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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 for 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 nonemployed or employed in worse jobs. The average effects mask significant heterogeneity by industry and demographic group, including substantive adverse effects for older, low-skilled workers in manufacturing. We also find some evidence that the same changes improve job opportunities for higher-skilled workers. 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, Dube, and Reich (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); and Powell (2016). Neumark (2017) reviews the very recent literature, classifying 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.[3,4]

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. As emphasized by Autor and Dorn (2013) and Goos, Manning, and Salomons (2014), the hollowing out of mid-skill occupations has been a significant channel through which automation has affected the occupation distribution over time. However, the advancement of technology in industry has also touched the occupations in which low-skilled individuals work. This is illustrated in Figure 1, which shows a clear downward trend in the degree to which job tasks of low-skilled individuals are automatable, from 1980-2015.[5] There is also evidence that this was spurred by computerization. As shown by Autor and Dorn (2013), computerization in industry has accelerated over the last four decades, and this technology diffused faster into areas that have higher shares of automatable employment. Such evidence suggests, as we would expect, that firms choose to substitute technology for workers as it becomes cheaper for them to do so.

The core idea or hypothesis underlying our analysis is that minimum wage increases have the potential to spur the automation of low-skilled jobs, via substituting technology for low-skilled workers. These minimum wages increases raise the price of low-skilled labor, increasing the cost savings from this substitution. The main aim of our paper is to explore this

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[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 minimum wage 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; and MaCurdy, 2015), and compression of wage differentials (see DiNardo, Fortin, and Lemieux, 1996; and Autor, Manning, and Smith, 2016).

[4] In a recent paper, Basker et al. (2017) explore a different kind of substitution of technology for labor (at least, the firm's labor) that can occur in response to a higher minimum wage – namely, substitution of a customer's labor for a worker's labor (in, e.g., a self-service gas station, or using a bank ATM). They suggest that this kind substitution may occur when low-skilled labor becomes expensive and technology enables labor replacement in tasks that are not easy to automate.

[5] Figure 1 is based on a measure of "routine task intensity" (*RTI*) discussed below (see equation (1)).

hypothesis, and in so doing 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 and skill groups.

Specifically, we first 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. We also explore other impacts on low-skilled workers, as well as whether job opportunities improve for higher-skilled workers in the industries where a high share of low-skilled employed was in automatable jobs.

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 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. We therefore attempt to provide a fuller picture of labor market adjustments across industries and a variety of demographic groups, which can uncover these important differential responses. As discussed below, this if of particular interest with respect to the broader minimum wage literature.

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 "job" (narrow occupation and broad industry) following a minimum wage increase. Finally, we extend the analysis to cover more outcomes for low-skilled workers, and to assess effects on higher-skilled workers.

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.[6] Moreover, many U.S. cities

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

have implemented minimum wages, with the minimum wage in Seattle (and nearby Sea-Tac) already 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 state-year cell an automatable employment share.[7] 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 the elasticity of this share with respect to the minimum wage is −0.10. 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 an elasticity of −0.18). 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.

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

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 nonemployed in the period following a minimum wage increase. These effects are relatively larger for individuals employed in manufacturing, and are larger for the oldest and youngest workers, for females and for blacks. Overall, this analysis points to important heterogeneity in the employment effects of minimum wages – including some potentially positive effects for higher-skilled workers in jobs where the minimum wage spurs substitution away from low-skilled workers in automatable jobs. Moreover, our evidence 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. Thus, a 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.

Analysis of Shares of Employment in Automatable Jobs

Methods

Most of our analysis focuses on low-skilled individuals, who we define as having a high school diploma equivalent or less. We use data from Autor and Dorn (2013) and Autor et al. (2015) to measure routine task intensity (*RTI*) in jobs held by low-skilled workers. These authors use *RTI* as a proxy for determining the degree to which the tasks within an occupation are automatable. 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.[8] Routine tasks involve a repeated sequence of actions, are easily codifiable, and

[8] 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.

are 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*.

We further calculate for each industry *i*, within each area *a* (defined as states divided into urban and nonurban areas), in year *t*, a routine employment share, as follows:

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

In equation (2), L_{iat} is equal to total employment in industry *i* in area *a* at time *t*. 1[.] is an indicator function equal to one if an occupation is in the top third of the employment-weighted distribution of *RTI* across occupations (RTI^{P66} denotes the 66th percentile), 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, area, and year.

Our analysis initially focuses on the following specification:

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

where MW_{st} denotes the minimum wage in state *s* at time *t*. We use the log of minimum wages following the literature on minimum wages in the last decade or more. Equation (3) also includes area (A_a) and year (T_t), fixed effects. Area is defined as state-specific dummy variables interacted with whether the individual lives in an urban 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.[9]

We next turn to disaggregating these effects across industries and demographic groups, 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 across demographic groups. For example, less-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). We therefore focus on differences in effects by age and sex, and we also examine differences by race.[10] 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 those 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:

$$RSH_{ciat} = (\sum_{k=1}^{K}(L_{ciat}) \cdot 1[RTI_k > RTI^{P66}])(\sum_{k=1}^{K}(L_{ciat}))^{-1} \quad .^{11} \tag{4}$$

In this case the numerator is the share of automatable employment held by a subgroup

[9] We also augmented equation (3) adding up to three lags of the minimum wage variable. The inclusion of lags allows for a period of adjustment to reorganize the factors of production away from labor and towards capital investments in technology (and perhaps other complementary labor). In all models, the lags were 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.

[10] 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).

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

in a specific industry, area, and year, and the denominator is total employment of a 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 services 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 employment, among low-skilled workers, is reported in column (1) of Table 1. Finance, retail, manufacturing, and public administration ("P. Adm.") 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 among low-skilled in the industry in question, and the ease and cost of automating tasks. 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 the 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.[12] We allow for a period of adjustment by defining the minimum wage as the

[12] These minimum wage data are available at https://www.socsci.uci.edu/~dneumark/datasets.html.

average over the current month plus the last 11 months. In addition, we do not include agriculture and mining in our subgroup 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.[13]

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.[14] *RTI*, described in equation (1), is provided by Autor and Dorn (2013) and is matched to the CPS data using this coding system. As noted earlier, we use data on low-skilled individuals with a high school diploma equivalent or less.

