The Minimum Wage and Labor-Saving Innovation

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Abstract

We show that an increase in the minimum wage leads to more labor-saving innovation. Larger minimum wage increases in a state are associated with a more positive change in automation patent applications by firms headquartered in that state. These findings are stronger in industries that hire more low-wage workers and have more automatable tasks. The results are also stronger in states with a higher binding wage percentile. The increase in automation patents following minimum wage hikes contributes to poorer employment outcomes for unskilled workers employed in routine tasks.

1. Introduction

Do minimum wage increases encourage labor-saving innovation? This is an important question considering the ongoing increase in the minimum wage across the United States. As of this writing, 30 states had a minimum wage higher than the federal minimum wage. In addition, cities such as Seattle and San Francisco have adopted minimum wages above their states' minimum wage and Democrats continue the push to more than double the federal minimum wage to $15.[1] Originally introduced as a 'fair' wage to reduce the exploitation of labor, the minimum wage has increasingly become synonymous with a 'living' wage – a wage necessary to help workers achieve self-sufficiency. However, if a government-mandated increase in wages encourages firms to develop labor-saving technology, low-skill workers could be displaced, and the minimum wage increase may not achieve this objective. Existing literature provides plausible reasons to be wary of this unintended consequence of minimum wage hikes. Acemoglu's (2010) theory of technological change implies that exogenous wage increases such as a minimum wage change can induce labor-saving innovation. Moreover, economic historians have long argued that technological advancement was faster in Britain during the eighteenth century and in the United States during the nineteenth due to labor shortages and higher wages relative to other countries (Habakkuk, 1962; Allen, 2009).

Yet, there is no comprehensive, large-sample evidence on the effect of minimum wage increases on labor-saving innovation. It is important to fill this gap in the literature because innovative activity can increase the pool of labor-saving technologies available for adoption, thereby rendering a wider range of jobs vulnerable to automation. This paper is the first to examine

[1] See "$15 Minimum-Wage Setback Tests Biden's Ability to Unite Democrats" *Wall Street Journal*, Feb. 27, 2021. Also see "Biden Signs Order Requiring $15 Minimum Wage for Federal Contractors", April 27, 2021.

whether minimum wage increases in the United States lead to a shift in corporate innovative effort toward automation technology.

There is cause to be skeptical about the hypothesis that minimum wage hikes encourage innovation. Industries that hire minimum-wage workers such as leisure and hospitality are not traditionally innovative industries. Firms in these industries are likely to purchase (i.e., adopt) existing automation technology when the minimum wage increases.[2] However, there are plausible channels through which minimum wage hikes can encourage the invention of new tools, technologies, and methods. First, prior research suggests that minimum wage increases spill over to low-wage workers earning just above the minimum wage (Card and Krueger,1995; Neumark and Wascher, 2007). Therefore, manufacturing firms employing low-wage workers may respond to the higher labor cost by developing in-house labor-saving innovation. Second, firms in the highly innovative information sector may ramp up investment in labor-saving innovation for sale to customer firms operating in minimum wage sensitive industries. Whether an increase in the minimum wage causes a shift in corporate innovative effort toward labor-saving technology is ultimately an empirical question.

We identify 142 state-years between 1987 and 2017 that experience an increase in the effective minimum wage following federal- or state-level changes to the minimum wage. The average increase in the minimum wage is 13.4%. To identify whether a patent relates to labor-saving technology, we use a natural language processing algorithm to search patent descriptions for keywords such as automatic, mechanize, robot, and other words synonymous with automation. Throughout the paper, patents meeting these criteria are referred to as automation patents while

[2] For example, a recent California debate on raising the minimum wage of fast-food workers to $22 caused the private equity owner of a fast-food chain to explore automating operations. See "California Fast-Food Wage Law Opponents Begin Effort to Block It" *Wall Street Journal*, Sep. 7, 2022

patents not meeting the criteria are referred to as non-automation patents. To address concerns about possible noise in our text-based classification of automation patents, we show that our measure of automation patents has the expected relation with the employment share and wage share of unskilled workers whose tasks are more vulnerable to automation. We also show that our results are robust to alternative proxies of automation patents.

Unobserved state-level labor conditions may affect both minimum wage policy and corporate effort in developing labor-saving innovation. This creates an endogeneity problem when comparing states that pass minimum wage legislation with those that do not. For this reason, our main regression specifications look at the intensive margin. Our primary analysis focuses only on states that experience an increase in the effective minimum wage and examines the link between the magnitude of the increase in the minimum wage and automation patents. We employ an event study approach focusing on innovation during the two years before and the two years after the minimum wage increase. We find that a larger percentage increase in the effective minimum wage elicits a more positive post-event change in both the number of automation patent applications by firms headquartered in that state as well as in the citations received by automation patents. In contrast, we find no relation between the minimum wage increase and the number of non-automation patents. The latter finding helps alleviate concerns that our results are driven by overall trends in innovation. In robustness tests, we confirm our results hold if we limit our analysis to firms whose headquarter state is also the state with the largest share of operations as per the measure of Garcia and Norli (2012). We also conduct falsification tests using a set of randomly selected words. Using a machine-reading algorithm, we construct two 'placebo' dependent variables - the number of patent applications containing the randomly selected words, and citations received by patents containing the random words. We find that these variables have no relation with the percentage increase in the minimum wage.

Our results are subject to a reverse causality concern. Prior growth in automation may cause some states to approve larger minimum wage increases. Our analysis captures the change in patents and citations both before the minimum wage hike as well as after. We find no evidence of a change in automation patents prior to the minimum wage increase. The positive link between the number of automation patents and the magnitude of the minimum wage change is observed only after the minimum wage increase.

Another identification challenge is that minimum wage increases are endogenous to local economic and labor-market conditions. We take two steps to address the endogeneity of state-level minimum wage decisions to local economic conditions. Firstly, we conduct a difference-in-differences test using control firms that are located across state borders in contiguous counties (i.e., firms that face similar economic conditions) that are not subject to minimum wage increases. We find that after the minimum wage increase, treatment firms experience an increase in automation patenting relative to control firms. This difference is observed for labor-saving innovation only. There is no difference between treated and control firms in the change in non-automation patents. This extensive-margin analysis also indicates that after controlling for local economic conditions, an increase in the minimum wage leads to more labor-saving innovation. Secondly, we restrict our sample only to federally mandated increases in the effective minimum of a state (i.e., cases where states have a minimum wage equal to the federal minimum wage). Doing so mitigates the endogeneity problem because the minimum wage hike was not a state-level decision. We find similar results in this subsample.

To further pin down the causal impact of the minimum wage increase, we subject our primary analysis to a few sub-sample tests. We show that larger minimum wage increases are followed by a more positive change in automation patents in industries with a high fraction of minimum-wage workers. In industries with few minimum-wage workers, there is no significant relation between the size of the minimum wage increase and labor-saving innovation. Second, we exploit cross-state variation in the 'bindingness' of the minimum wage. We show that in states where the fraction of workers earning at or below the new minimum wage is high, there is a strong positive association between the change in the minimum wage and the number of automation patents. In states with a low binding wage percentile (i.e., fewer workers earning at or below the minimum wage), we do not observe a significant change in automation patent applications. Third, using the Autor et al. (2003) classification of routine-task industries, we find that larger minimum wage increases are followed by a bigger increase in the number of automation patent applications in routine-task industries. In non-routine-task industries, by contrast, there is no discernible link between the minimum wage change and automation patents. We note that our finding that automation patent applications go up specifically in industries that have automatable tasks provides some validation of our text-based identification of automation patents. In our final subsample tests, we show that our results are driven by small firms in the manufacturing sector and information sector. These firms are more likely to have local operations, and therefore, their labor cost (or the labor cost of their customers) is likely more sensitive to local minimum-wage increases.

Our study is the first to provide evidence that minimum wage increases affect innovation. Next, we examine the implications of our findings for workers employed in automatable jobs. Prior research shows that minimum wage increases lead to job losses for unskilled workers performing routine tasks (Aaronson and Phelan, 2019; Lordan and Neumark, 2018; Dai and Qiu, 2022). We provide new evidence that directly links this loss of employment for unskilled workers to the increased focus by corporations on developing labor-saving innovation. Following prior literature, we define unskilled workers as workers without any college education. Our results indicate that, in the period following minimum wage hikes, a 10% increase in automation patents is associated with a 1.6 percentage point decline in the employment share and a 1.2 percentage point decline in the wage share of unskilled workers employed in routine tasks. In contrast, in industries where tasks are not easily automatable, we do not find a significant statistical relation between automation patents and the employment outcomes of unskilled workers. The significant negative relation between our measure of automation patents and the employment outcomes of workers engaged in automatable tasks provides further reassurance that our classification method captures labor-saving innovation.

Our evidence contributes to a somewhat mixed literature on the impact of minimum wage increases on corporate investment. Gustafson and Kotter (2022) show that minimum wage increases lead to lower capital expenditures in minimum wage sensitive industries. Cho (2016) also provides evidence of lower corporate investment after minimum wage increases. In contrast, a few studies find evidence of labor-to-capital substitution after minimum wage hikes. Geng, Huang, Lin, and Liu (2022) find that minimum wage increases in China lead to higher capital investment. Hau, Huang, and Wang (2020) show that low-wage firms in China accelerate labor-to-capital substitution after wage increase. Dai and Qiu (2022) show that minimum wage increases in the U.S. cause firms to increase their information technology budgets. We focus not on capital expenditure but on the invention of new labor-saving tools, technologies, and methods. Our findings are supportive of the labor-to-capital substitution hypothesis - minimum wage hikes increase the demand for labor-saving technology and consequently the composition of corporate innovation shifts to fill this demand.

