there are many more larger, significant, and negative effects reported in Table 5, suggesting that higher minimum wages lead to a good deal of occupational switching among low-skilled workers in automatable jobs, in addition to transitions to unemployment; this occupational switching is presumably another cost of higher minimum wages for these workers. In addition, the evidence of such effects within industries suggests there is substantial re-allocation of labor within industries because of the minimum wage increase.

Turning to some specific magnitudes, the estimates imply that a $1 increase in the minimum wage leads, overall, to a 0.50 percentage point decrease in the probability of holding the same occupation. The effects are largest in transportation (1.39 percentage points), services (1.08 percentage points), and finance (0.78 percentage point), and also negative and significant in manufacturing (0.25 percentage point). In Table 5, in contrast to the earlier tables, the estimated negative effects are sometimes sizable and significant for workers aged 26-39 – in particular, for transportation (1.24 percentage points), finance (1.34 percentage points), and services (1.14 percentage points). For younger workers (aged 25 and under), as well, the estimates are often large and negative. In contrast, for older workers these negative effects are more modest (compare, e.g., the estimated effects for transportation, finance, and services). The differences by age when we look at employment declines overall versus the combined effects of minimum wages on switching occupations or becoming unemployed suggest that younger and middle-aged workers in automatable jobs are more able to respond to higher minimum wages by switching occupations, whereas older workers are not.

Comparing effects for females and males, the estimated overall negative impact of minimum wages on workers in automatable jobs remaining employed in the same occupation is larger for women (0.69 versus 0.54 percentage point). There are more substantial differences across industries. And the effects are much larger for whites than for blacks (0.50 versus 0.15 percentage point, with the effect not significant for blacks). This difference by race may imply that blacks in automatable jobs are less able to change jobs in response to minimum wage increases, like older workers. The effect for whites arises in manufacturing, transportation, finance, and services, while there is only a significant (and negative) effect for blacks in transportation.

Hours Effects

Our analysis so far has focused on employment. However, there is also a potential for hours to decrease in automatable employment following a minimum wage increase. We consider hours explicitly by re-estimating equation (3) and relating minimum wage variation to an alternate dependent variable. Here, the dependent variable is the share of hours worked among low-skill workers in automatable employment, in a particular industry, area, and year.

We also re-estimate equation (5) with the difference in reported usual hours worked between this year and last year by an individual as the dependent variable. We focus only on those who are employed in the two periods, with positive hours worked.

The results from these analyses are reported in Table 6. The pooled estimates imply that a minimum wage increase of $1 causes a 0.33 percentage point decrease in the share of hours in automatable jobs done by low-skilled workers overall. The estimated decline in manufacturing is 1.03 percentage points. The share of hours analysis suggests that females are most affected (although the estimate for females is not statistically significant), along with older workers and the youngest workers (as compared to 26-39 year-olds).

The individual-level analysis considers the difference in the usual hours worked per week between period 1 and period 2. The data for both periods are recalled in the same interview period. By construction, the sample only includes individuals who kept their jobs between the two periods, so the sample sizes are lower than for the employment regressions. There is also loss due to non-response on the "hours worked last year" question. The estimates reported in the second panel of Table 6 suggest significant decreases in hours worked for those initially in automatable jobs following a minimum wage increase. Based on the pooled estimate, a $1 increase in the minimum wage generates a 0.23 decrease in hours worked for low-skilled individuals who held an automatable job in the previous period. The decline is negative and statistically significant in manufacturing, transport, wholesale, retail, and services (sometimes only at the 10-percent level). Overall, the results indicate that those in automatable low-skilled work are vulnerable to hours reductions following a minimum wage increase.

Across demographic groups, the estimated coefficients are mostly significant and negative. For example, a $1 increase in the minimum wage is estimated to reduce hours worked for low-skilled males who held an automatable job in the previous period by 0.17. For females the decrease is 0.1 hours. Low-skilled workers aged 26-39 and 40+ years have similar decreases in hours in response to a $1 increase (about 0.25 hours); the coefficient for individuals aged 25 or below is closer to zero and not significant. White low-skilled workers who held an automatable job in the previous period have a decrease of about 0.26 hours in response to a $1 increase. However, there is no significant decrease for low-skilled blacks.

Are the Effects Stronger in More Recent Data?

It is interesting to re-estimate these models using a shorter, more-recent time period, at the risk of losing observations, given that the move towards automation has likely accelerated over time, as technology has been getting cheaper, and labor more expensive. To this end, in Table 7 we report estimates covering 1995-2016, rather than going back to 1980. (We do not report estimates by industry crossed with demographic subgroups.) Comparisons with Tables 2-5 reveal that the overall estimates are generally stronger in the more recent sub period. This suggests that the substitution response to minimum wages was higher in more-recent years, likely because of increased ease of automation (and perhaps minimum wages reaching higher levels). However, individuals who are getting a high school diploma or less are also changing over time, with people on average now getting higher levels of education. Therefore, there is a risk that negative selection into our definition of the low-skilled also partially explains the strengthening of the results in the most recent time period.

In the pooled analysis for the share of employment in automatable jobs, we find that a $1 increase in the minimum wage leads to a 0.57 percentage point decrease in this share (compared to a 0.43 percentage point decrease from Table 2). We note that the manufacturing estimate is attenuated slightly (0.85 percentage point, versus 0.99 percentage point in Table 3, which translates into an implied elasticity of −0.14, versus −0.17). However, the estimates also imply that a minimum wage increase of $1 causes a 1.18 percentage point decrease in the share of automatable jobs done by low-skilled workers in transport (as compared to a 0.76 percentage point decrease in Table 2), and a 2.08 percentage point decrease in public administration (as compared to a 1.77 percentage point decrease in Table 2).