Individual-Level Analysis

Methods

Even if the share of automatable jobs declines for low-skilled workers (per the prior analysis), employment opportunities need not decline if these workers are reallocated to non-automatable jobs. We therefore also estimate regressions using individual-level data on low-skilled individuals to explore whether job prospects worsen for those low-skilled workers who were in routine jobs when the minimum wage increases. Specifically, we estimate the model:

$$Emp_{jiai+1} = b_1 \cdot RSH_{jiat} \cdot Log(MW_{at}) + b_2 RSH_{jiat} + T_t \cdot A_s \lambda + \varepsilon_{jiat} \quad , \qquad (5)$$

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 nonemployed in *t+1*. The sample consists of those employed in period *t*, and either employed or nonemployed (i.e., unemployed or not in the labor force) in period *t+1*.

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

[14] 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.

Equation (5) relates this job loss to workers having held a routine job in period t, and faced a minimum wage increase, with the coefficient b_1 on the interaction $RSH_{jiat} \cdot Log(MW_{at})$ capturing whether a person in automatable work is more vulnerable to job loss following a minimum wage increase, compared to those not in automatable work. Note that the minimum wage and the routine share (*RSH*) are measured in period t, and the employment transition is measured from period t to period $t+1$.[15] All control variables are also measured at time t. We can only look at those initially employed because we need to classify jobs by *RTI*; hence, we capture only flows out of employment.[16]

Equation (5) also includes a full set of area-by-year interactions (where area is defined by state and urban or nonurban areas within states), to allow flexibly for differential yearly shocks to states and subareas of states.[17] Given the inclusion of the area-by-year interactions, the main effect Log(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 areas across time.[18]

All other definitions are consistent with equations (1) through (4). If individuals working in automatable jobs at the time of a minimum wage increase are more likely to lose

[15] One might want to measure *RSH* prior to when the minimum wage is measured, to avoid contemporaneous changes associated with the minimum wage. But we do not have longer lagged information on employment with which to lag the measurement of *RSH.*

[16] We cannot investigate models with lags or additional leads as we do not know where the individual was working beyond two periods.

[17] We cannot allow this much flexibility in the share analysis because this is the level at which the minimum wage variation arises in that analysis. In contrast, here we can because we are interested in the effect of the interaction between *RSH* and the minimum wage.

[18] We cannot meaningfully document the overall 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.

jobs by the next period, compared to individuals affected by the same minimum wage increase but who are in jobs that are not automatable, we would expect the coefficient on b_1 to be negative. As in the share analysis, we explore heterogeneity in b_1 by estimating equation (5) separately by industry and by demographic subgroup.

We complement these regressions with analyses that consider a dependent variable that equals one if an individual had the same narrow occupation code (3-digit) and broad industry code (1-digit) in the interview year, and zero otherwise (including both the nonemployed and "job" switchers). In these analyses, $b_1 < 0$ would reflect transitions to other employment or to nonemployment – with the former presumably reflecting, to some extent, movements of out of employment in automatable tasks following a minimum wage increase.

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 include information on the occupation and industry of the job held by respondents in the previous year, which is period t in the analysis described above. Thus, RSH is based on this occupation. Columns (2) and (3) of Table 1 report the average probabilities that employed, low-skilled workers in automatable jobs remain employed, or in the same "jobs" (for those who remain in the labor force).

Identification

A potential issue in estimating the effects of minimum wages is whether minimum wage variation is correlated with shocks to low-skill labor markets – possibly due to endogenous policy – in which case we may not identify causal effects of minimum wages. This issue has arisen prominently in recent exchanges on the employment effects of minimum wages; see, most recently, Allegretto, Dube, and Reich (2017) and Neumark and

Wascher (2017).[19] However, we are estimating effects on a subgroup of low-skilled workers, and it seems less plausible that policy is chosen endogenously with respect to outcomes for one subgroup of low-skilled workers. Moreover, our individual-level analysis is even more insulated from this identification issue, because we control in an unrestricted fashion for yearly shocks to states, and their urban and nonurban areas separately. This approach of isolating the effects of minimum wages controlling for state or substate shocks has been advocated by Allegretto et al. (2011) and Dube et al. (2010). While this approach may raise other concerns (see Neumark et al., 2014a), it does have the virtue of potentially controlling for shocks to low-skilled labor markets that are correlated with minimum wage changes.

Finally, evidence of leading minimum wage effects could provide evidence that minimum wage changes respond to expected future changes, in which case our evidence may not be causal. We can assess this evidence for our share analysis, which is based on a panel on observations on areas and industries over time. We estimated versions of equation (3) allowing up to three annual leading terms; these were never statistically significant, and were centered around zero.

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 shown in column (1), we find that minimum wage increases cause a statistically significant reallocation of labour away from automatable tasks. We find that a 10 percent increase in the minimum wage leads to a 0.31 percentage point decrease in the share of automatable jobs done by low-skilled workers, implying an

[19] Recent work by Clemens and Wither (2015) and Baskaya and Rubinstein (2012) indicates that, if anything, the employment effects are more negative when accounting for correlated shocks, suggesting that policy variation is correlated with positive shocks.

elasticity of −0.10.[20]

When we look separately by industry, the estimated effects in construction, wholesale, retail, finance, and public administration are small, centered around zero, and not statistically significant. In contrast, the effects are larger for manufacturing, transport, and services, and significant at the 5- or 10-percent level for manufacturing and transport. For example, the estimates imply that the elasticity of the share of automatable jobs among low-skilled workers in manufacturing with respect to the minimum wage is −0.18.

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 and (in columns (2)-(9) by industry. The estimates point to 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 low-skilled workers in automatable jobs for all three age groups (only at the 10-percent level in two cases), but the magnitudes are larger for the youngest and oldest workers. Looking by both age and industry, for older workers (≥ 40 years old) the negative effect mainly arises in manufacturing, retail, and public administration, while for younger workers (≤ 25 years old) the effects are large in many sectors, but the estimate is close to zero in manufacturing, and statistically significant only in services. For the middle age group (26-39) there is sizable estimated decline in manufacturing, but it is well under one-half the effect for older workers. Thus, older workers appear more vulnerable to substitution away from automatable jobs in manufacturing when the minimum wage increases. Moreover, the general adverse effect of the minimum wage for older jobs in automatable jobs is interesting in light of the typical focus of the minimum wage literature – and the evidence of disemployment effects – for very young workers.

[20] We do not include industry fixed effects in the pooled estimates, so that we can detect changes in the share of employment in automatable jobs arising from industry reallocation. However, the estimates including industry fixed effects were very similar.