Our paper adds to the existing evidence on the response of corporate innovation to government regulations such as tax laws (Atanassov and Liu, 2020; Mukherjee et al., 2017), bankruptcy laws (Acharya and Subramanian, 2009), and labor laws (Acharya, Baghai, and Subramanian, 2014; Bena, Ortiz-Molina, and Simintzi, 2022). Our paper is related to the literature on automation and skill-biased technological change. Acemoglu and Restrepo (2020) document robust negative effects of robots on employment and wages. Acemoglu and Restrepo (2021) show that an aging population is associated with greater automation.[3] Finally, our paper is related to a large literature on the effect of the minimum wage on employment. While some studies, such as Card and Krueger (1994) conclude that minimum wage hikes have no disemployment effects,[4] others document a decline in employment following minimum wage increases.[5] Our findings provide one possible explanation for the latter – innovation expands the set of tools and technologies available to replace unskilled workers.

The rest of the paper is organized as follows. Section 2 presents the hypotheses. Section 3 describes the data and variables. Section 4 presents the main results. Section 5 examines the link between automation patents and employment outcomes for low-skill workers. Section 6 presents robustness tests and Section 7 concludes.

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[3] Moreover, numerous papers show that technological advancement has shifted demand from unskilled workers toward college-educated workers (Berman et al., 1994; Levy and Murnane, 1996; Doms et al., 1997; Berman, Bound, and Machin, 1998; Autor et al., 1998).

[4] See Katz and Krueger (1992), Card (1992a, 1992b), Card and Krueger (1994, 2000), Dube et al. (2007), Allegretto et al. (2011), Addison et al. (2013), Dube et al. (2016).

[5] Studies that find evidence of a decline in employment following minimum wage increases include Neumark and Wascher (1992), Deere et al. (1995), Burkhauser et al. (2000), Neumark and Wascher (2000), Neumark (2001), Singell and Terborg (2007), Thompson (2009), Sabia et al. (2012), Wang and Gunderson (2012), Fang and Lin (2013), Neumark et al. (2014a), Meer and West (2016), Powell (2021). Summaries of the large literature on the impact of the minimum wage on employment can be found in Brown et al. (1982), Neumark and Wascher (2007) and Neumark (2017).

2. Hypothesis development

In this section, we delineate the hypotheses that guide our empirical analysis. Our central question is whether an increase in the minimum wage induces the development of labor-saving technology. A key result of Acemoglu (2010) is that the response of innovation to labor scarcity and cost of labor depends on whether the innovation increases the marginal product of labor (i.e., is labor-complementary) or reduces the marginal product of labor (i.e., is labor-saving). The model implies that an exogenous increase in the cost of labor such as a minimum wage increase will encourage labor-saving innovation. This prediction serves as the foundation for the hypotheses we wish to test.

A plausible strategy to test this prediction might be to compare labor-saving innovation by firms located in treated states (i.e., states experiencing a minimum wage increase) with labor-saving innovation by firms in states that do not raise the minimum wage. However, this strategy poses a significant challenge in establishing causality. Unobserved economic and political factors that cause state legislatures to pass minimum-wage increases may also affect corporate innovation in the state. For example, the Democrat-led state of California has passed several minimum-wage increases over the last decade. It is also the home of the highly innovative information and business services industries. We mitigate this empirical challenge by centering our main empirical tests on the intensive margin. In our primary empirical method, we look only at states that experienced an increase in the minimum wage and examine the link between the magnitude of the increase in the minimum wage and labor-saving innovation. We argue that larger increases in the effective minimum wage imply greater upward pressure on the cost of low-wage labor and will, therefore, incentivize firms to develop labor-saving technology.

Hypothesis 1: Larger minimum wage increases will be followed by more labor-saving innovation by firms located in the affected state.

There are two potential channels through which an increase in a state's effective minimum wage can lead to more labor-saving innovation in that state. In the first channel, which we refer to as the direct effect, firms that employ low-wage workers experience an increase in labor costs and step up the development of labor-saving technology. In the indirect channel, technology firms (which may not employ low-wage workers themselves) develop labor-saving innovations for sale to local customer firms that are adversely affected by the minimum wage shock. We expect both channels to be stronger for smaller firms. Large firms tend to have operations in multiple states and are less likely to adjust the composition of their innovative effort in response to a local shock to the minimum wage. Our tests do not capture the adoption of labor-saving technology, only its development as measured by automation patents. However, we show that our results hold if we control for labor-saving patents developed by supplier firms (who might be the sellers of technology). We discuss these issues further in Section 3.2. and 4.6.

If a higher minimum wage causes adversely affected firms to step up in-house labor-saving innovation, we expect this effect to be stronger in subsamples that have more low-wage workers. Specifically, we expect the positive relation between minimum wage increases and labor-saving innovation to be driven by industries that employ more minimum-wage workers. We emphasize that our hypothesis is not that low-wage industries develop more labor-saving innovation than high-wage industries on average. Rather, the hypothesis is that the sensitivity of labor-saving innovation to changes in the minimum wage will be stronger for industries that employ more low-wage workers. Similarly, we expect that firm-level labor-saving innovation will be more sensitive to minimum wage increases in states that have more minimum wage workers. Thus, the second hypothesis we test is as follows:

Hypothesis 2: The positive relation between a minimum wage increase and labor-saving innovation (proposed in Hypothesis 1) will be stronger in

2a. industries that employ more minimum-wage workers

2b. states with more minimum-wage workers

Our third hypothesis is motivated by existing literature that documents a strong positive relation between the adoption of computers and the use of college-educated labor. Autor et al (2013) argue that computing technology substitutes for human activities that require repetitive cognitive and manual tasks but complements activities that require interactive problem-solving. They show that the computerization of tasks explains a significant percentage of the increased demand for college-educated labor relative to non-college-educated labor. Since routine tasks are more easily automatable, humans employed in such tasks are more likely to be replaced by machines when the cost of labor increases. Therefore, we formulate the following hypothesis.

Hypothesis 3: The positive relation between a minimum wage increase and the change in labor-saving innovation (proposed in Hypothesis 1) will be stronger for industries with routine manual and cognitive tasks.

In addition to testing these three hypotheses, we conduct a variety of tests to further explore the link between minimum wage increases and labor-saving innovation. For example, in supplementary tests, we look at the extensive margin by comparing the change in labor-saving patents of treatment firms relative to control firms in bordering counties that do not experience increases in the minimum wage. In Section 5, we examine how changes in automation patents around minimum wage increases affect the employment outcomes of unskilled workers.

3. Data and variables

In this section, we describe the minimum wage data, the sample of firms affected by minimum wage increases, our measures of labor-saving innovation, and control variables used throughout the analysis.

3.1. Minimum wage data

Data on the federal minimum wage and the minimum wage level of the 50 U.S. states are obtained from the Department of Labor for the period 1983 till 2019. The solid line in Figure 1A (Figure 1B) shows the nominal value (real value in 1982 dollars) of the federal minimum wage. The decline in the real value of the federal minimum wage is well documented in prior literature.[6] Due to continuing state-level legislation, 29 states had a minimum wage greater than the federal minimum wage by the year 2019. Employees subject to both state and federal minimum wages are entitled to the higher of the two. We call this the "effective" minimum wage in a given state-year. The dotted line in Figure 1A (Figure 1B) shows the nominal (real) value of the average effective minimum wage across all states. It is evident from the graph that the gap between the federal and average state minimum wage has widened over the last decade. This differing state-level legislative activity on the minimum wage offers one source of variation that we use to identify the effect of the minimum wage on corporate innovation.

Like Gustafson and Kotter's (2022) study of capital expenditures around minimum wage increases, we take an event-study approach and examine patent applications (that were eventually granted) and citations per patent of firms in a treated state during the two years before and the two years after an increase in the state's effective minimum wage.[7] An increase in the effective

[6] See, for example, DeNardo et al. (1996) and Lee (1999).
[7] Since our patent data spans the period 1985 through 2019, the earliest (latest) minimum wage event in our sample occurs in 1987 (2017).

minimum wage of a state is classified as a minimum wage event if there was no increase in the effective minimum wage of that state in the previous three years. Finally, for a minimum wage event to be included in our sample, we require an additional condition to hold - there must be at least one publicly traded firm headquartered in that state for which Compustat data are available and which applied for at least one patent during the two years before or two years after the event. This strategy gives us 142 state-years spanning the period 1987 to 2017 that experienced an increase in the effective minimum wage. These minimum wage events are summarized in Table 1. Of the 142 minimum wage events in our sample, 111 (i.e., 70%) are due to three increases in the federal minimum wage that occurred in 1990, 1996, and 2007 while the rest are due to state-level minimum wage increases. Each of the two earlier federal events in 1990 and 1996 accounts for more than 20% of the events in our sample. In untabulated robustness tests, we confirm that our results hold if we drop either of these two federal events from our sample.

For each of the 142 events, we calculate the percentage increase in the effective minimum wage, *ΔMinWage*, as the dollar increase in the effective minimum wage divided by the effective minimum wage in the year prior to the shock. Table 2 summarizes this variable. The average change in the minimum wage across the 142 events is 13.4%. Figure 2 plots the distribution of the percentage change in the minimum wage. For just over 60% of the events, the percentage increase in the minimum wage lies between 12% to 15%. For the remaining events, the percentage increase is evenly spread between 1.4% and 35%. We use this variation in the minimum wage increase to examine whether larger percentage increases in the minimum wage lead to more automation patent applications. In Section A of the accompanying internet appendix, we use wage data from the Current Population Survey (CPS) Merged Outgoing Rotation Groups database to check the bindingness of the minimum wage. Our data confirm prior evidence that minimum wage increases spill over to earnings at the lower end of the wage scale. We also show that the 'bindingness' of the minimum wage varies by state. The fraction of workers affected by the minimum wage hike (i.e., those earning between the old and the new minimum wage) differs by state. In Section 4.5, we exploit the variation by state in the bindingness of the minimum wage to identify the effect of the minimum wage on corporate innovation.