The subgroups of individuals that are the most affected largely remain the same as in the full-period estimates in Table 3. A higher minimum wage affects older (≥ 40), younger (≤ 25), and female workers in jobs that are automatable to the greatest extent.

Table 7 also reports estimates of the effects of a minimum wage increase on the probability that an individual who holds an automatable job remains employed in the next period, versus becoming unemployed. These estimates are also larger compared to the full-sample estimates (Table 4). The pooled estimates imply that a $1 minimum wage increase lowers the probability that a worker in automatable employment remains employed by 0.40 percentage point. The effect in manufacturing is 0.68 percentage point. Overall, the pattern of results is qualitatively similar to that documented in Table 4, and those whose employment probabilities decline the most following a minimum wage increase are generally the same (except for whites and blacks).

A similar conclusion is drawn if we consider the analysis where the dependent variable is equal to one if an individual stayed in the same occupation in the subsequent period. These analyses suggest that higher minimum wages lead to occupational switching, alongside job loss, among low-skilled workers in automatable jobs. Specifically, the pooled estimates imply that a $1 increase in the minimum wages leads, overall, to a 0.90 percentage point decrease (compared to 0.50 percentage point in Table 5) in the probability of holding the same occupation in the next period. Consistent with Table 5, the effects are largest in transportation and services. In contrast, the estimate for finance is much smaller in Table 7 as compared to Table 5. For Table 7 (as in Table 5), the estimated negative effect is sizable for workers aged 26-39; however, the estimate is still largest for the youngest workers. Overall, the comparison of the estimates in Table 7 with the earlier estimates indicates that the substitution response towards automation in place of low-skilled workers in response to a minimum wage increase is stronger in more recent years.

Probing the Effects in Manufacturing

Returning to Tables 3-5, many of our results by industry pointed to declines in the share of automatable jobs, and increased job loss, in manufacturing. These types of findings are unusual in the minimum wage literature, which usually focuses on very low-skilled workers (hence the emphasis on teenagers, for example). Then again, our analysis does not focus on manufacturing in the aggregate, but on low-skilled workers in automatable jobs. Nonetheless, if the effects we estimate in manufacturing are in fact driven by minimum wage increases, they should be generated from low-wage rather than high-wage workers.

To that end, we estimate our key results for higher-wage and lower-wage workers in the manufacturing industry, based on wages in occupations within manufacturing. For each low-skill occupation (defined as having a majority presence of low-skilled workers[15]) within manufacturing, we compute average wages from the 1980-2016 Merged Outgoing Rotation Groups of the CPS. The low-wage subsample is then defined as the bottom tertile of occupations in this distribution, and the high-wage subsample as the top tertile. These definitions are then matched to the data used for the analyses in Tables 3-5, and separate analyses of equations (3) and (5) are conducted for the two sub-samples. Examples of occupations that fall into the high-wage and low-wage categories under this definition are given in Table 8. Those occupations classified as low wage are typically machine operators of some description; in contrast, high-wage earners more commonly maintain and install machinery.[16] Notably, those in these low-wage occupations in the bottom tertile regularly earn wages at or near the minimum wage.

[15] In practice we calculate the proportion of low-skilled workers in each occupation. Those with shares greater than 0.5 are defined as being low-skilled occupations.
[16] We consider an alternative definition whereby for each low-skill sub-industry (at the two-digit level) within manufacturing, we compute average wages from the 1980-2016 Merged Outgoing Rotation Groups of the CPS. The low-wage sub-sample is the bottom tertile of industries in this distribution, and the high-wage subsample is the top tertile. These definitions are again matched to the data used for the previous analyses. The results are shown in Appendix A. As compared to Table 9, the estimates are often slightly attenuated, although the overall conclusions are the same.

The estimates in Table 9 are strongly consistent with the adverse effects of minimum wages on the share of employment in automatable jobs arising from low-wage jobs. Specifically, the coefficient estimates for the high-wage regressions are small, mostly not significant, and mainly centered around zero. In contrast, the coefficients in the models for low-wage jobs are sizable and significant for the pooled model, for the employment share in automatable jobs, as well as for many sub-groups. The estimates in the top panel of Table 9, in column (1), imply that a $1 increase in the minimum wage leads to a 2.03 percentage point decrease in the share of automatable jobs done by low-skilled, low-wage workers in manufacturing. This effect is substantial for males and females, and for whites and blacks, but is smaller and insignificant for the youngest workers.

The estimates in Table 9 also indicate that a $1 minimum wage increase reduces the employment probability of workers originally in automatable jobs. For low-wage jobs, we find significant negative effects for all age groups (largest for the young), and for females. Table 9 also provides evidence consistent with some workers who are in automatable employment being less likely to hold the same job in the next period; most of the estimates are negative, but none are significant.

Interestingly, in both of the individual-level analyses, we find positive effects for females in higher-wage jobs. This suggests that employment prospects for some workers in higher-wage occupations are boosted by minimum wage increases, consistent with a story in which some jobs are lost to automation, while others are created. However, those that are created are for higher-wage workers among the lower-skilled workers, and perhaps – given that result emerges for women – among jobs less likely to involve manual or physically-demanding labor. This is also consistent with the jobs represented in the top and bottom wage tertiles listed in Table 8. For instance, operators (more likely to be male) can be replaced with robotic arms, but the robotic arms need maintenance and troubleshooting.