On average, females are affected more adversely than males: in the aggregate estimates in column (1), the negative estimate is negative and significant only for females, and is ten times larger, indicating that, for females, 10 percent increase in the minimum wage reduces the share of automatable jobs (among the low-skilled) by 0.78 percentage point (an elasticity of −1.53). Across industries, these negative effects for females are concentrated in manufacturing, services, and public administration. For males, none of the industry-specific estimates are statistically significant, but the estimated effects are negative and sizable for manufacturing and retail.

Table 3 also points to more adverse effects on the share in automatable employment for blacks than for whites, with the effect more than double for blacks.[21] However, the effects are heterogeneous across industries. There are sizable adverse estimated effects for whites in manufacturing, transport, services, and public administration, although only the transport estimate is statistically significant. For blacks, there are much larger, and statistically significant, decreases in automatable shares in manufacturing and transport.[22]

Effects on Remaining Employed[23]

The evidence discussed thus far indicates that higher minimum wages lead to substitution away from labor doing routine tasks, among low-skilled workers. However, the

[21] The implied elasticities −0.22 and −0.10 respectively.

[22] We have run the state-level results in Table 2 and 3 with state-specific linear trends. The point estimates are generally consistent with what is reported in Tables 2 and 3 (results available upon request), although the increases in standard errors tend to make the estimated effect insignificant (although not always). In our view, the value of this kind of specification check is sometimes overstated. For example, over long sample periods, the linear restriction is typically unjustified, and linear trends imposed over long periods can lead to nonsensical results (like outcomes that must be positive becoming negative). Moreover, we can largely end up substantially reducing the identifying information. Finally, note that in the individual-level analysis we are able to add state-by-urban-by-year fixed effects, which completely subsume any area-specific trends (which are just restricted versions of arbitrary state-by-year fixed effects). This is an important advantage of the individual-level analysis.

[23] As in the employment shares analysis, we focus here on a dummy indicating whether or not a person is in automatable employment. Appendix B reports similar analyses to those in this subsection, but using a continuous measure of *RTI*. The overall conclusions are generally qualitatively similar and in some cases stronger.

decline in the share of employment in automatable tasks may be accompanied by reallocation of these low-skilled workers to less routine, less automatable tasks. Still, it seems unlikely that job prospects would not have worsened for low-skilled workers in the aggregate, assuming that to some extent jobs with less routine, less automatable tasks are higher skilled.

To study whether a higher minimum wage increases transitions to nonemployment 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.

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 nonemployment among low-skilled workers who were initially doing automatable jobs. Looking across industries in the pooled estimates in column (1), we find evidence (significant at the 10-percent level) of a decline in the probability of remaining employed – and hence an increase in the probability of becoming nonemployed. The −0.001 estimate translates into a small elasticity of the probability of a transition to nonemployment with respect to the minimum wage, −0.013.[24] Examining the results by industry, there is some correspondence between the results in Table 4 and Table 2. For example, the decline in the probability of remaining employed is large in manufacturing, and is sizable (and significant at the 10-percent level) for services. Of course, we do not necessarily expect a tight correspondence between the two types of results across industries, as the possibilities for reallocation low-skilled workers from automatable jobs may vary by industry. There appears to be a tighter correspondence between the results by demographic group, with the evidence in Table 4 pointing stronger effects on job loss for younger workers and black workers.

[24] In computing these elasticities for the estimates of equation (5), note that we use the baseline proportion who become nonemployed (or, in Table 5, change jobs); these are one minus the types of mean probabilities shown in columns (2) and (3) of Table 1.

In Table 4, the estimates in columns (2)-(9) for the second row and below report results disaggregating by both industry and demographic group. One interesting results is that, in manufacturing, there are adverse employment effects for both the oldest and youngest groups of workers in automatable jobs, with implied declines in the probability of employment, from a 10 percent minimum wage increase, of 0.25 and 0.22 percentage point, respectively. The implied elasticities of the probability of becoming nonemployed are −0.28 for older workers in manufacturing, and −0.17 for younger workers in manufacturing. Again, this evidence points to subsets of workers who are not typically considered in the minimum wage literature, yet who are vulnerable to job loss from higher minimum wages. Note, also, that within manufacturing, the adverse effect on employment arises for women, but not for men, and there is statistically significant evidence of job loss for whites, but not blacks (although the point estimate is larger for blacks). On the other hand, looking by industry, the estimates point to larger job loss effects for blacks in transport, wholesale, retail, finance, and services (although the estimates for the latter two industries fall well short of statistical significance).

Effects on Job Switching

Table 5 reports estimates of the same specification, but redefining the dependent variable to equal to one if an individual stayed in the same "job" in the subsequent period, and zero otherwise. A person is defined as being in the same job in *t+1* if they have the same 3-digit occupation code and 1-digit industry code. As in Table 4, the sample is restricted to those employed in period *t*; in addition, those employed must 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 and broad industry, with a "decline" captured in either non-employment *or* a change of jobs.

Overall, there are many additional larger, significant, and negative effects reported in Table 5, suggesting that higher minimum wages lead to a good deal of job switching among low-skilled workers in automatable jobs, in addition to transitions to nonemployment; this job 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 overall pooled estimate of −0.0213 implies an elasticity, with respect to the minimum wage, of the probability of changing or losing one's job of −0.15. Across industries, the effect is negative and significant in manufacturing, transport, wholesale, finance, services, and public administration. The estimate is positive only in retail. By demographic group, the adverse effects are, as in Table 5, larger for the youngest and oldest workers. Interestingly, once we include job switching as well as transitions to nonemployment, as we do in Table 5, the evidence of adverse effects for white workers becomes more pronounced, and arises in every industry but retail. In contrast, when we looked only at transitions to nonemployment, in Table 4, the evidence of adverse effects for whites was much weaker. This, again, suggests that negative effects of minimum wages for low-skill workers in automatable jobs arise for groups that have not been the focus of traditional work on the employment effects of minimum wages.

Transitions to Low-Wage Industries

A natural follow-on question is whether individuals who are in automatable employment who switch jobs because of minimum wage increases are more likely to end up in specific industries. Autor and Dorn (2013) argue that workers displaced from automatable jobs tend to move to the retail and services sectors. To explore the evidence in the context of minimum wage effects, we can re-estimate equation (5). We restrict the sample to those employed in period t, as before, but also to those employed only in industries aside from retail or services. We then define the dependent variable to equal one if a person moves to retail or services industry in $t+1$, and zero if they remain employed in an industry outside these two sectors; in the top panel, those nonemployed in period $t+1$ are also coded as zero.