3.2 Sample of firms and classification of automation patents.

For each of the 142 state-years experiencing a minimum wage event, we use Compustat to identify publicly traded firms headquartered in that state in that year.[8] As in prior studies, we measure the corporate innovative output with patenting activity (see, for example, Lerner et al., 2011; Seru, 2014; Fang et al., 2014). A firm is retained in our sample if it applied for at least one utility patent (that was eventually granted) in the two years before or two years after the minimum wage event and has financial data available from Compustat. Firm-level patent and citation data from 1985 through 2019 are obtained from the National Bureau of Economic Research (NBER) Patent Data Project and Kogan et al. (2017). Our sample contains 2,578 firms that applied for 550,190 utility patents in the United States during the two years preceding and two years following the minimum wage events. In our primary sample, we exclude SIC 283 (Drug Manufacturing) because a significant proportion of patents filed by drug manufacturers relate to chemical compositions, and in these patents, keywords such as automatic are likely to be used in a context other than labor-saving technology.[9]

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[8] In our main analysis, we use the current location of headquarters from Compustat. In additional tests presented in Table 8, we show that our results hold if we restrict our sample to headquarter states that are also the firm's main operating sites as per Garcia and Norli (2012)

[9] Prior research documents significant robotization of the production process in the chemicals industry (Acemoglu and Restrepo, 2020). To allow for the possibility that drug manufacturers apply for patents relating to automation of the drug production process, we include drug manufacturers in the sample in robustness tests and find qualitatively similar evidence (see Section 6).

We machine-read descriptions of all patents in our sample and search for words that are indicative of technology that replaces manual labor such as "automatic", "robotic", "mechanize", and variations of these words. A complete list of keywords used in the search is presented in Main Appendix A included at the end of this article. Of the 550,190 patents in our sample, 226,723 patents (about 41%) contained at least one keyword.[10] We classify these patents as automation patents. In Section B of the internet appendix, we provide a few examples of automation patents filed by firms in the business services industry, leisure and hospitality industry, retail industry, and manufacturing sector.

We recognize that not all patents containing the selected keywords necessarily replace low-wage workers. Later in the paper, we take a few steps to address concerns about possible noise in our measure of automation patents. In Section 4.5.3, we show that our measure of automation patents is the most sensitive to minimum wage shocks in industries that have automatable tasks. In Section 5, we present evidence that our measure of automation patents has the expected relation with the employment and wage share of unskilled labor. Finally, in Section 6, we show that our results are robust to alternate measures of automation patents.

Table 4 lists select industries along with the number of automation patents and the percentage of automation patents in the industry. The percent of minimum wage workers (obtained from the Bureau of Labor Statistics) is also provided. [11] To test Hypothesis 1, we examine whether firms located in states with larger increases in the effective minimum wage experience a more positive increase in automation patents. This empirical design necessitates a discussion of the

[10] Mann and Püttmann (2018) find that the percentage of automation patents increased in the U.S. from 25% in 1967 to 67% in 2014. The 41% share of automation patents in our sample falls within this range. Note that our sample of patents is limited to those applied for during the four years surrounding each minimum wage event. Therefore, our data cannot speak to time trends in automation patent applications.
[11] The classification of industries is from the Bureau of Labor Statistics. https://www.bls.gov/bls/naics_aggregation.htm

possible disconnect between firms that innovate and firms whose cost of labor rises due to the minimum wage change. For example, firms in the manufacturing sector account for a large fraction of automation patents but have relatively low dependence on low-wage workers. According to the Bureau of Labor Statistics (BLS), on average, only about 3% of the workers in the manufacturing sector earn a minimum wage. Moreover, firms in the information industry, which account for a large fraction of innovative activity, tend to have highly paid skilled workers and are unlikely to be affected by minimum wage increases. In contrast, traditionally low-wage industries (e.g., leisure and hospitality) which tend to experience an increase in labor costs when the minimum wage increases account for relatively few patents.

We discuss each of these industries in turn. Firms in the manufacturing sector account for more than 55,000 automation patents and almost 65% of the firm-years in our sample. While on average only about 3% of the workers in the manufacturing sector earn a minimum wage, there is significant variation within the manufacturing sector in the employment of low-wage workers, with several industries experiencing years in which the percentage of minimum wage employees is in the double digits. For firms in these manufacturing industries, a large increase in the minimum wage would cause a significant increase in labor costs, thereby creating an incentive for the manufacturers to develop automation technology as a substitute for labor. We exploit this cross-industry variation in the percentage of minimum wage workers to identify the causal role of minimum wage increases.

The business services and information industry together account for more than 150,000 automation patents. While these are not low-wage industries, they may develop automation technology for sale to firms experiencing a rise in labor costs. Recall that our empirical method examines the impact of an increase in a state's minimum wage on automation patents developed by all firms in that state. If firms in the business services and information industries develop labor-saving technology for local customer firms whose labor cost has risen due to the increase in the state's minimum wage, this effect would be captured by our analysis.

The data show some evidence of automation patenting within industries that typically hire low-wage workers such as the leisure and hospitality industry. Table 4 shows that while the leisure and hospitality industry and the retail sector have few patents in total, the percentage of automation patents in these industries is quite high. For example, 76% of the patents filed in the leisure and hospitality industry are automation patents. Section B of the internet appendix includes examples of labor-saving patents in the retail sector (Example 2) and in the leisure and hospitality sector (Example 3).

Table 5 presents a broad firm-level overview of automation and non-automation patents across the entire sample period. Table 5, Panel A summarizes the total patent applications and citations for the 2,578 firms over the entire sample period 1985 through 2019. Both patents and citations suffer from a truncation bias (Hall, Jaffe, and Trajtenberg, 2001). To adjust for this truncation problem, we divide each patent for each firm-year by the mean number of patents of all firms for that year. We adjust for the truncation bias in citations by dividing the citations of a given patent by the total number of citations received by all patents in that year in the same technology class. Truncation-bias-adjusted total patents and citations are summarized in Panel B of Table 5. In the robustness section, we address the truncation bias issue more aggressively by dropping the last five years of our sample period and find robust results.

4. Impact of minimum wage on automation

In this section, we address our primary research question. Do increases in the minimum wage lead to more labor-saving innovation?

4.1 Dependent and independent variables

Our analysis is at the firm-year level with up to four observations per firm per event (two years preceding the event and two years following the event, with the event year itself excluded). Our primary dependent variable is the total number of truncation-bias-adjusted automation patents (in logs), *A_Pat*, applied for in each firm-year. We also calculate the total number of truncation-bias-adjusted non-automation patents (in logs), *NA_Pat*, applied for in each firm-year. Examining the change in non-automation patent applications helps assess whether any changes observed after minimum wage increases are restricted to automation patents only or capture overall shifts in innovation. The secondary variable we use to capture a possible shift toward labor-saving innovation is the total truncation-bias-adjusted forward citations (in logs), *A_Cite*, received by automation patents. For comparison, we also calculate the truncation-bias-adjusted forward citations (in logs), *NA_Cite*, received by non-automation patents.

Table 6 Panel A presents summary statistics of our dependent variables A_Pat, A_Cite, NA_Pat, NA_Cite for all firm-years in our sample. This table also summarizes several control variables. The construction of all variables is described in Main Appendix B. We split our sample of firm-years into two subsamples based on the percentage increase in the minimum wage across our 142 events and present differences-in-means in Panel B of Table 6. We see that automation patenting is not, on average, higher in states that approve larger minimum wage increases. Panel B shows significant differences across the two subsamples in various firm characteristics. Our regressions control for these variables and employ firm-fixed effects to control for unobserved firm characteristics.

4.2. Baseline results on the change in automation patenting

In this sub-section, we test the first hypothesis outlined in Section 2 – do larger increases in the minimum wage encourage labor-saving innovation? We focus on firms headquartered in the 142 state-years that experience a minimum wage event and examine the change in patents and citations from two years before the event till two years after the event.[12] The year of the event itself is excluded. We define three event-year dummy variables. For a minimum wage event *m* in year *T* in a state *s*, the dummy variable *Before1* takes the value of one for the year *T-1* and zero otherwise. The dummy variable *After1* takes the value of one for the year *T+1* and zero otherwise. Finally, *After2* takes the value of one for the year *T+2* and zero otherwise. The coefficients on these event-year dummy variables capture changes in automation patents that would have occurred around the event year had the minimum wage increase been zero. We interact each of these event-year dummy variables with the percentage change in the minimum wage, ΔMinWage, previously described in Section 3.1. The interaction terms help us determine whether larger increases in the minimum wage elicit more positive changes in automation patents. We run the following regression with firm-fixed effects (α_i) and time-fixed effects (τ_t):

$$X_{i,m,t} = \beta_0 + \beta_1\, Before1_{m,t} \times \Delta\, MinWage_m + \beta_2\, After1_{m,t} \times \Delta\, MinWage_m + \beta_3\, After2_{m,t} \times \Delta\, MinWage_m + \beta_4\, \Delta\, MinWage_m + \beta_5\, Before1_{m,t} + \beta_6\, After1_{m,t} + \beta_7\, After2_{m,t} + \gamma\, Firm\ Controls_{i,m,t} + \alpha_i + \tau_t + \varepsilon_{i,m,t} \qquad (1)$$

[12] To address concerns that a state's minimum wage regulation is endogenous to local economic conditions that also influence innovation, we also run this analysis restricting the sample to federally mandated increases in the minimum wage. Federal increases lead to an increase in the effective minimum wage of bounded states, i.e., states with minimum wage equal to the federal minimum wage. Focusing on this subsample, takes the minimum wage decision out of the hands of individual states and helps address endogeneity concerns. In these untabulated results, our findings are qualitatively similar. In Section 4.4 of the paper, we further account for local economic conditions using control firms in neighboring counties across state borders.