Conclusions

This study empirically assesses whether there is labor reallocation away from automatable employment following increases in the minimum wage, and how this reallocation affects the type of employment held in the United States, within industries and for particular demographic groups. We focus specifically on jobs that tend to be held by low-skilled workers, for which labor costs increase the most in response to minimum wage increases. We estimate the impact of minimum wage increases on the share of low-skilled employment in automatable jobs, and on the probability that a low-skilled individual working in an automatable job stays employed (or in the same occupation), declines following a minimum wage increase. We explore and document considerable heterogeneity in these effects across demographic groups, and across industries. The analysis goes beyond the types of workers usually considered in the conventional, long-standing research on the employment effects of minimum wages, such as teenagers – studying, for example, the effects of minimum wages on older less-skilled workers who are in jobs where it is easier to replace people with machines.

Based on CPS data from 1980-2015, we find that increasing the minimum wage decreases significantly the share of automatable employment held by low-skilled workers. The average effects mask significant heterogeneity by industry and demographic group. For example, one striking result is that the share in automatable employment declines most sharply for older workers. An analysis of individual transitions from employment to unemployment (or to employment in a different occupation) leads to similar overall conclusions, and also some evidence of adverse effects for older workers in particular industries. Overall, our analysis points to important heterogeneity in the employment effects of minimum wages for worker in automatable jobs, and suggests that groups often ignored in the minimum wage literature are in fact quite vulnerable to job loss because of automation following a minimum wage increase.

Our work suggests that sharp minimum wage increases in the United States in coming years will shape the types of jobs held by low-skilled workers, and create employment challenges for some of them. Our findings identify some workers on whom the more general minimum wage literature is silent, but who are vulnerable to substitution of machines for people. Given data limitations, we cannot address the permanence of the effects. However, the decision to use labor-saving technology seems likely to be relatively permanent, especially if – as is becoming increasingly common – minimum wages are indexed so that a minimum wage increase results in permanently higher relative costs of low-skilled labor (Sorkin, 2015).

We have followed the definitions of automatable work as provided by Autor and Dorn (2013). These are very useful definitions for a retrospective analysis, given that the occupations identified as automatable are highly credible. However, in the future many more occupations that employ low-skill workers are on track to be automated, even if they are not currently labelled as 'automatable.' These include, for example, taxi drivers,[17] cashiers,[18] and bricklayers.[19] Therefore, it is important to acknowledge that increases in minimum wage will give incentives for firm to adopt new technologies that replace workers earlier. While these adoptions undoubtedly lead to some new jobs, there are workers who will be displaced that do not have the skills to do the new tasks. Our paper has identified workers whose vulnerability to being replaced by machines has been amplified by minimum wage increases. Such effects may spread to more workers in the future.

[17] For example, Uber is currently troubleshooting their driverless car.

[18] There is increasing use of innovations in app technology that allow customers to help themselves to the products they need, pay online and never see a cashier or checkout. This technology has already been adopted for low-value purchases in Apple Stores and in Amazon GO (Amazon's new grocery store).

[19] For example, Fastbrick Robotics has now developed Hadrian X – a robot that lays 1,000 standard bricks in 60 minutes.

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Table 1: Descriptive Statistics for the Dependent Variable

	Shares of automatable employment	P(employed in next period | initially in automatable job)	P(employed in next period in same occupation | initially in automatable job)
Total routine	30%	0.92	0.86
Construction	5%	0.92	0.88
Manufacturing	41%	0.88	0.88
Transport	22%	0.95	0.92
Wholesale	26%	0.92	0.88
Retail	40%	0.91	0.83
Finance	39%	0.95	0.89
Services	32%	0.92	0.88
P. Adm.	37%	0.96	0.90
Male	19%	0.91	0.87
Female	51%	0.92	0.85
≥ 40 years old	29%	0.89	0.86
26-39 years old	28%	0.95	0.89
≤ 25 years old	31%	0.88	0.79
White	29%	0.92	0.87
Black	31%	0.87	0.86

Notes: The average minimum wage is $6.77 in 2015 dollars.

Table 2: Full Sample Estimates, Shares of Employment in Automatable Jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	Construction	Manufacturing	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Dependent Variable = Share of Automatable Employment									
Min Wage	-0.0043	0.0005	-0.0099	-0.0076	0.0038	-0.0027	-0.0005	-0.0072	-0.0177
	(0.0021)	(0.0026)	(0.0051)	(0.0045)	(0.0062)	(0.0033)	(0.0085)	(0.0050)	(0.0133)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060

Notes: OLS coefficient estimates are reported, with standard errors in parentheses. Standard errors are clustered by State. Low-skilled workers are defined as those who have a high school diploma equivalent or less. The definition of automatable employment is provided by Autor and Dorn (2013) and Autor Dorn and Hanson (2015). A job is classified as automatable at the three-digit occupation code level. The share of automatable employment is calculated by industry, state, and year. The share of automatable hours worked is calculated in the same manner. All regressions include area (state x metro) and year fixed effects. The pooled regression also has industry fixed effects. The minimum wage is measured in 2015 dollars.