Thus, $b_1 > 0$ in equation (5) (the coefficient on the interaction $RSH_{jiat} \cdot Log(MW_{at})$) implies that a higher minimum wage pushes low-skilled workers who were in automatable jobs into the retail or services sectors. The results reported in Table 6 indicate that this is the case for both retail and services – whether considered separately or together.

Hours Effects

Our analysis so far has focused on employment. However, there is also a potential for hours in automatable work to decrease following a minimum wage increase. We consider hours explicitly by re-estimating equation (3) using as the dependent variable the share of hours worked among low-skilled workers in automatable employment. We also re-estimate a version of equation (5), for the difference between an individual's usual hours worked in year $t+1$ and year t. In this case, we focus only on those who are employed in the two periods, with positive hours worked, to focus on the intensive margin response.

The results of this analysis to some extent parallel the employment share results in Table 3 and the employment transition results in Table 4. The pooled estimates in the top panel of Table 7 imply that a minimum wage increase of $1 causes a 0.15 percentage point decrease in the share of hours in automatable jobs done by low-skilled workers overall (an elasticity of −0.05), although this estimate is not statistically significant. However, as for employment, there is a much larger negative effect in manufacturing. We also find larger hours share reductions for women and for blacks, paralleling the findings in Table 3, and large hours share reductions for older workers.

The individual-level analysis is reported in the lower Panel of Table 7. The data for both periods are recalled in the same interview period. The samples are smaller than in table 4 because it only includes individuals who kept their jobs between the two periods. There is also loss due to non-response on the "hours worked last year" question. The estimates suggest significant decreases in hours worked for those initially in automatable jobs following a minimum wage increase. Based on the pooled estimate, a 10 percent increase in the minimum wage generates a 0.16 decrease in hours worked for low-skilled individuals who held an automatable job in the previous period – a small but statistically significant effect. The estimated decline is negative, typically larger, and statistically significant in construction, manufacturing, transport, wholesale, finance, services, and public administration (in the last case 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. The estimated hours reductions are larger for older workers and the middle age group, for males versus females, and for whites versus 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 8 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 subperiod. 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).

Moreover, the qualitative pattern across industries and demographic groups often remains similar, although not always. For example, we still find large negative estimates for manufacturing and transport, although the manufacturing estimate is attenuated slightly relative to Table 2. One difference is that in Table 8, there is a considerably larger negative estimated effect for public administration (marginally significant), which could be related to more recent diffusion of personal computers into this industry.

Looking at demographic subgroups, one striking difference is the sharper adverse effect of minimum wages on remaining employed (or employed in the same job) for older workers. This estimated negative effect is largest for older workers in Table 8 (in both the middle and lower panels), but not in Tables 4 or 5. The implication is that, in more recent years, the adverse effect of minimum wages on employment for those in automatable jobs has become relatively worse for older workers, which could reflect a combination of a lower likelihood of retaining a job in the automatable subset of jobs, or a lower ability or willingness to make a transition to a non-automatable job.

One potential concern with comparing results across sample periods is that who gets only a high school diploma or less is changing over time, with people achieving higher levels of education in more recent years. 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. However, the most important concern would be if this selection is associated with changes in the minimum wage; based on other research, we regard this as unlikely.[25]

Probing the Effects in Manufacturing

Returning to Tables 3-5, many of our results by industry point 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, and retail or restaurant workers). 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

[25] Some past research suggests that minimum wages may lower schooling, possibly by drawing some workers out of school and into full-time work, displacing from the job market high school dropouts who are already working (Neumark and Nizalova, 2007; Neumark and Wascher, 2003). Newer work, however, finds little evidence of such an effect (Neumark and Shupe, in progress). Note also that many of our interesting and in some ways novel results refer to workers who – unlike much past minimum wage research – are not teenagers or young adults, for whom any such schooling response is likely to be largely non-existent.

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 within manufacturing,[26] 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 we estimate equations (3) and (5) separately 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 9. Those occupations classified as low wage are typically machine operators of some description; in contrast, high wage earners more commonly maintain and install machinery. Notably, those in these low-wage occupations in the bottom tertile regularly earn wages at or near the minimum wage.

The estimates in Table 10 are strongly consistent with the adverse effects of minimum wages on the share of employment in automatable jobs in manufacturing arising from low-wage jobs. Specifically, the coefficient estimates for the high-wage regressions are small, almost never statistically significant, and centered around zero. In contrast, the coefficients in the models for low-wage jobs are uniformly negative, and often sizable and statistically significant. For example, the pooled estimates for low-wage occupations are negative and statistically significant in all three panels, as are the estimates for older workers for the share of employment and the probability of remaining employed (the middle panel). The only case where the evidence of adverse effects for low-wage workers in manufacturing is statistically

[26] 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.

weak is in the lower panel, for the probability that workers who are in automatable employment hold the same job in the next period; the estimates are always negative, but only the pooled estimate is statistically significant.[27]

Effects on Higher-skilled Workers

We might expect that as the minimum wage reduces jobs for low-skilled workers in automatable jobs, it could also increase jobs for higher-skilled workers who “tend” the machines. For instance, going back to our manufacturing analysis, operators can be replaced with robotic arms, but the robotic arms need maintenance and troubleshooting.

We explore this in Table 11. We estimate the same specification as in equation (5), with the only difference being that we define the dependent variable (and hence the sample) for higher-skilled workers). We continue to define routine work for low-skilled workers, so that we obtain a parallel analysis to the earlier analysis in Tables 4 and 5, but now asking whether the interaction of the minimum wage with a higher share of routine work for low-skilled workers – which reduces job opportunities for them – at the same time increases job opportunities for higher-skilled workers. The estimates in the top panel of Table 11 are for the probability of remaining employed (as in Table 4), and the estimates in the bottom panel are for the probability of remaining employed in the same job (as in Table 5).