In our primary analysis, the dependent variable $X_{i,m,t}$ in the equation above is either A_Pat, the number of automation patents of a firm i headquartered in the state experiencing the minimum wage event m in year t, where $T - 2 \leq t \leq T + 2$ or A_Cite, the number of forward citations received by the automation patents. If the minimum wage increase causes firms to focus more on the development of automation technology, coefficients β_2 or β_3 or both are expected to be positive. That is, larger minimum wage increases are expected to be followed by larger increases in automation patent applications and citations of automation patents. The coefficient β_1 is also of interest. If a larger minimum wage hike causes an increase in automation patenting and not the other way around, we expect β_1 to be insignificant.

We also run the same analysis using non-automation patents as the dependent variable. This serves as a falsification test. If our classification of automation patents distinguishes labor-saving innovation from other types of innovation (even if with some noise), we do not expect to observe a relationship between the size of the minimum wage increase and non-automation patents.

Regression results for automation patents and citations are presented in columns 1 through 4 of Table 7. All regressions include firm-fixed effects and year-fixed effects and standard errors clustered by state. The regressions in columns 3 and 4 also include several additional firm-level control variables. We first note that the coefficient β_1 is statistically insignificant in all four columns. Recall that β_1 captures whether the change in automation patents (columns 1 and 3) or citations (columns 2 and 4) in the year prior to the minimum wage event is significantly related to the percentage increase in the minimum wage. The statistically insignificant value of β_1 indicates that larger minimum wage increases are not preceded by an increase in automation patents applications or citations. In contrast, we see that in all regression specifications shown in columns

1 through 4, either β_2 or β_3 (or both) is positive and statistically significant. This finding supports Hypothesis 1 and implies that larger minimum wage increases are followed by more automation patent applications as well as more citations received by automation patents.

We want to address the criticism that the positive association between automation patents and the size of the minimum wage increase is reflective of overall changes in corporate innovation and not just changes in labor-saving innovation. To this end, we repeat regression equation 1 using non-automation patents (NA_Pat), and citations received by non-automation patents (NA_Cite) as dependent variables. If corporate innovative activity is, in general, positively associated with the size of the minimum wage increase, the coefficients β_2 and β_3 would also be positive in regressions where the dependent variable is non-automation patents or citations received by non-automation patents. In all regressions specifications shown in columns 5 through 8, both β_2 and β_3 are statistically insignificant. Thus, an increase in the minimum wage is unrelated to non-automation patents and citations received by non-automation patents. Together the results in Table 7 show automation patents and citations increase after minimum wage hikes but non-automation patents and citations do not.

A firm experiencing an increase in labor cost due to the minimum wage increase may purchase and adopt labor-saving technology (such as software or machinery) developed by other firms. We control for externally sourced innovation by creating an industry-level variable capturing automation innovation conducted by supplier industries. We use the input-output tables provided by the Bureau of Economic Analysis (BEA) and classify supplier industries as industries that provide at least 5% of the downstream industry's input usage. Assuming that the input share weights from the BEA use tables also apply to the supply of innovations embedded in intermediate goods (Delgado and Mills, 2017), we compute the weighted sum of supplier automation patents for each industry in each year. These measures of upstream labor-saving innovation are included as control variables in equation 1. The results are presented in columns 1 through 4 of Table 8. We see that either β_2 or β_3 (or both) is positive and statistically significant indicating that our main results hold after controlling for upstream labor-saving innovation. In columns 3 and 4, the dependent variables are non-automation patents and citations respectively. As before, β_2 and β_3 are both insignificant.

To address concerns that the headquarter state may not be state in which a firm has most of its operations, we use Garcia and Norli's (2012) measure of geographic dispersion based on how many times a state is mentioned in a firm's 10-K reports. By this measure, for about 65% of firms in our sample, the state of headquarters is the primary state of operations. The findings remain qualitatively unchanged in this subsample. We see that either β_2 or β_3 is positive and statistically significant for automation patents (columns 5 and 6 of Table 8), while for non-automation patents, β_2 and β_3 are both insignificant (columns 7 and 8 of Table 8).

4.3. Falsification test using random-word classification

Our methodology identifies automation patents based on the appearance in the patent descriptions of keywords indicative of labor-saving technology. One concern about this approach is that the likelihood of any given word appearing in the description of a patent can depend on unobserved time-varying factors that are correlated with minimum wage changes. This would lead to a spurious relation between minimum wage increases and our proxy of automation patents.

We address this issue using a falsification test in which we divide our sample of patents into two groups based on the appearance of a set of randomly selected words in the patent description. From our sample of more than half a million patents, we randomly select 10% of the patents and extract the text descriptions of all the patents in this sample. We tokenize all the text descriptions of this random subsample and drop frequently occurring 'stop words' such as *the*, *of*, *patent, claim* etc. From the remaining tokenized list of words, we randomly select 25 words. These 25 words are listed in Section C of the internet appendix. Next, we search the patent descriptions of our full sample of more than half a million patents for the appearance of this set of 25 randomly selected words. If a patent description contains one or more of the random words, we classify it as a *'random-hit'* patent. If the patent description does not contain any of the random words, we call it a *'random-miss'* patent. For each firm-year, we calculate the number (in logs) of random-hit patents and the number (in logs) of random-miss patents. For each firm-year, we also calculate the number (in logs) of citations received by random-hit patents and random-miss patents.

We estimate equation 1 again but define the dependent variable as either the number of random-hit patents or the number of citations received by random-hit patents. Since, by design, the number of random-hit patents and random-miss patents carries no information about automation technology, we expect the coefficients β_2 and β_3 to be insignificant. Results for random-hit patents and citations are presented in columns 1 through 4 of Table 9. We see that the coefficients β_2 and β_3 are indeed statistically insignificant in all four columns. In columns 5 through 8, we define the dependent variable as either the number of random-miss patents or the number of citations received by random-miss patents. Again, the coefficients β_2 and β_3 are insignificant. The results in Table 9 indicate that when the patent classification method contains no information about automation technology, there is no observable link between minimum wage increases and the number of patents and citations.

4.4. Comparing to firms in neighboring counties

Next, we account for the possibility that unobserved economic factors cause both an increased corporate focus on automation technology as well as greater political support for minimum wage increases. To this end, we identify control firms that are likely to experience similar economic conditions as the treated firms but are not affected by a minimum wage increase. Specifically, for each state experiencing a minimum wage event *m*, we identify control firms headquartered in bordering counties in states not experiencing a minimum wage increase at that time. To be included in the sample, the control firm must have applied for at least one patent in the two years before or two years after the minimum wage increase in the treated state.

We then conduct a difference-in-differences analysis using the following equation with firm-fixed effects (α_i) and year-fixed effects (τ_t):

$$Y_{i,m,t} = \gamma_0 + \gamma_1\, Before1_{m,t} \times Treated_i + \gamma_2\, After1_{m,t} \times Treated_i + \gamma_3\, After2_{m,t} \times Treated_i + \gamma_4\, Before1_{m,t} + \gamma_5 After1_{m,t} + \gamma_6 After2_{m,t} + \eta\, Firm\ Controls_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,m,t} \quad (2)$$

In equation 2, the dependent variable $Y_{i,m,t}$ is the number of automation patents or citations of a treated firm or a control firm in a neighboring county during the two years before and two years after the minimum wage event *m* in the treated state. *Treated* is a dummy variable that takes the value 1 if the firm lies in the state that experienced a minimum wage event and a value of 0 if it is a control firm from a neighboring county that did not experience a minimum wage increase. If automation patents increase due to the change in the minimum wage, and not due to changes in local market conditions, the increase in automation patenting would be greater for the treated firms as compared to the control firms in contiguous counties. That is, the coefficients γ_2 or γ_3 (or both) would be positive and statistically significant. Column 1 (column 2) of Table 10 presents estimates of equation 2 when the dependent variable is A_Pat (A_Cite). In both columns, the coefficients γ_2 and γ_3 are positive and statistically significant. That is, firms that face an increase in their state's effective minimum wage have larger increases in automation patenting than control firms in neighboring counties. For comparison, we also look at changes in non-automation patents and citations across treated and control firms (columns 3 and 4) and find that γ_2 or γ_3 are both insignificant. Thus, there is no difference across treated and control firms in innovation that does not relate to automation. Overall, the findings in Table 10 help mitigate concerns that local economic shocks cause both the minimum wage increase and the increase in automation patents.

4.5. Subsample tests to support the causal role of minimum wage increases

In this section, we present a few subsample tests to support the causal argument that minimum wage increases lead to increased effort in automation patenting. In the interest of space, these tests focus on our main dependent variable only - the number of automation patents.