Table 3: Disaggregated Estimates, Shares of Employment in Automatable Jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	Construction	Manufacturing	Transport	Wholesale	Retail	Finance	Services	P. Adm.
≥ 40 Years Old									
Min Wage	-0.0072	0.0015	-0.0168	-0.0033	0.0013	-0.0100	0.0084	0.0015	-0.0350
	(0.0040)	(0.0028)	(0.0100)	(0.0084)	(0.0149)	(0.0070)	(0.0172)	(0.0081)	(0.0141)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060
26-39 Years Old									
Min Wage	-0.0049	0.0001	-0.0121	-0.0066	-0.0001	-0.0017	-0.0017	-0.0094	-0.0134
	(0.0036)	(0.0077)	(0.0059)	(0.0096)	(0.0065)	(0.0098)	(0.0067)	(0.0135)	(0.013)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060
≤ 25 Years Old									
Min Wage	-0.0094	0.0027	-0.0020	-0.0138	-0.0084	-0.0019	-0.0217	-0.0128	-0.0142
	(0.0040)	(0.0033)	(0.0102)	(0.0115)	(0.0158)	(0.0047)	(0.0146)	(0.0048)	(0.0208)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060
Males									
Min Wage	-0.0013	-0.0010	-0.0062	0.0013	0.0087	-0.0072	0.0050	-0.0028	0.0035
	(0.0023)	(0.0009)	(0.0030)	(0.0032)	(0.0063)	(0.0055)	(0.0126)	(0.0043)	(0.0075)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060
Females									
Min Wage	-0.0105	0.0085	-0.0248	-0.0082	0.0003	0.0002	0.0112	-0.0118	-0.0367
	(0.0038)	(0.0118)	(0.0109)	(0.0105)	(0.0148)	(0.0044)	(0.0069)	(0.0066)	(0.0142)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060
White									
Min Wage	-0.0057	-0.0014	-0.0119	-0.0011	0.0042	-0.0005	-0.0002	-0.0075	-0.0153
	(0.0023)	(0.029)	(0.0061)	(0.0088)	(0.0080)	(0.0047)	(0.0111)	(0.0050)	(0.0150)
N	30963	3157	3157	3152	3141	3157	3138	3156	3150
Black									
Min Wage	-0.0072	0.0004	-0.0458	-0.0452	0.0130	0.0196	-0.0182	0.0027	0.0086
	(0.0048)	(0.0062)	(0.0182)	(0.0166)	(0.0235)	(0.0164)	(0.0253)	(0.0153)	(0.0194)
N	22800	2273	2538	2274	1891	2730	1782	2787	2105

Notes: See notes to Table 2.

Table 4: Probability of Being Employed in the Next Period, for those Initially in Automatable Job

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	Construction	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Full Sample									
Min Wage	-0.0012	-0.0013	-0.0018	0.0002	0.0004	-0.0003	-0.0020	-0.0015	-0.0018
x Routine	(0.0004)	(0.0025)	(0.0008)	(0.0013)	(0.0025)	(0.0017)	(0.0015)	(0.0008)	(0.0017)
Routine	0.0089	0.0810	0.0044	0.0157	-0.0094	-0.0177	0.0302	0.0188	-0.0000
	(0.0016)	(0.0110)	(0.0030)	(0.0040)	(0.0093)	(0.0065)	(0.0072)	(0.0033)	(0.0057)
N	956232	88957	242539	68224	36844	166940	47750	240142	42854
≥ 40 Years Old									
Min Wage	-0.0026	0.0002	-0.0028	-0.0010	0.0002	-0.0009	-0.0030	-0.0033	-0.0018
x Routine	(0.0007)	(0.0037)	(0.0013)	(0.0021)	(0.0043)	(0.0024)	(0.0030)	(0.0014)	(0.0035)
Routine	0.0160	0.0781	0.0089	0.0275	-0.0029	-0.0138	0.0467	0.0312	0.0152
	(0.0025)	(0.0142)	(0.0046)	(0.0070)	(0.0157)	(0.0090)	(0.0117)	(0.0058)	(0.0126)
N	403189	36220	108634	32975	15538	52278	20610	104844	22842
26-39 Years Old									
Min Wage	-0.0005	-0.0006	0.0001	0.0005	0.0006	-0.0005	-0.0011	0.0003	0.0007
x Routine	(0.0008)	(0.0043)	(0.0013)	(0.0019)	(0.0044)	(0.0028)	(0.0025)	(0.0011)	(0.0030)
Routine	0.0068	0.0673	-0.0022	0.0151	-0.0047	-0.0139	0.0265	0.0108	-0.0020
	(0.0028)	(0.0159)	(0.0046)	(0.0069)	(0.0160)	(0.0100)	(0.0085)	(0.0041)	(0.0099)
N	328683	34750	88997	25652	13727	47033	16600	79412	14540
≤ 25 Years Old									
Min Wage	-0.0052	-0.0021	-0.0079	-0.0016	0.0034	-0.0006	-0.0006	-0.0042	0.0082
x Routine	(0.0013)	(0.0087)	(0.0025)	(0.0060)	(0.0076)	(0.0027)	(0.0081)	(0.0029)	(0.0102)
Routine	0.0322	0.1065	0.0338	0.0630	-0.0044	-0.0099	0.0729	0.0437	0.0387
	(0.0045)	(0.0325)	(0.0082)	(0.0177)	(0.0279)	(0.0107)	(0.0301)	(0.0112)	(0.0304)
N	224360	17987	44908	9597	7579	67629	10540	55886	5472
Males									
Min Wage	-0.0013	-0.0042	-0.0020	0.0014	-0.0035	0.0037	0.0009	-0.0034	-0.0015
x Routine	(0.0007)	(0.0050)	(0.0010)	(0.0018)	(0.0043)	(0.0023)	(0.0023)	(0.0019)	(0.0025)
Routine	0.0022	0.0557	-0.0007	0.0109	0.0007	-0.0444	0.0258	0.0154	0.0103
	(0.0025)	(0.0167)	(0.0033)	(0.0056)	(0.0137)	(0.0076)	(0.0106)	(0.0075)	(0.0069)
N	534311	83224	156879	52227	25701	77921	13665	82106	24064
Females									
Min Wage	-0.0019	-0.0033	-0.0067	0.0031	-0.0028	-0.0039	-0.0029	-0.0006	-0.0031
x Routine	(0.0006)	(0.0066)	(0.0016)	(0.0035)	(0.0032)	(0.0018)	(0.0022)	(0.0008)	(0.0026)
Routine	0.0145	0.1118	0.0330	-0.0006	0.0066	0.0047	0.0207	0.0144	0.0172
	(0.0022)	(0.0272)	(0.0059)	(0.0120)	(0.0142)	(0.0075)	(0.0097)	(0.0029)	(0.0103)
N	421921	5733	85660	15997	11143	89019	34085	158036	18790
White									
Min Wage	-0.0004	0.0005	-0.0017	0.0015	0.0011	0.0003	0.0002	-0.0002	0.0009
x Routine	(0.0005)	(0.0028)	(0.0008)	(0.0015)	(0.0025)	(0.0019)	(0.0015)	(0.0008)	(0.0019)
Routine	0.0068	0.0698	0.0048	0.0102	-0.0129	-0.0159	0.0188	0.0144	-0.0017
	(0.0017)	(0.0113)	(0.0030)	(0.0043)	(0.0091)	(0.0074)	(0.0070)	(0.0030)	(0.0069)
N	824135	80827	211855	59242	33225	147053	42306	194902	34351
Black									
Min Wage	-0.0022	0.0042	-0.0034	-0.0120	-0.0174	-0.0074	-0.0104	-0.0032	0.0010
x Routine	(0.0017)	(0.0137)	(0.0026)	(0.0056)	(0.0131)	(0.0056)	(0.0082)	(0.0017)	(0.0050)
Routine	0.0052	0.1490	-0.0196	0.0623	0.0481	0.0078	0.0788	0.0071	0.0039
	(0.0062)	(0.0558)	(0.0095)	(0.0204)	(0.0496)	(0.0173)	(0.0291)	(0.0065)	(0.0158)
N	104510	6141	24830	7522	2745	13921	4264	37204	6922