The evidence indicates that job opportunities are improved for higher-skilled workers. Nearly every estimated coefficient in Table 11 is positive, and the estimates are often sizable and in some cases statistically significant. For example, in the top panel, we find significant

[27] We consider an alternative definition based on industry, in which 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. Compared to Table 10, the results are quite similar. One difference is that, in this case, the is stronger statistical evidence of adverse effects on the probability of remaining in the same job, by demographic subgroup (e.g., for the oldest and youngest workers, and for women). estimates are often slightly attenuated, although the overall conclusions are the same.

positive effects for the youngest workers and those aged 26-39, and in the bottom panel we find significant (or marginally significant) positive effects for women, and in transport, services, and public administration. Notably, we do not find evidence of a positive effect for older higher-skill workers in either panel, perhaps because the kinds of job opportunities opened up by automation require skills that these older workers are less likely to have or obtain.

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, overall, 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 stays employed in the same job). 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, and on manufacturing workers in such jobs.

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 rather sharply for older workers – and within manufacturing, most sharply for this age group. An analysis of individual transitions from employment to nonemployment (or to employment in a different job) leads to similar overall conclusions. The heterogeneous adverse effects we document indicate that some groups typically ignored in the minimum wage literature are in fact quite vulnerable to job loss because of automation following a minimum wage increase. At the same time, we find that some of the adverse employment effects among low-skilled workers in automatable jobs are offset by increased employment opportunities for higher-skilled workers, likely because automation of low-skilled work creates other kinds of jobs.

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. 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,[28] cashiers,[29] and bricklayers.[30] 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

[28] For example, Uber is currently troubleshooting their driverless car.
[29] 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).
[30] For example, Fastbrick Robotics has now developed Hadrian X – a robot that lays 1,000 standard bricks in 60 minutes.

adoptions undoubtedly lead to increased job opportunities for some workers – for which we find some evidence – it is likely that there are workers who will be displaced that do not have the skills to do the new tasks. We have 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.

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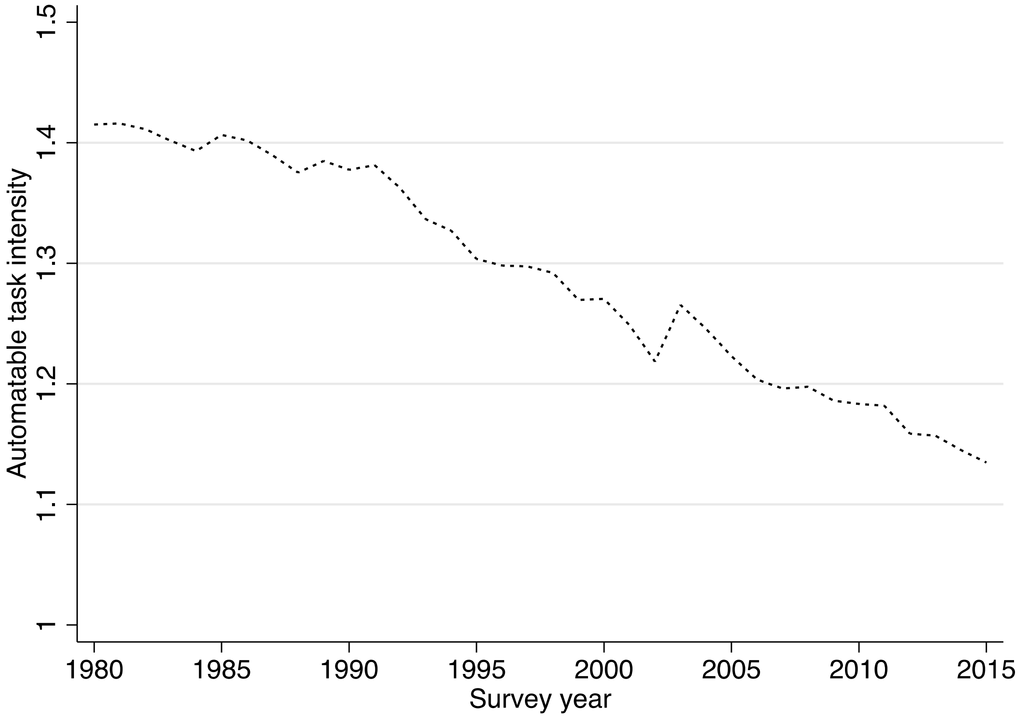
Figure 1: Low-skilled jobs and the level of automation over time



Notes: We plot the average routine task intensity for each year, as given by equation (1). In this figure, the routine task intensity variable is standardized to have a mean of zero and a standard deviation of one.

Table 1: Descriptive Statistics for the Dependent Variables for Each Analysis					
	(1)	(2)	(3)	(4)	(5)
	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)	Shares of automatable hours	Difference in hours worked from t to t+1
Total routine	30%	0.92	0.86	29%	0.56
Construction	5%	0.92	0.88	4%	0.39
Manufacturing	41%	0.88	0.88	40%	0.50
Transport	22%	0.95	0.92	19%	0.67
Wholesale	26%	0.92	0.88	25%	0.49
Retail	40%	0.91	0.83	41%	0.47
Finance	39%	0.95	0.89	36%	0.43
Services	32%	0.92	0.88	29%	0.62
P. Adm.	37%	0.96	0.90	35%	0.71
Male	19%	0.91	0.87	19%	0.57
Female	51%	0.92	0.85	48%	0.54
≥ 40 years old	29%	0.89	0.86	29%	0.53
26-39 years old	28%	0.95	0.89	28%	0.61
≤ 25 years old	31%	0.88	0.79	32%	0.58
White	29%	0.92	0.87	28%	0.56
Black	31%	0.87	0.86	31%	0.59

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									
Log Min Wage	-0.031	0.003	-0.073	-0.052	0.025	-0.021	-0.002	-0.049	-0.013
	(0.014)	(0.018)	(0.040)	(0.025)	(0.043)	(0.023)	(0.059)	(0.035)	(0.095)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060

Notes: OLS coefficient estimates of equation (3) 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 share of automatable employment is based on equation (2), with data derived from Autor and Dorn (2013) and Autor et al. (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. All regressions include area (state x urban) and year fixed effects. The minimum wage is measured in 2015 dollars (for which the average minimum wage is $6.77).