4.5.1 Subsample tests based on the fraction of minimum wage workers in an industry

Our results indicate that minimum wage increases in a state lead to more labor-saving innovation by firms headquartered in that state. In Hypothesis 2a, we argue that if firms develop automation technology in-house, this result should be observed in industries with more low-wage workers. We test this explanation by comparing two subsamples based on the fraction of minimum-wage workers employed in an industry. Specifically, we use the CPS data to calculate the percentage of minimum wage workers in each industry at the 3-digit SIC level and estimate regression equation 1 separately in the subsample of industries with a high (i.e., above-median) fraction of minimum wage workers and a low (i.e., below-median) fraction of minimum wage workers.[13]

The findings are presented in the first two columns of Panel A Table 11. All control variables are included but not tabulated for brevity. The sample in columns 1 (column 2) is restricted to firms in industries with an above-median (below-median) fraction of minimum wage workers. The dependent variable is A_Pat, the number of automation patents. We see that in column 1, both β_2 and β_3 are positive and statistically significant. That is, in industries that have

[13] We match the industry classification from CPS to SIC codes using the crosswalk table provided by David Dorn: https://www.ddorn.net/data.htm.

a high fraction of minimum wage workers, larger minimum wage increases are followed by an increase in automation patents. In column 2, both β_2 and β_3 are insignificant indicating that in industries with few low-wage workers, there is no link between the size of the minimum wage increase and labor-saving innovation. To summarize, we find support for Hypothesis 2a.

4.5.2 Subsample tests based on bindingness of the minimum wage

Hypothesis 2b states that if the minimum wage increase causes firms to develop more automation technology, the results should be stronger in states that have more low-wage workers. In this test, we identify the fraction of workers in a state affected by the minimum wage increase, i.e., those earning at or below the new minimum wage. There is significant variation across states and over time in the maximum percentile of the wage distribution at which the state minimum wage or federal minimum wage binds. More information on this variation in the bindingness of the minimum wage is presented in Section A of the internet appendix. For each state *s* experiencing a minimum wage event in year *T*, we calculate the maximum percentile at which the new minimum wage binds in years *T-2* and *T-1* and take an average of the two values. This average percentile captures the fraction of workers in the state earning below the new minimum wage during the period leading up to the minimum wage increase. Descriptive statistics for this average percentile across the 142 minimum wage events in our sample are provided in Table A1 of Section A of the internet appendix. We use this variable to split our sample of minimum wage events into two groups at the median value. In the subsample of events with high (i.e., above-median) values of the binding percentile, the fraction of workers affected by the minimum wage increase is greater. If the previously documented increase in automation patents and citations is due to minimum wage increases, we expect to find stronger evidence in the subsample with a high binding wage percentile.

In column 3 (column 4) of Panel A in Table 11, we present estimates of equation 1 in subsamples of firms in states with above-median (below-median) binding-wage percentile. The dependent variable is the number of automation patents. In column 3, we see that the coefficient β_3 is positive and statistically significant at the 1% level. Thus, we find support for Hypothesis 2b - in states that have a larger fraction of workers affected by the minimum wage increase, there is a significant increase in the number of automation patents. In column 4, which is restricted to the low-binding-wage subsample, both β_2 and β_3 are statistically insignificant. Thus, in states where the fraction of workers affected by the minimum wage hike is small (by virtue of already earning above the new minimum wage), there is no observable increase in automation patents.

4.5.3 Subsamples based on routine-task industries

In this sub-section, we test Hypothesis 3. If the minimum wage increase causes firms to develop more automation technology, the results should be stronger in industries that follow set rules and routines and require little analytical problem-solving. We follow Autor et al. (2003) and use the U.S. Department of Labor's Dictionary of Occupational Titles (DOT) to identify routine-task industries. We focus on four DOT categories: STS (set limits, tolerances, or standards), FINGDEX (finger dexterity), DCP (Direction, Control, and Planning), and MATH (analytical reasoning). For each of these four indices, we calculate the average value within each 2-digit SIC code in the pre-event period and assign this average value to all firm years belonging to that 2-digit SIC. Description and summary statistics of the DOT indices for all available firm-years are presented in Main Appendix C. Using these indices, we employ two methods to identify routine-task industries. In the first method, which we call FINGDEX+STS, we combine routine manual tasks and routine cognitive tasks and define routine-task industries as those with above-median values for the sum of FINGDEX and STS. Industries with below-median values are classified as non-routine task industries. In the second classification method, we combine DCP and MATH, the measures of interactive and analytical activities. Since higher values of the DCP and MATH indices indicate non-routine activity, we classify industries with below-median values of the sum of DCP and MATH as routine-task industries.

Next, we examine whether minimum wage hikes lead to more automation patent applications in routine-task industries. Estimates of equation 1 in the subsample of routine-task (non-routine-task) industries based on the FINGDEX+STS classification of routine tasks are presented in column 1 (column 2) of Panel B of Table 11. In column 1, we see that the coefficient β_2 is positive and statistically significant, which indicates that in routine-task industries, larger minimum wages are accompanied by an increase in the number of automation patent applications in the year following the minimum wage increase. In column 2, on the other hand, both β_2 and β_3 are statistically insignificant. Thus, there is no statistical relation between minimum wage increases and automation patent applications in non-routine-task industries. Similar evidence is seen in columns 3 and 4 where we identify routine tasks based on the DCP+MATH classification. Overall, the results in Panel B of Table 11 provide a consistent picture that minimum wage increases are followed by an increase in automation patent applications in industries in which jobs follow fixed routines – i.e., jobs that are more easily automatable. Finally, we note that the evidence in Panel B that an increase in automation patents is observed only in industries that have automatable jobs helps alleviate concerns about noise in our measure of automation patents.

4.6. Additional subsample tests

Manufacturing firms and information firms account for about 90% of the firm-year observations in our sample. In this section, we examine whether our results hold within both of these industries. In Table 12 Panel A, we present estimates of equation 1 in two subsamples using automation patents as the dependent variable. Column 1 presents the results for firms in the manufacturing sector only. We see that β_2 and β_3 are both positive and statistically significant indicating that our findings hold within the manufacturing sector. In column 2 we limit the sample to firms in the information industries only and, again, find that β_2 and β_3 are both positive and statistically significant.

In our next set of tests, we account for the role of firm size. Smaller firms are more likely to have local operations, and therefore, we expect their investment in labor-saving innovation to be more sensitive to increases in the state's effective minimum wage. Large firms are more likely to have operations in multiple states and their total labor cost across all employees nationwide may not be significantly affected by an increase in the effective minimum wage of the state in which the firm is headquartered. We divide our firms into two size groups based on median market capitalization and estimate equation 1 in both size subsamples. Results for the small-firm (large-firm) subsample are presented in column 1 (column 2) of Table 12 – Panel B. The ceofficient β_2 is positive and significant in column 1, indicating that larger increases in the minimum wage are associated with more positive changes in automation patents of small firms. In column 2, both β_2 and β_3 are insignificant. This lack of significance in the large-firm subsample suggests that innovation by large firms does not respond to local wage shocks. In columns 3 and 4 (columns 5 and 6), we look at subsamples of small and large manufacturing (information) firms respectively. The same pattern persists. In both manufacturing and information industries, automation patenting by small firms has a positive association with larger minimum wage increases while automation patenting by large firms is not significantly related to the state's minimum wage.

5. Employment-share and wage-share of unskilled workers

Prior research shows that in industries with automatable jobs, the employment of unskilled laborers declines after minimum wage increases (Lordan and Neumark, 2018; Aaronson and Phelan, 2019). The conclusion these studies draw is that the higher cost of labor causes firms to substitute technology for low-skilled workers. While this is a reasonable conclusion considering prior evidence on the substitutability of technology for unskilled labor[14], there is no evidence directly linking the decline in unskilled employment following minimum wage hikes to corporate innovation. In this section, we examine whether an increase in automation patents following minimum wage hikes affects the employment of low-skilled workers employed in routine tasks. If our text-based identification of automation patents is a good proxy for the development of automation technology, we expect to find evidence that an increase in automation patents is associated with a decline in the employment share and wage share of low-skill workers employed in routine tasks.

5.1. Employment share and wage share of unskilled workers

As is common in prior literature, we rely on college education as a proxy for skill. Using the CPS data, we calculate the employment share (*Emp_share*) and wage share (*Wage_share*) of unskilled workers in each industry. Both variables are described in Main Appendix B. In Panel A (Panel B) of Table 13, we present descriptive statistics of Emp_share (Wage_share) in routine-task and non-routine-task industries. Panel A shows unskilled workers hold a significantly larger fraction of jobs in routine-task industries than they do in non-routine-task industries. In Panel B,

[14] See Acemoglu and Restrepo, 2020; Autor, Levy, and Murnane, 2003; Krusell et al., 2000; Autor, Katz, and Krueger, 1998; Machin and Van Reenen, 1998; Berman, Bound, and Machin; 1998, Bound, and Griliches, 1994.

we see that the wage share of unskilled workers is also greater in routine-task industries. Table 13 highlights the vulnerability of unskilled workers to replacement by automation technology.