Notes: See also notes to Table 2. Dependent variable is equal to 1 if a person is employed in *t*+1, 0 if they are unemployed. All regressions include state x year fixed effects and a metropolitan area dummy variable.

Table 5: Probability of Being Employed in the Same Occupation in the Next Period, for those Initially in Automatable Job

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	Construction	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Full Sample									
Min Wage	-0.0050	-0.0075	-0.0025	-0.0139	-0.0037	0.0033	-0.0078	-0.0108	0.0029
x Routine	(0.0006)	(0.0048)	(0.0010)	(0.0024)	(0.0034)	(0.0017)	(0.0026)	(0.0010)	(0.0028)
Routine	0.0140	0.0538	0.0011	0.0376	-0.0069	-0.0335	0.0309	0.0482	-0.0132
	(0.0021)	(0.0194)	(0.0031)	(0.0084)	(0.0133)	(0.0065)	(0.0102)	(0.0036)	(0.0101)
N	894885	75561	226891	64580	35439	154317	46879	229714	41846
≥ 40 Years Old									
Min Wage	-0.0045	-0.0048	-0.0019	-0.0057	-0.0037	-0.0036	-0.0037	-0.0075	0.0056
x Routine	(0.0006)	(0.0054)	(0.0015)	(0.0036)	(0.0047)	(0.0029)	(0.0028)	(0.0013)	(0.0038)
Routine	0.0121	0.0190	0.0012	0.0117	-0.0014	-0.0000	0.0092	0.0301	-0.0195
	(0.0024)	(0.0197)	(0.0047)	(0.0131)	(0.0168)	(0.0105)	(0.0105)	(0.0049)	(0.0137)
N	385809	32647	105222	31910	15277	49025	20523	102706	22601
26-39 Years Old									
Min Wage	-0.0061	-0.0095	-0.0037	-0.0124	0.0001	0.0028	-0.0134	-0.0114	0.0007
x Routine	(0.0010)	(0.0071)	(0.0022)	(0.0042)	(0.0059)	(0.0035)	(0.0045)	(0.0018)	(0.0041)
Routine	0.0191	0.0332	0.0069	0.0360	-0.0089	-0.0299	0.0610	0.0502	-0.0126
	(0.0037)	(0.0270)	(0.0077)	(0.0156)	(0.0225)	(0.0142)	(0.0170)	(0.0071)	(0.0139)
N	307294	28867	83304	23948	13106	44595	16369	75399	14317
≤ 25 Years Old									
Min Wage	-0.0102	-0.0155	-0.0049	-0.0516	-0.0235	0.0076	-0.0447	-0.0125	-0.0219
x Routine	(0.0017)	(0.0157)	(0.0032)	(0.0103)	(0.0105)	(0.0053)	(0.0122)	(0.0034)	(0.0178)
Routine	0.0499	0.1435	0.0192	0.1804	0.0536	-0.0316	0.2259	0.0771	0.1189
	(0.0059)	(0.0565)	(0.0108)	(0.0324)	(0.0390)	(0.0127)	(0.0399)	(0.0131)	(0.0529)
N	201782	14047	38365	8722	7056	60697	9987	51609	4928
Males									
Min Wage	-0.0054	-0.0210	-0.0037	-0.0147	0.0067	0.0013	-0.0069	-0.0184	0.0042
x Routine	(0.0008)	(0.0078)	(0.0014)	(0.0038)	(0.0049)	(0.0027)	(0.0044)	(0.0027)	(0.0042)
Routine	-0.0027	0.0631	-0.0006	0.0225	-0.0605	-0.0962	0.0074	0.0537	-0.0339
	(0.0031)	(0.0273)	(0.0049)	(0.0134)	(0.0191)	(0.0111)	(0.0166)	(0.0104)	(0.0129)
N	496746	70365	148313	49454	24852	72440	13707	77673	23537
Females									
Min Wage	-0.0069	-0.0359	-0.0014	-0.0090	-0.0169	-0.0013	-0.0049	-0.0049	-0.0133
x Routine	(0.0008)	(0.0135)	(0.0028)	(0.0046)	(0.0059)	(0.0022)	(0.0030)	(0.0014)	(0.0042)
Routine	0.0196	0.1938	-0.0022	0.0484	0.0668	0.0092	0.0162	0.0306	0.0661
	(0.0030)	(0.0575)	(0.0087)	(0.0157)	(0.0239)	(0.0084)	(0.0123)	(0.0049)	(0.0179)
N	398139	5196	78578	15126	10587	81877	33172	152041	18309
White									
Min Wage	-0.0050	-0.0062	-0.0026	-0.0119	-0.0042	0.0026	-0.0082	-0.0125	0.0044
x Routine	(0.0006)	(0.0049)	(0.0010)	(0.0025)	(0.0032)	(0.0019)	(0.0029)	(0.0011)	(0.0030)
Routine	0.0157	0.0463	0.0019	0.0317	-0.0042	-0.0336	0.0352	0.0607	-0.0185
	(0.0022)	(0.0198)	(0.0033)	(0.0090)	(0.0126)	(0.0073)	(0.0109)	(0.0036)	(0.0104)
N	775940	69074	199529	56349	32120	137111	41793	187723	33962
Black									
Min Wage	-0.0015	-0.0015	0.0005	-0.0284	-0.0041	-0.0037	-0.0035	-0.0018	-0.0009
x Routine	(0.0018)	(0.0347)	(0.0051)	(0.0085)	(0.0206)	(0.0059)	(0.0074)	(0.0040)	(0.0093)
Routine	-0.0102	-0.0066	-0.0278	0.0767	-0.0377	-0.0138	-0.0340	-0.0172	0.0019
	(0.0068)	(0.1374)	(0.0168)	(0.0314)	(0.0704)	(0.0226)	(0.0286)	(0.0172)	(0.0328)
N	93549	4879	21995	6905	2479	11655	3967	34427	6445