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									
Log Min Wage	-0.051	0.010	-0.132	-0.027	0.012	-0.073	0.049	0.011	-0.239
	(0.027)	(0.020)	(0.071)	(0.059)	(0.103)	(0.048)	(0.124)	(0.055)	(0.098)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060
26-39 Years Old									
Log Min Wage	-0.036	0.001	-0.051	-0.076	-0.006	-0.014	-0.015	-0.064	-0.097
	(0.019)	(0.025)	(0.033)	(0.043)	(0.066)	(0.044)	(0.070)	(0.047)	(0.096)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060
≤ 25 Years Old									
Log Min Wage	-0.074	0.018	-0.009	-0.098	-0.125	-0.014	-0.134	-0.088	-0.113
	(0.029)	(0.024)	(0.074)	(0.079)	(0.110)	(0.031)	(0.102)	(0.034)	(0.143)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060
Males									
Log Min Wage	0.007	-0.007	-0.046	0.006	0.042	-0.047	0.035	-0.018	0.090
	(0.016)	(0.006)	(0.034)	(0.022)	(0.045)	(0.038)	(0.091)	(0.028)	(0.072)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060
Females									
Log Min Wage	-0.078	0.067	-0.177	-0.090	0.011	-0.005	0.077	-0.080	-0.257
	(0.026)	(0.083)	(0.078)	(0.074)	(0.102)	(0.030)	(0.049)	(0.046)	(0.100)
N	30963	3157	3157	3152	3147	3157	3138	3156	3060
White									
Log Min Wage	-0.028	-0.010	-0.065	-0.071	0.030	-0.007	0.005	-0.052	-0.110
	(0.016)	(0.020)	(0.041)	(0.033)	(0.057)	(0.033)	(0.077)	(0.036)	(0.106)
N	30963	3157	3157	3152	3141	3157	3138	3156	3150
Black									
Log Min Wage	-0.067	0.026	-0.322	-0.316	0.080	0.139	-0.105	0.035	0.078
	(0.036)	(0.044)	(0.129)	(0.112)	(0.165)	(0.117)	(0.180)	(0.104)	(0.136)
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									
Log Min Wage	-0.0010	-0.0244	-0.0048	0.0063	-0.0009	-0.0053	-0.0055	-0.0038	0.0023
x Routine	(0.0006)	(0.0101)	(0.0021)	(0.0039)	(0.0075)	(0.0042)	(0.0055)	(0.0021)	(0.0054)
N	1070647	92826	255203	71470	38970	177495	50855	258671	45706
≥ 40 Years Old									
Log Min Wage	-0.0062	0.0154	-0.0251	0.0039	-0.0104	0.0002	-0.0141	-0.0014	0.0031
x Routine	(0.0017)	(0.0141)	(0.0045)	(0.0073)	(0.0093)	(0.0043)	(0.0073)	(0.0034)	(0.0042)
N	442627	37310	113679	34030	16449	56512	22175	113640	24171
26-39 Years Old									
Log Min Wage	-0.0004	-0.0254	-0.0007	0.0174	-0.0037	-0.0016	-0.0164	0.0010	0.0043
x Routine	(0.0018)	(0.0162)	(0.0034)	(0.0093)	(0.0451)	(0.0073)	(0.0086)	(0.0053)	(0.0055)
N	372237	37251	95876	27700	14805	51022	17918	86850	15753
≤ 25 Years Old									
Log Min Wage	-0.0154	-0.0459	-0.0224	0.0061	0.0132	-0.0143	0.0082	-0.0127	-0.0031
x Routine	(0.0029)	(0.0269)	(0.0092)	(0.0214)	(0.0243)	(0.0082)	(0.0201)	(0.0087)	(0.0363)
N	255783	18265	45648	9740	7716	69961	10762	58181	5782
Males									
Log Min Wage	-0.0039	-0.0574	-0.0033	0.0127	-0.0145	0.0041	-0.0040	-0.0124	-0.0013
x Routine	(0.0021)	(0.0152)	(0.0034)	(0.0088)	(0.0111)	(0.0081)	(0.0102)	(0.0059)	(0.0072)
N	585546	86709	164507	54742	27107	81671	14970	87839	25612
Females									
Log Min Wage	-0.0028	0.0143	-0.0198	0.0072	-0.0055	-0.0141	-0.0200	-0.0025	-0.0134
x Routine	(0.0020)	(0.0262)	(0.0056)	(0.0119)	(0.0124)	(0.0059)	(0.010)	(0.0035)	(0.0114)
N	485101	6117	90696	16728	11863	95824	35885	170832	20094
White									
Log Min Wage	-0.0016	-0.0184	-0.0045	0.0132	0.0017	-0.0010	-0.0003	-0.0013	0.0024
x Routine	(0.0012)	(0.0108)	(0.0023)	(0.0105)	(0.0067)	(0.0047)	(0.0057)	(0.0032)	(0.0052)
N	919099	84306	223215	62070	35172	156556	45125	209997	36738
Black									
Log Min Wage	-0.0038	-0.0445	-0.0074	-0.0324	-0.0767	-0.0263	-0.0328	-0.0077	0.0012
x Routine	(0.0051)	(0.0693)	(0.0081)	(0.0201)	(0.0424)	(0.0202)	(0.0363)	(0.0054)	(0.0163)
N	120221	6460	25866	7870	2870	14621	4497	40118	7263

Notes: See notes to Table 2. OLS coefficient estimates of equation (3) are reported, with standard errors in parentheses. Standard errors are clustered by state. Dependent variable is equal to 1 if a person is employed in *t+1*, 0 if they nonemployed. Sample is those employed in period *t*. All regressions include state x urban x year fixed effects, and an urban dummy variable.