5.2. The effect of automation patents on unskilled employment

In this subsection, we test whether the changes in labor-saving innovation following minimum wage increases affect the employment opportunities of low-skilled workers. This analysis is conducted at the industry-year level. For each year *t*, we calculate the total number of automation patents, *IndAuto_Pat*, applied for by firms in industry *j* in the state experiencing the minimum wage event m. As in prior regressions, we focus on the four years surrounding a minimum wage event. That is, $T-2 \leq t \leq T+2$ where T is the event year. We also calculate the total number of citations received by automation patents, *IndAuto_Cite* across firms in industry *j* in the state experiencing the minimum wage event m. We examine the link between unskilled employment share (or wage share) and automation patents both before and after the minimum wage shock using the following regression with industry-fixed effects (φ_j) and year-fixed effects (τ_t):

$$Emp\_share_{j,m,t} \text{ or } Wage\_share_{j,m,t} = \delta_0 + \delta_1 Before1_{m,t} \times IndAuto\_Pat_{j,m,t} + \delta_2 After1_{m,t} \times IndAuto\_Pat_{j,m,t} + \delta_3 After2_{m,t} \times IndAuto\_Pat_{j,m,t} + \delta_4 IndAuto\_Pat_{j,m,t} + \delta_5 Before1_{m,t} + \delta_6 After1_{m,t} + \delta_7 After2_{m,t} + \gamma \, Industry\ Controls + \varphi_j + \tau_t + \varepsilon_{j,m,t} \quad (3)$$

The event-year dummy variables *Before1*, *After1*, and *After2* are described in Section 4.1 above. To understand the relation between automation patents applications and the employment share of unskilled labor after an increase in the minimum wage, we interact each of these event-year dummy variables with the total number of automation patents, IndAuto_Pat, applied for by firms in industry j in the state experiencing the minimum wage event m. In alternative specifications, we use, IndAuto_Cite instead of IndAuto_Pat. The coefficients of interest are δ_2 and δ_3. We estimate equation 3 separately in sub-samples of routine-task industries and non-routine-task industries. The routine-task classification identifies industries in which jobs are vulnerable to automation. In the period following minimum wage increases, we predict a negative relation between the number of automation patent applications in routine-task industries and the employment outcomes of unskilled labor. That is, we expect the coefficients δ_2 or δ_3 (or both) to be negative in the subsample of routine-task industries. As a comparison, we also run the analysis in non-routine task industries. In these industries, jobs are less vulnerable to automation as they require cognitive thinking, reasoning, and planning. Thus, in non-routine task industries, there is no expectation of negative relation between unskilled employment and automation patents following minimum wage increases.

In Table 14, we present estimates of equation 3 with Emp_share, the employment share of unskilled workers, as the dependent variable. In Panel A (Panel B), the classification of routine-task industries is based on the FINGDEX+STS (DCP+MATH) job descriptions. In the interest of space, only the coefficients on the interaction terms are shown. Looking at Panel A first, the analysis is restricted to the sub-sample of routine-task industries in columns 1 and 2. In column 1, the explanatory variable IndAuto_Pat captures the development of automation technology in the industry. We see that the coefficient δ_3 is negative and statistically significant at the 5% level indicating that two years after the minimum wage increase, the employment share of unskilled workers is significantly lower in industries that experienced a bigger increase in automation patent applications. The magnitude of the coefficient δ_3 indicates that a 10% increase in automation patent applications leads to a 1.6 percentage point decline in the employment share of unskilled workers.[15]

[15] Since the independent variable, IndAuto_Pat, is log transformed, the change in the dependent variable for a 10% increase in the independent variable is calculated as δ_3*ln(1.10)= -0.016 when δ_3 is -0.17

In column 2 of Panel A, we use IndAuto_Cite instead of IndAuto_Pat to capture automation technology. The coefficient δ_3 is negative again and statistically significant at the 1% level. Thus, both industry-level measures of automation - the number of patent applications and citations received by automation patents, are associated with a decline in the employment share of unskilled workers after minimum wage increases. For comparison, in columns 3 and 4 of Panel A, we repeat the analysis in non-routine-task industries. We see no evidence of a negative link between unskilled employment share and labor-saving innovation after minimum wage hikes. Whether we use IndAuto_Pat or IndAuto_Cite to capture labor-saving innovation, δ_2 and δ_3 are either insignificant or positive in columns 3 and 4. In Panel B of Table 14, we repeat the analysis using DCP and MATH to classify routine-task industries. The results are qualitatively similar to those in Panel A and we do not discuss them here to avoid repetition.

Next, we present estimates of equation 3 with unskilled wage share as the dependent variable. In Panel A of Table 15, the classification of routine-task industries is based on the FINGDEX and STS job descriptions. In columns 1 and 2 of Panel A, the analysis is restricted to routine task industries only. In both columns, the coefficients δ_2 and δ_3 are negative and statistically significant, indicating that in the period following the minimum wage increase, the wage share of unskilled workers is significantly lower in industries that experienced a bigger increase in automation patent applications or a bigger increase in citations received by automation patents. The magnitude of the coefficient δ_3 in column 1 of Panel A indicates that a 10% increase in automation patent applications is associated with an unskilled wage share that is 1.2 percentage points lower two years after the minimum wage increase.[16]

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[16] Since the independent variable, IndAuto_Pat, is log transformed, the change in the dependent variable for a 10% increase in the independent variable is calculated as δ_3*ln(1.10)= -0.0117 when δ_3 is -0.12

Similar evidence is observed in columns 1 and 2 of Panel B, which uses job descriptions DCP and MATH to classify routine-task industries. The coefficients δ_2 and δ_3 continue to be negative and statistically significant. Notably, in columns 3 and 4 of both Panels A and B, which focus on the subsample of non-routine-task industries, there is no evidence of a negative link between unskilled wage share and labor-saving innovation.

Together the results in Tables 14 and 15 show that the poorer employment outcomes for unskilled workers after minimum wage increases are partly attributable to the corporate effort on developing labor-saving innovation. These results are noteworthy for two reasons. First, these findings are the first direct evidence that changes in corporate innovative output around minimum wage events have a significant impact on the employment share and wage share of unskilled workers. Second, our text-based measures of automation patents correlate as expected (i.e., negatively) with the employment share and wage share of unskilled workers. This provides some validation that our proxies indeed capture labor-saving innovation.

6. Robustness

We conduct several robustness checks which we mention briefly with details provided in the internet appendix. In Section D1 of the internet appendix, we present the robustness of our baseline results in Table 7 to two alternative classifications of automation patents. In Section D2 of the internet appendix, we include the drug industry (SIC 283) in our analysis and find the results are qualitatively similar. In Section D3, we use a different strategy to account for the truncation bias inherent in patent counts and citations - we drop the last five years of our sample period and find that our main results still hold. In Section D4, we use historical data on the firm's headquarters from Gao, Leung, and Qiu (2021) instead of the current headquarters and find consistent results.

7. Conclusion

We argue that the greater demand for labor-saving technology due to minimum wage hikes encourages firms to shift innovative efforts toward automation technology. We provide the first comprehensive evidence that larger minimum wage increases are followed by an increase in the number of automation patent applications as well as in the number of forward citations received by automation patents. No such relation is observed between the minimum wage increase and non-automation patents or citations. To identify the role of the minimum wage, we exploit cross-industry variation in the percentage of minimum wage workers and cross-state variation in the bindingness of the minimum wage. We find that the increase in the number of automation patents and citations is greater in states where a larger fraction of workers earns at or below the new minimum wage and in industries that have a higher fraction of minimum wage workers.

The increase in automation patent applications after minimum wage hikes is driven by industries that employ workers in routine tasks, i.e., in tasks involving a limited and well-defined set of activities that are more easily programmable for a computer. Our result is consistent with prior evidence that an increase in the minimum wage decreases the share of automatable jobs held by unskilled workers. We posit that the minimum wage increase, and the resulting increase in the cost of low-skill labor, spur the development of new technology that replaces low-skill workers. Indeed, our analysis shows that in routine-task industries, the greater the number of automation patent applications (or citations of automation patents) following minimum wage increases, the lower the employment share and wage share of unskilled workers. Our findings suggest that minimum wage legislation can have the unintended consequence of increasing labor-saving innovation that ultimately displaces the very same workers the legislation was designed to help.

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Main Appendix A: Identifying automation patents

A1. Identifying automation patents (Primary Classification)

We machine-read patent descriptions and classify a patent as an 'automation' patent if it meets any one of the following four criteria:

1. One or more appearances of the following words:
   - automatic or automatically
   - automate, automation, or automatization
   - mechanize or mechanization
   - robot, robotic, robotize, or robotization
   - labor-saving
2. To identify computer-assisted manufacturing: One or more appearances of the following bulleted list of words **and** the word *machine*, *manufacturing*, *equipment*, or *apparatus*
   - computer aided or computer-aided
   - computer assisted or computer-assisted
   - computer supported or computer-supported
3. To identify computer numerical control (cnc) patents which indicate automated control of machine tools: One or more appearances of the following words
   - numerically controlled or numerically-controlled
   - numeric control or numeric-control
   - cnc
4. To identify self-operated equipment: One or more appearances of the word 'self-' **and** the word *machine*, *manufacturing*, *equipment*, or *apparatus*

As is evident in Table A1, the words *automatic* or *automatically* are the most frequent with almost 1.4 million appearances across 150,700 patents. The next most frequent is *robot** (including robotic, robotize etc.) which appears 412,996 times in 16,551 patents. The word *self-* (combined with the appearance of the words *machine*, *manufacturing*, *equipment*, or *apparatus* in the same patent) is the third-most frequent with a total of 319,244 appearances.

Table A1: Automation words description

This table shows the occurrence of keywords indicative of labor-saving technology in patents filed by firms headquartered in states experiencing increases in the effective minimum wage. Of 550,190 patent applications during the two years before and two years after the minimum wage shock, 226,723 contained at least one of the words listed below. The column titled "# of appearances" shows the total number of appearances of the word across all 226,723 patents. The column titled "# of patents" shows the number of patents in which the word appeared at least once.

Appearances of words synonymous with automation in patent descriptions

Word	# of appearances	# of patents	Word	# of appearances	# of patents
automatic*	1,360,693	150,700	computer assisted	5,800	1,666
robot*	412,996	16,551	numerically controlled	3,716	1,124
self-	319,244	69,818	mechaniz*	2,852	1,298
automate	241,939	59,752	computer supported	870	560
automation	66,398	17,904	numeric control	267	185
computer aided	17,554	7,902	labor-saving	38	25
cnc	10,270	4,102			

Main Appendix B: Variable definitions

ΔMinWage: The percentage change in the effective minimum wage, calculated as the new, higher effective minimum wage less the prior effective minimum wage divided by the prior effective minimum wage. The effective minimum wage is the higher of the prevailing federal minimum wage and the state minimum wage.