Notes: See notes to Table 2. Dependent variable is equal to 1 if a person is employed in the same occupation in t+1, 0 if they are unemployed or in another occupation. Samples are smaller than in Table 4 because all respondents needed to have a valid occupation code in period t, and respondents who stayed employed in period t and period t+1 need to have a valid occupation code in both periods. Those who do not meet these criteria are excluded from the sample.

Table 6: Hours Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable = Share of Hours in Automatable Jobs								
	Pooled	≥ 40 Years Old	26-39 Years Old	≤ 25 Years Old	Male	Female	White	Black
Min Wage	-0.0033	-0.0073	-0.0024	-0.0082	-0.0011	-0.0048	-0.0033	-0.0400
	(0.0024)	(0.0041)	(0.0033)	(0.0046)	(0.0017)	(0.0035)	(0.0024)	(0.0051)
N	30963	30963	30963	30963	30963	30963	30963	22800
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Min Wage	0.0009	-0.0103	-0.0073	0.0065	-0.0040	0.0039	-0.0097	-0.0122
	(0.0027)	(0.0041)	(0.0043)	(0.0065)	(0.0044)	(0.0109)	(0.0057)	(0.0139)
N	3017	3017	3011	3000	3017	2990	3016	3006
Dependent Variable = Hours Difference from Period 1 to Period 2								
	Pooled	≥ 40 Years Old	26-39 Years Old	≤ 25 Years Old	Male	Female	White	Black
Min Wage x Routine	-0.2282	-0.2490	-0.2588	-0.0832	-0.1747	-0.0978	-0.2590	0.0959
	(0.0240)	(0.0351)	(0.0425)	(0.0541)	(0.0389)	(0.0307)	(0.0265)	(0.0731)
Routine	0.8008	0.8048	1.0004	0.0335	0.8884	-0.0932	0.8974	0.4930
	(0.1436)	(0.2139)	(0.2511)	(0.3155)	(0.2360)	(0.1819)	(0.1572)	(0.4380)
N	696432	330014	225466	140952	384574	311858	568524	82581
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Min Wage x Routine	-0.1851	-0.1972	-0.2779	-0.2638	-0.0840	-0.0591	-0.0761	-0.1379
	(0.1568)	(0.0372)	(0.0955)	(0.1371)	(0.0491)	(0.1280)	(0.0393)	(0.1091)
Routine	-0.5174	0.7316	-0.2775	1.1842	0.5282	-0.3942	-0.2190	-0.0942
	(0.9559)	(0.2127)	(0.5628)	(0.7451)	(0.2980)	(0.6856)	(0.2550)	(0.5918)
N	696432	77628	122638	46009	23443	138791	29655	208287

Notes: See notes to Table 2. In the bottom panel, the sample only includes individuals who remained employed between the two periods, so the sample sizes are lower than for the employment regressions.