Table 5: Probability of Being Employed, in the Same Job, 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									
Log Min Wage	-0.0213	-0.0197	-0.0168	-0.0323	-0.0282	0.0514	-0.0432	-0.0407	-0.0348
x Routine	(0.0015)	(0.0157)	(0.0051)	(0.0092)	(0.0129)	(0.0054)	(0.0078)	(0.0046)	(0.0071)
N	1070647	92826	255203	71470	38970	177495	50855	258671	45706
≥ 40 Years Old									
Log Min Wage	-0.0265	0.0204	-0.0194	-0.0179	0.0017	0.0284	-0.0319	-0.0301	-0.0196
x Routine	(0.0022)	(0.0223)	(0.0055)	(0.0113)	(0.0197)	(0.0087)	(0.0121)	(0.0058)	(0.0124)
N	442627	37310	113679	34030	16449	56512	22175	113640	24171
26-39 Years Old									
Log Min Wage	-0.0039	-0.0253	-0.0091	0.0174	0.016	-0.0025	-0.0165	0.0013	0.0093
x Routine	(0.0027)	(0.0163)	(0.0037)	(0.0098)	(0.0154	(0.0088)	(0.0091)	(0.0054)	(0.0082)
N	372237	37251	95876	27700	14805	51022	17918	86850	15753
≤ 25 Years Old									
Log Min Wage	-0.0468	-0.1000	-0.0019	-0.1088	-0.1352	0.0695	-0.0512	-0.0503	-0.0737
x Routine	(0.0039)	(0.0474)	(0.0121)	(0.0372)	(0.0450)	(0.0095)	(0.0458)	(0.0098)	(0.0375)
N	255783	18265	45648	9740	7716	69961	10762	58181	5782
Males									
Log Min Wage	-0.0172	-0.0126	-0.0110	-0.0174	0.0068	0.0291	-0.0950	-0.0593	-0.0573
x Routine	(0.0023)	(0.0234)	(0.0040)	(0.0159)	(0.0247)	(0.0086)	(0.0136)	(0.0111)	(0.0127)
N	585546	86709	164507	54742	27107	81671	14970	87839	25612
Females									
Log Min Wage	-0.0079	-0.1672	0.0069	-0.0767	-0.1012	0.0709	-0.0943	-0.0257	-0.1096
x Routine	(0.0022)	(0.0326)	(0.0103)	(0.0181)	(0.0416)	(0.0089)	(0.0193)	(0.0047)	(0.0127)
N	485101	6117	90696	16728	11863	95824	35885	170832	20094
White									
Log Min Wage	-0.0152	-0.0191	-0.0101	-0.0308	-0.0276	0.0559	-0.0779	-0.0456	-0.0229
x Routine	(0.0017)	(0.0160)	(0.0033)	(0.0105)	(0.0096)	(0.0063)	(0.0084)	(0.0060)	(0.0079)
N	919099	84306	223215	62070	35172	156556	45125	209997	36738
Black									
Log Min Wage	-0.0142	0.0995	0.0274	-0.0319	0.0021	-0.0093	0.0225	-0.0198	-0.0865
x Routine	(0.0050)	(0.0853)	(0.0192)	(0.0228)	(0.0544)	(0.0224)	(0.0304)	(0.0110)	(0.0335)
N	120221	6460	25866	7870	2870	14621	4497	40118	7263

Notes: See notes to Tables 2 and 4. . Dependent variable is equal to 1 if a person is employed in the same 3-digit occupation and 1-digit industry in *t*+1, and 0 if they are nonemployed or not in the same “job.”

Table 6: Probability of Being Employed in a Specific Industry in *t+1* if Employed in an Automatable Job in Period *t*

	(1)	(2)	(3)
	Retail	Services	Retail or Services
Dependent Variable = Employed in Retail/Services in *t+1*			
Include nonemployed in *t+1*			
Log Min Wage	0.0190	0.0101	0.0106
	(0.0009)	(0.0012)	(0.0010)
N	893152	811976	634481
Exclude nonemployed in *t+1*			
Log Min Wage	0.0147	0.0135	0.0129
	(0.0008)	(0.0012)	(0.0013)
N	818733	797465	545551

Notes: See notes to Table 4. Sample is the subsample of Table 4 that is employed in period *t*, but not in retail or services (or both, depending on the column). In bottom panel, those nonemployed in *t+1* are excluded. Dependent variable is equal to 1 if a person moves to the indicated industry in *t*+1, and 0 if they are continued to work in a different industry (or, in top panel, are nonemployed). For example, in the bottom panel of column (1), the sample is those employed, but not in retail, in period *t*; the dependent variable is equal to 1 if the person is employed in retail in *t+1*, and zero otherwise.

Table 7: 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
Log Min Wage	-0.015	-0.077	-0.006	-0.014	-0.023	-0.094	-0.013	-0.074
	(0.017)	(0.035)	(0.021)	(0.039)	(0.0016)	(0.0028)	(0.019)	(0.035)
N	30963	30963	30963	30963	30963	30963	30963	22800
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Log Min Wage	-0.010	-0.084	-0.052	0.077	0.003	0.060	-0.018	-0.125
	(0.012)	(0.041)	(0.040)	(0.060)	(0.027)	(0.072)	(0.024)	(0.068)
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
Log Min Wage x Routine	-1.646	-2.508	-3.607	0.555	-2.669	-0.975	-2.562	-0.896
	(0.175)	(0.272)	(0.447)	(0.561)	(0.380)	(0.266)	(0.293)	(0.603)
N	696432	330014	225466	140952	384574	311858	568524	82581
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Log Min Wage x Routine	-10.356	-3.035	-5.790	-3.096	0.022	-2.748	-1.401	-1.942
	(1.674)	(1.516)	(1.338)	(1.478)	(0.567)	(0.934)	(0.460)	(1.101)
N	77628	122638	46009	23443	138791	29655	208287	39762

Notes: See notes to Table 2. In the top panel, the share of automatable hours worked is calculated in the same manner as the share of automatable employment in 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 8: 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
Log Min Wage	-0.038	-0.069	-0.025	-0.050	-0.021	-0.058	-0.029	-0.030
	(0.022)	(0.034)	(0.027)	(0.037)	(0.020)	(0.034)	(0.022)	(0.059)
N	19154	11886	11860	11510	12020	11553	12025	8264
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Log Min Wage	0.001	-0.066	-0.079	0.093	-0.024	-0.021	-0.036	-0.147
	(0.017)	(0.062)	(0.048)	(0.057)	(0.030)	(0.068)	(0.031)	(0.090)
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
Log Min Wage x Routine	-0.020	-0.037	-0.027	-0.008	-0.017	-0.025	-0.028	0.027
	(0.009)	(0.015)	(0.011)	(0.030)	(0.012)	(0.0013)	(0.0009)	(0.040)
N	642054	215655	299300	127095	352971	289083	537369	71820
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Log Min Wage x Routine	-0.091	-0.067	0.027	-0.067	0.047	-0.037	-0.002	-0.012
	(0.069)	(0.029)	(0.057)	(0.048)	(0.028)	(0.032)	(0.012)	(0.037)
N	69579	114738	40614	23340	110355	32364	175239	23043
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
Log Min Wage x Routine	-0.042	-0.059	-0.034	-0.058	-0.018	-0.044	-0.044	-0.020
	(0.011)	(0.020)	(0.013)	(0.039)	(0.013)	(0.016)	(0.012)	(0.037)
N	642054	215655	299300	127095	352971	289083	537369	71820
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Log Min Wage x Routine	-0.128	-0.050	0.005	0.023	0.053	-0.008	-0.176	-0.056
	(0.122)	(0.028)	(0.053)	(0.077)	(0.036)	(0.043)	(0.038)	(0.047)
N	69579	114738	40614	23340	110355	32364	175239	23043
Notes: See notes to Table 2 and 4.								