After1: Dummy variable equal to one for the year *T+1* in state s and zero otherwise, where *T* is the year of the minimum wage event in state *s*.

After2: Dummy variable equal to one for the year *T+2* in state s and zero otherwise, where *T* is the year of the minimum wage event in state *s*.

A_Cite: The natural log of (1 + truncation-biased adjusted forward citations of automation patents). Truncation-bias-adjusted citations are the number of forward citations received by automation patents applied for by firm *i* in year *t* divided by the mean number of citations received by firms in year *t* in the same technology class. Classification of patents as automation and non-automation patents is provided in Appendix A.

A_Pat: The natural log of (1 + truncation-biased adjusted automation patents). Truncation-bias-adjusted patents are calculated as the number of automation patents applied for by firm *i* in year *t* divided by the mean number of patents of all firms in year *t*. Classification of patents as automation and non-automation patents is described in Appendix A

Before1: Dummy variable equal to one for the year *T-1* in state s and zero otherwise, where *T* is the year of the minimum wage event in state *s*.

Capex: total capital expenditures divided by the book value of total assets

Emp_share: the fraction of workers in industry *j* in a state *s* without any college education (also referred to as the fraction of unskilled workers).

Herfindahl Index: is the sum of squares of market shares of all firms in an industry

IndAuto_Cite: The total number (in logs) of truncation-bias-adjusted, non-self forward citations received by automation patents applied for by firms in industry *j* in state *s* in year *t*.

IndAuto_Pat: The total number of truncation-bias-adjusted automation patents (in logs) applied for by all firms in industry *j* in state *s* in year *t*

Leverage: book value of long-term debt divided by the book value of total assets

Market-to-book: market value of equity plus total assets less common equity and deferred taxes all divided by total assets.

NA_Cite: The natural log of (1 + truncation-biased adjusted forward citations of nonautomation patents). Truncation-bias-adjusted citations are calculated as the number of citations received by patents applied for by firm *i* in year *t* divided by the mean number of citations received by firms in year *t* in the same technology class. Classification of patents as automation and non-automation patents is provided in Appendix A

NA_Pat: The natural log of (1 + truncation-biased adjusted non-automation patents). Truncation-bias-adjusted patents are calculated as the number of nonautomation patents applied for by firm *i* in year *t* divided by the mean number of patents of all firms in year *t*. Classification of patents as automation and non-automation patents is provided in Appendix A.

PPE: property, plant, and equipment divided by the book value of total assets

R&D: research and development expenditures divided by the book value of assets (0 if missing)

Return on Assets: the operating income before depreciation divided by the book value of assets

Size: logarithm of firm *i*'s market capitalization.

Wage_share: The wage share of unskilled workers in industry *j* in state *s*. It is calculated as the total earnings of unskilled workers in that year divided by the total earnings of all workers in industry *j* in state *s* in that year. Skilled workers are defined as those with at least some college education and unskilled workers are those with a high school diploma or less.

Years public: the logarithm of the years since the firm was listed on a U.S. exchange.

Main Appendix C

Table C1: Routine-task measures

This table presents task composition data from the Director of Occupational Titles, which are used to identify routine-task jobs. The task categories used are (i) STS (set limits, tolerances, or standards): a measure of routine cognitive activity defined as adaptability to work requiring the precise attainment of set limits, tolerances, or standards; (ii) FINGDEX: a measure of routine manual activity defined as finger dexterity, i.e., the ability to move fingers and manipulate small objects with fingers, rapidly or accurately, (iii) DCP (Direction, Control, and Planning): a measure of non-routine interactive tasks of activities such as adaptability to accepting responsibility for the direction, control, and planning of an activity, and (iv) MATH: a measure of non-routine analytical tasks that require mathematics and general quantitative reasoning. Each of these indices is averaged by 2-digit SIC over the pre-event period and all firm-years in that 2-digit SIC code are assigned this average pre-event value.

	N	Mean	Median	SD	p10	p90
FINGDEX	12913	4.039	4.105	0.300	3.584	4.322
STS	12913	5.729	6.539	1.284	3.603	6.900
DCP	12913	2.383	2.072	0.789	1.767	3.715
MATH	12913	3.675	3.670	0.659	2.949	4.229

Figure 1: Federal minimum wage and average state minimum wage

Figure 1A plots the nominal federal minimum wage as well as the average nominal value of the effective minimum wage across all US states from 1983 till 2019. The effective minimum wage in a state is the higher of the federal minimum wage and the state minimum wage. Figure IB plots the real value of the federal minimum wage (in 1982 dollars) and the average real value of the effective minimum wage (in 1982 dollars) across all US states from 1983 till 2018

Figure 1A: Nominal minimum wages

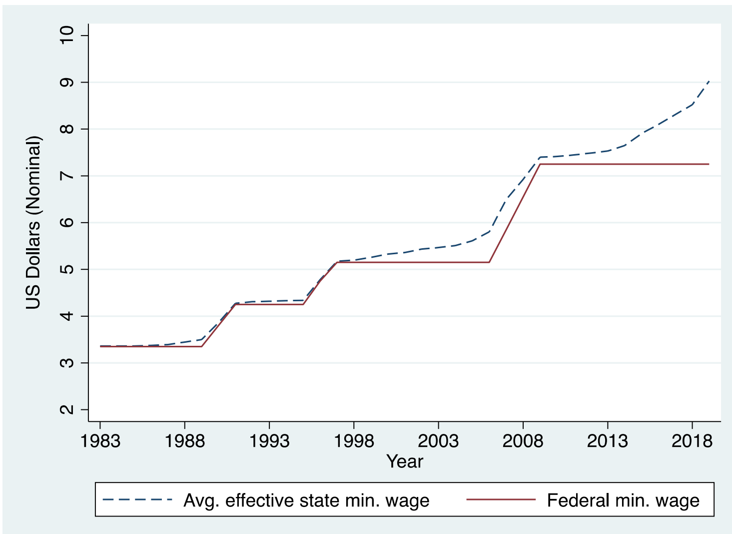

Figure 1B: Real minimum wages (1982 dollars)

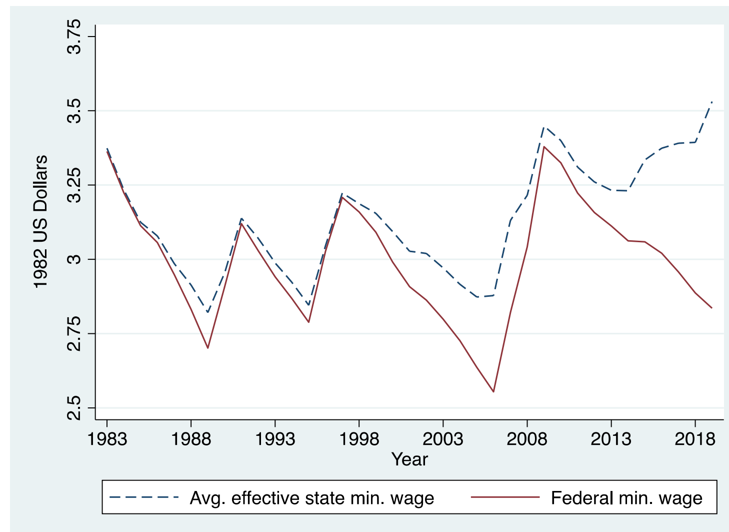

Figure 2: Distribution of the percentage change in the effective minimum wage

This figure plots the distribution of the percentage change in the nominal effective minimum wage, (ΔMinWage), for 142 minimum wage events in the United States between 1987 to 2017. The effective minimum wage in a state-year is the higher of the prevailing federal minimum wage and the state minimum wage. An increase in the effective minimum wage of a state (either due to an increase in the federal minimum wage or the state minimum wage) is classified as a minimum wage event if it was not preceded by an increase in the effective minimum wage in the preceding three years. The percentage change in the effective minimum wage is calculated as the new, higher effective minimum wage less the prior effective minimum wage divided by the prior effective minimum wage.