Table 7: Contemporary Analysis, 1995-2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable = Share of Employment in Automatable Jobs								
	Pooled	≥ 40 Years Old	26-39 Years Old	≤ 25 Years Old	Male	Female	White	Black
Min Wage	-0.0057	-0.0088	-0.0039	-0.0078	-0.0013	-0.0079	-0.0062	-0.0029
	(0.0031)	(0.0041)	(0.0033)	(0.0053)	(0.0021)	(0.0047)	(0.0033)	(0.0077)
N	19154	11886	11860	11510	12020	11553	12025	8264
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Min Wage	0.0002	-0.0085	-0.0118	0.0047	-0.0039	-0.0066	-0.0095	-0.0208
	(0.0025)	(0.0089)	(0.0069)	(0.0082)	(0.0044)	(0.0095)	(0.0045)	(0.0108)
N	1964	1964	1959	1954	1964	1945	1963	1957
Dependent Variable = Probability of Being Employed in the Current Period								
	Pooled	≥ 40 Years Old	26-39 Years Old	≤ 25 Years Old	Male	Female	White	Black
Min Wage x Routine	-0.0040	-0.0074	-0.0046	-0.0077	-0.0001	-0.0041	-0.0072	0.0008
	(0.0012)	(0.0017)	(0.0012)	(0.0038)	(0.0017)	(0.0015)	(0.0013)	(0.0036)
Routine	0.0312	0.0365	0.0265	0.0395	0.0030	0.0160	0.0388	-0.0133
	(0.0058)	(0.0087)	(0.0065)	(0.0186)	(0.0085)	(0.0079)	(0.0070)	(0.0169)
N	322827	119340	140110	63377	144667	178160	272342	34614
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Min Wage x Routine	-0.0121	-0.0068	-0.0057	0.0025	0.0059	-0.0039	-0.0016	0.0054
	(0.0084)	(0.0027)	(0.0046)	(0.0061)	(0.0032)	(0.0034)	(0.0018)	(0.0037)
Routine	0.1282	0.0314	0.0368	-0.0237	-0.0480	0.0350	0.0151	-0.0310
	(0.0441)	(0.0133)	(0.0220)	(0.0325)	(0.0153)	(0.0198)	(0.0087)	(0.0180)
N	34395	65414	21674	12412	58907	16496	91089	12387
Dependent Variable = Probability of Having the Same Job in the Current Period								
	Pooled	≥ 40 Years Old	26-39 Years Old	≤ 25 Years Old	Male	Female	White	Black
Min Wage x Routine	-0.0090	-0.0102	-0.0069	-0.0164	-0.0067	-0.0073	-0.0094	-0.0073
	(0.0015)	(0.0029)	(0.0019)	(0.0057)	(0.0021)	(0.0028)	(0.0019)	(0.0053)
Routine	0.0334	0.0409	0.0232	0.0828	0.0381	0.0036	0.0365	0.0178
	(0.0075)	(0.0144)	(0.0101)	(0.0286)	(0.0106)	(0.0135)	(0.0095)	(0.0253)
N	325936	120069	140684	65183	146763	179173	274888	35054
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Min Wage x Routine	-0.0258	-0.0050	-0.0179	0.0035	-0.0020	-0.0031	-0.0201	-0.0065
	(0.0119)	(0.0037)	(0.0075)	(0.0061)	(0.0040)	(0.0057)	(0.0035)	(0.0069)
Routine	0.1192	0.0125	0.0467	-0.0420	-0.0078	-0.0256	0.0936	0.0294
	(0.0598)	(0.0175)	(0.0389)	(0.0312)	(0.0197)	(0.0309)	(0.0177)	(0.0342)
N	34559	65833	21776	12482	60061	16503	92229	12458

Notes: See notes to Tables 2 and 4.

Table 8: Examples of Top and Bottom Tertile Wage Occupations in Manufacturing

	Top Tertile	Bottom Tertile
1	Repairers of data processing equipment	Sawing machine operators
2	Water and sewage treatment plant operators	Assemblers of electrical equipment
3	Millwrights	Food roasting and baking machine operators
4	Supervisors of mechanics and repairers	Cooks
5	Elevator installers and repairers	Packers
6	Repairers of electrical equipment	Parking lot attendants
7	Plant and system operators, stationary engineers	Metal platers
8	Railroad conductors and yardmasters	Textile sewing machine operators
9	Electricians	Clothing pressing machine operators
10	Tool and die-makers and die-setters	Molders and casting machine operators

Table 9: Manufacturing Low-Wage versus High-Wage Occupations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	≥ 40 Years Old	26-39 Years Old	≤ 25 Years Old	Male	Female	White	Black
Dependent Variable = Share of Employment in Automatable Jobs								
				Low-Wage				
Min Wage	-0.0203	-0.0358	-0.0199	-0.0108	-0.0164	-0.0212	-0.0301	-0.0400
	(0.0078)	(0.0144)	(0.0090)	(0.0126)	(0.0074)	(0.0118)	(0.0069)	(0.0168)
N	4403	4403	4403	3968	4403	4401	4403	3386
				High-Wage				
Min Wage	0.0027	0.0013	0.0015	-0.0042	0.0090	-0.0084	0.0151	0.0131
	(0.0062)	(0.0092)	(0.0080)	(0.0181)	(0.0174)	(0.0083)	(0.0074)	(0.0167)
N	4551	4551	4551	2055	4551	4548	4551	1627
Dependent Variable = Probability of Being Employed in the Current Period								
				Low-Wage				
Min Wage	-0.0016	-0.0038	-0.0055	-0.0107	0.0007	-0.0055	-0.0010	0.0035
x Routine	(0.0012)	(0.0018)	(0.0019)	(0.0035)	(0.0016)	(0.0019)	(0.0012)	(0.0035)
Routine	0.0167	0.0233	0.0372	0.0495	0.0045	0.0372	0.0161	-0.0118
	(0.0041)	(0.0057)	(0.0073)	(0.0113)	(0.0063)	(0.0073)	(0.0043)	(0.0134)
N	135685	40904	67773	27008	67912	67773	115050	16687
				High-Wage				
Min Wage	0.0002	-0.0037	0.0006	-0.0088	0.0003	0.0093	0.0005	0.0013
x Routine	(0.0038)	(0.0079)	(0.0076)	(0.0265)	(0.0040)	(0.0053)	(0.0036)	(0.0066)
Routine	-0.0023	0.0040	-0.0041	0.0063	-0.0009	-0.0361	-0.0032	0.0142
	(0.0124)	(0.0245)	(0.0247)	(0.0679)	(0.0135)	(0.0221)	(0.0123)	(0.0325)
N	24078	14501	7963	1614	19500	4578	22986	758
Dependent Variable = Probability of Being Employed in the Current Period								
				Low-Wage				
Min Wage	-0.0020	-0.0079	-0.0066	-0.0125	-0.0032	0.0018	0.0004	-0.0686
x Routine	(0.0036)	(0.0073)	(0.0072)	(0.0316)	(0.0053)	(0.0103)	(0.0035)	(0.1288)
Routine	-0.0036	0.0146	0.0129	0.0279	0.0014	-0.0260	-0.0108	0.2456
	(0.0039)	(0.0049)	(0.0076)	(0.0101)	(0.0072)	(0.0087)	(0.0050)	(0.0129)
N	135685	61436	47241	27008	67912	67773	115050	16687
				High-Wage				
Min Wage	0.0017	0.0014	-0.0000	-0.0030	0.0006	0.0051	0.0011	0.0113
x Routine	(0.0013)	(0.0029)	(0.0021)	(0.0033)	(0.0016)	(0.0018)	(0.0013)	(0.0052)
Routine	-0.0004	-0.0006	0.0058	0.0170	-0.0012	-0.0108	0.0028	-0.0406
	(0.0136)	(0.0198)	(0.0222)	(0.0405)	(0.0212)	(0.0246)	(0.0148)	(0.0364)
N	24078	14501	7963	1614	19500	4578	22986	758