Table 9: 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 10: 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								
Log Min Wage	-0.161	-0.189	-0.117	-0.131	-0.123	-0.156	-0.182	-0.443
	(0.058)	(0.087)	(0.077)	(0.146)	(0.054)	(0.093)	(0.055)	(0.145)
N	3157	3157	3157	3157	3157	3157	3157	2273
High-Wage								
Log Min Wage	-0.035	-0.080	0.015	-0.086	-0.004	-0.065	0.027	0.168
	(0.056)	(0.079)	(0.072)	(0.075)	(0.061)	(0.084)	(0.065)	(0.160)
N	3157	3157	3157	3157	3157	3157	3157	2273
Dependent Variable = Probability of Being Employed in the Current Period								
Low-Wage								
Log Min Wage	-0.014	-0.043	-0.0002	-0.035	-0.016	-0.015	-0.018	-0.009
x Routine	(0.003)	(0.005)	(0.006)	(0.010)	(0.005)	(0.006)	(0.003)	(0.009)
N	137719	47797	75558	27759	68542	69177	116763	16930
High-Wage								
Log Min Wage	0.003	-0.008	0.002	-0.024	0.007	0.014	0.004	0.010
x Routine	(0.012)	(0.024)	(0.025)	(0.075)	(0.012)	(0.021)	(0.011)	(0.041)
N	24243	12974	9624	1645	19617	4626	23140	767
Dependent Variable = Probability of Being Employed in the Same Job in the Current Period								
Low-Wage								
Log Min Wage	-0.025	-0.017	-0.028	-0.015	-0.018	-0.024	-0.013	-0.240
x Routine	(0.012)	(0.016)	(0.042)	(0.079)	(0.021)	(0.022)	(0.011)	(0.454)
N	137714	75554	47795	27759	68537	69177	116758	16930
High-Wage								
Log Min Wage	0.005	-0.001	0.005	-0.012	0.002	0.015	0.003	0.036
x Routine	(0.004)	(0.006)	(0.009)	(0.009)	(0.005)	(0.005)	(0.004)	(0.015)
N	24230	14611	7975	1644	19606	4624	23129	766
Notes: See notes to Tables 2, 3, and 4.								

Table 11: Higher-Skill Workers Related to the Interaction Between Minimum Wage and the Share of Low-Skill Routine Work								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	0.0562	0.0539	0.0980	0.1992	0.0496	0.0648	0.0351	0.0133
x Share of Low-Skill Routine Work	(0.0474)	(0.0551)	(0.0443)	(0.0958)	(0.0420)	(0.0558)	(0.0390)	(0.0934)
N	1178234	602114	576120	152538	600762	576120	981685	196549
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Min Wage	0.8058	0.0141	0.0923	0.0351	-0.0968	-0.0365	0.0782	-0.0293
x Share of Low-Skill Routine Work	(0.6797)	(0.0946)	(0.1559)	(0.1039)	(0.1032)	(0.0420)	(0.0641)	(0.0362)
N	50495	135336	58552	37394	134000	95834	533856	77500
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	0.0151	-0.00083	0.0241	0.0225	0.0243	0.0603	0.0130	0.0293
x Share of Low-Skill Routine Work	(0.0173)	(0.0115)	(0.0248)	(0.0369)	(0.0213)	(0.0170)	(0.0178)	(0.0398)
N	1178234	602114	576120	152538	600762	576120	981685	196549
	Construct	Manu.	Transport	Wholesale	Retail	Finance	Services	P. Adm.
Min Wage	0.3163	0.0196	0.3296	-0.0048	0.0147	-0.0193	0.1308	0.1338
x Share of Low-Skill Routine Work	(0.5400)	(0.1187)	(0.1829)	(0.1417)	(0.2332)	(0.0415)	(0.0845)	(0.0462)
N	50495	135336	58552	37394	134000	95834	533856	77500

Notes: The Share of Low-Skill Routine Work is defined as the share in the individual's area, year, and industry. This share is calculated following equation (5) and matched into the dataset used for the analysis in Table 4 based on industry, area, and year. In this case the data retains higher-skill individuals only in the sample. Higher-skilled individuals are those with more than a high school degree. See also notes to Table 2.

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	-0.109	-0.147	-0.091	-0.068	-0.094	-0.149	-0.128	-0.213
	(0.051)	(0.077)	(0.054)	(0.010)	(0.054)	(0.073)	(0.055)	(0.133)
N	3157	3157	3157	3157	3157	3157	3157	2273
High-Wage								
Min Wage	0.012	0.009	0.055	0.157	-0.006	-0.061	0.005	-0.101
	(0.042)	(0.068)	(0.062)	(0.084)	(0.050)	(0.064)	(0.053)	(0.124)
N	3157	3157	3157	3157	3157	3157	3157	2273
Dependent Variable = Probability of Being Employed in the Current Period								
Low-Wage								
Log Min Wage	-0.010	-0.029	-0.006	-0.035	-0.004	-0.021	-0.008	-0.010
x Routine	(0.004)	(0.006)	(0.007)	(0.012)	(0.006)	(0.008)	(0.004)	(0.012)
N	90175	48311	31037	17272	48065	42110	77096	10258
High-Wage								
Log Min Wage	0.005	-0.005	0.000	-0.011	0.005	-0.025	0.007	0.014
x Routine	(0.004)	(0.009)	(0.010)	(0.017)	(0.005)	(0.011)	(0.004)	(0.021)
N	66188	32402	23434	8968	50941	15247	57967	7216
Dependent Variable = Probability of Being Employed in the Same Job Current Period								
Low-Wage								
Log Min Wage	-0.019	-0.018	-0.013	-0.043	-0.0011	-0.025	-0.011	-0.033
x Routine	(0.005)	(0.008)	(0.012)	(0.015)	(0.007)	(0.014)	(0.005)	(0.021)
N	90167	48308	31035	17272	48058	42109	77088	10258
High-Wage								
Log Min Wage	0.002	0.003	0.002	0.002	-0.003	0.009	0.003	0.006
x Routine	(0.001)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.001)	(0.006)
N	66179	32401	23433	8968	50925	115244	57961	7214

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 sub-sample is the bottom tertile of industries in this distribution, and the high-wage subsample is the top tertile.