Notes: see notes to Tables 2, 3, and 4.

Appendix A: Manufacturing Low-Wage Industries versus High-Wage Industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	≥ 40 Years Old	26-39 Years Old	≤ 25 Years Old	Male	Female	White	Black
Dependent Variable = Share of Employment in Automatable Jobs								
Low-Wage								
Min Wage	-0.0199	-0.0201	-0.0061	-0.0207	-0.0166	-0.0219	-0.0142	-0.0281
	(0.0081)	(0.0085)	(0.0074)	(0.0168)	(0.0870)	(0.0100)	(0.0076)	(0.0168)
N	4515	4515	4515	4254	4515	4515	4406	2917
High-Wage								
Min Wage	0.0035	-0.0031	0.0094	0.0240	0.0014	-0.0860	0.0027	-0.0063
	(0.0067)	(0.0099)	(0.0109)	(0.0134)	(0.0080)	(0.0101)	(0.0082)	(0.0208)
N	4515	4515	4515	3780	4515	4515	4505	2917
Dependent Variable = Probability of Being Employed in the Current Period								
Low-Wage								
Min Wage	-0.0032	-0.0049	-0.0014	-0.0095	-0.0006	-0.0076	-0.0027	-0.0010
x Routine	(0.0014)	(0.0020)	(0.0022)	(0.0038)	(0.0017)	(0.0025)	(0.0015)	(0.0044)
Routine	0.0127	0.0179	0.0014	0.0457	0.0051	0.0285	0.0106	0.0078
	(0.0061)	(0.0087)	(0.0088)	(0.0119)	(0.0059)	(0.0105)	(0.0065)	(0.0154)
N	88809	41360	30675	16774	47635	41174	75950	10091
High-Wage								
Min Wage	0.0014	-0.0009	0.0006	-0.0040	0.0018	-0.0099	0.0021	0.0034
x Routine	(0.0015)	(0.0032)	(0.0032)	(0.0065)	(0.0014)	(0.0034)	(0.0015)	(0.0065)
Routine	-0.0096	-0.0045	-0.0093	0.0130	-0.0116	0.0454	-0.0104	-0.0330
	(0.0052)	(0.0106)	(0.0115)	(0.0212)	(0.0044)	(0.0130)	(0.0051)	(0.0228)
N	65650	33496	23327	8827	50638	15012	57490	7163
Dependent Variable = Probability of Being Employed in the Same Job Current Period								
Low-Wage								
Min Wage	-0.0021	-0.0051	-0.0042	-0.0116	-0.0007	-0.0068	-0.0032	0.0092
x Routine	(0.0017)	(0.0027)	(0.0039)	(0.0052)	(0.0023)	(0.0044)	(0.0017)	(0.0072)
Routine	0.0073	0.0219	0.0179	0.0480	-0.0035	0.0429	0.0111	-0.0381
	(0.0069)	(0.0099)	(0.0144)	(0.0161)	(0.0084)	(0.0155)	(0.0070)	(0.0219)
N	88809	41360	30675	16774	47635	41174	75950	10091
High-Wage								
Min Wage	0.0024	0.0030	0.0020	0.0017	-0.0028	0.0086	0.0029	0.0059
x Routine	(0.0014)	(0.0028)	(0.0033)	(0.0041)	(0.0018)	(0.0026)	(0.0015)	(0.0062)
Routine	-0.0170	-0.0194	-0.0155	-0.0160	0.0006	-0.0386	-0.0182	-0.0290
	(0.0050)	(0.0103)	(0.0130)	(0.0135)	(0.0072)	(0.0091)	(0.0052)	(0.0225)
N	65650	33496	23327	8827	50638	15012	57490	7163

Notes: See notes to Tables 2, 3, and 4. For each low-skill sub-industry (at the two-digit level) within manufacturing, we compute average wages from the 1980-2016 Merged Outgoing Rotation Groups of the CPS. The low-wage subsample is the bottom tertile of industries in this distribution, and the high-wage subsample is the top tertile.