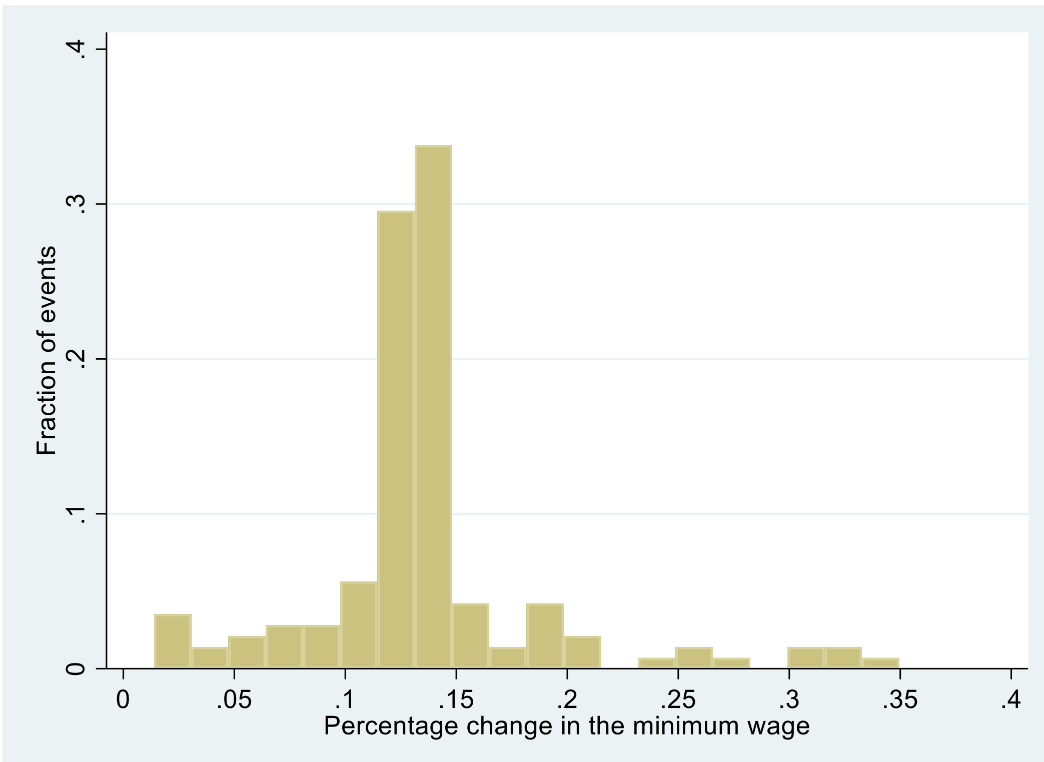

Table 1. Minimum wage events

This table lists 142 minimum wage events across fifty U.S. states between 1987 and 2017. State-years that experienced a minimum wage event are flagged with the number 1. A state-year is classified as having experienced a minimum wage event if the effective minimum wage in the state increased in that year but experienced no changes in the previous three years. The effective minimum wage in a state-year is the higher of the prevailing federal minimum wage and the state minimum wage. The last column shows the total number of minimum wage events experienced by each state in our sample. The last row of the table shows the total number of events by year.

	87	88	89	90	91	92	93	94	95	96	97	98	99	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	Total
Alabama				1						1											1											3
Arizona				1						1											1											3
Arkansas				1						1										1									1			4
California		1								1											1							1				4
Colorado				1						1											1											3
Connecticut	1									1																		1				3
Delaware				1						1											1							1				4
Florida				1						1										1												3
Georgia				1						1											1											3
Hawaii		1														1													1			3
Idaho				1						1											1											3
Illinois				1						1								1														3
Indiana				1						1											1											3
Iowa				1						1											1											3
Kansas				1						1											1											3
Kentucky				1						1											1											3
Louisiana				1						1											1											3
Maine										1																					1	2
Maryland				1						1											1								1			4
Massachusetts										1											1								1			3
Michigan				1						1										1												3
Minnesota		1								1									1									1				4
Mississippi										1																						1
Missouri				1						1											1						1					4
Montana				1						1											1											3
Nebraska				1						1											1								1			4
Nevada				1						1										1												3
New Hampshire	1									1											1											3
New Jersey				1							1								1									1				4
New Mexico				1						1																						2

New York				1						1									1									1				4
North Carolina				1						1											1											3
North Dakota			1																													1
Ohio				1						1											1											3
Oklahoma				1						1											1											3
Oregon			1								1						1															3
Pennsylvania			1							1											1											3
Rhode Island										1								1									1					3
South Carolina				1						1											1											3
South Dakota				1						1											1								1			4
Tennessee				1						1											1											3
Texas				1						1											1											3
Utah				1						1											1											3
Virginia				1						1											1											3
Washington			1					1																								2
West Virginia										1																						1
Wisconsin			1							1									1													3
Total	2	3	5	32	0	0	0	1	0	42	2	0	0	0	0	1	1	2	4	4	28	0	0	0	0	0	2	6	6	0	1	142

Table 2: Summary of the percentage change in the minimum wage

This table summarizes the percentage change in the nominal effective minimum wage (ΔMinWage) for 142 minimum wage events in the United States from 1987 to 2017. The effective minimum wage in a state-year is the higher of the prevailing federal minimum wage and the state minimum wage. An increase in the effective minimum wage of a state (either due to an increase in the federal minimum wage or the state minimum wage) is classified as a minimum wage event if it was not preceded by an increase in the effective minimum wage in the preceding three years. The percentage change in the effective minimum wage for each event is calculated as the new, higher effective minimum wage less the prior effective minimum wage divided by the prior effective minimum wage.

		ΔMinWage: Percentage change in the nominal minimum wage				
Period	N	Mean	Median	SD	Min	Max
All	142	0.134	0.134	0.055	0.014	0.350
1984-1990	42	0.130	0.134	0.036	0.015	0.269
1991-2000	45	0.114	0.118	0.023	0.020	0.158
2001-2010	40	0.173	0.136	0.075	0.062	0.350
2011-2017	15	0.100	0.103	0.052	0.014	0.200

Table 3: Change in wages after minimum wage increases

This table presents the change in the real hourly wage at different wage percentiles after the minimum wage events listed in Table 1. For each of the 142 events experiencing a minimum wage event between 1987 and 2017, the CPS Merged Outgoing Rotation Groups database is used to calculate the hourly wage at the 10th percentile (p10), 20th percentile (p20) and so on. Hourly wages at each percentile are first calculated for each state-year. The value for the pre-event (post-event) period in this table is the average of the percentile value over the two years preceding (following) the minimum wage event. A difference-in-means test is presented at each percentile level. Since the before and after values span a 5-year period, all wage data are deflated to 1982 dollars using CPI-U deflator from the Bureau of Labor Statistics.

Real hourly wage at percentile: (N=142)	p10	p20	p50	p80	p90
Pre-Event	3.478	4.235	6.857	11.540	14.960
Post-Event	3.556	4.266	6.821	11.487	14.979
Post - Pre	0.077	0.031	-0.036	-0.053	0.019
P-Value	[0.003]	[0.227]	[0.336]	[0.375]	[0.467]
Percentage increase	2.23%	0.74%	-0.53%	-0.46%	0.13%

Table 4: Automation patents for select industries

This table presents the number and percentage of automation patents in select industries. The percent of minimum wage workers (obtained from the Bureau of Labor Statistics) is also provided. The percentage of automation patents in an industry is calculated as the total number of automation patents in the industry divided by the total number of patents in the industry during the sample period. Patents are included in the sample if the applying firm is headquartered in a state experiencing a minimum wage event between the years 1987 and 2017 and if the application year falls in the two years before or two years after the event. Only patents that are eventually granted are included in the sample. The minimum wage events are described in Table 1. The method used to identify automation patents is described in Appendix A1.

Industry description	Total number of patents	Total number of automation patents	% of automation patents	% of minimum wage workers
Agriculture and related industries	3,704	3,166	85.5%	1.0%
Leisure and hospitality	1,418	1,083	76.4%	57.5%
Business and Financial Services	116,590	67,174	57.6%	4.5%
Education and health services	418	229	54.8%	8.4%
Wholesale & Retail trade	1,310	567	43.3%	11.7%
Information	220,488	86,926	39.4%	0.8%
Construction	46	18	39.1%	1.0%
Manufacturing	167,927	55,890	33.3%	2.9%
Public sector	25,470	8,171	32.1%	5.0%
Mining, quarrying, oil, gas extraction	11,636	3,007	25.8%	0.1%

Table 5: Summary of firm-level data on automation and non-automation patents and citations

Panel A shows descriptive statistics of total automation patents and total forward citations received by automation patents for a sample of 2,578 firms between 1985 and 2019. For each firm, we add the automation patents and citations received by automation patents across all years in the sample period and present summary statistics of these totals. In the same manner, descriptive statistics of non-automation patents are also provided. The classification of a patent as an automation patent or a non-automation patent is provided in Appendix A.

Panel B shows descriptive statistics of truncation-bias-adjusted total patents and citations. For each firm, we add up truncation-bias-adjusted patents and citations across all years in the sample period and present summary statistics of these totals. Truncation-bias-adjusted patents are calculated as the number of patents applied for by firm *i* in year *t* divided by the mean number of patents of all firms in year *t*. Truncation-bias-adjusted citations are calculated as the number of citations received by patents applied for by firm *i* in year *t* divided by the mean number of citations received by firms in year *t* in the same technology class.

Panel A: Total patents and citations (not adjusted for truncation bias)

	N	mean	median	p10	p90
Automation Patents	2578	88	3	0	87
Automation Citations	2578	1430	53	0	1492
Non-Automation Patents	2578	125	5	0	125
Non-Automation Citations	2578	1716	64	0	1577

Panel B: Truncation-bias-adjusted total patents and citations

	N	mean	median	p10	p90
Automation Patents	2578	0.095	0.005	0	0.101
Automation Citations	2578	104.10	3.374	0	105.24
Non-Automation Patents	2578	0.162	0.007	0	0.167
Non-Automation Citations	2578	117.56	4.031	0	119.29

Table 6: Summary statistics of firm-level dependent and independent variables

This table summarizes the main dependent and independent variables as well as control variables. Panel A presents the summary statistics of a sample of 16,153 firm-years comprising 2,578 unique firms. The sample includes all firms-years in states affected by minimum wage events from two years before the event till two years after the event (but excluding the event year itself) provided the firm applied for at least one patent in the two years before or two years after the minimum wage event. Since some states experience more than one minimum wage event, firms may appear more than once in the sample. *Automation patents* (A_Pat) is the logarithm of the number of truncation-bias-adjusted automation patents filed by firm *i* in year *t*. Since many firm years in our sample have zero patents, we follow prior literature and add 1 before taking logs. See Appendix A for the method used to identify automation patents. *Automation citations* (A_Cite) is the logarithm of the number of truncation-bias-adjusted, non-self-citations received by firm *i*'s automation patents in year *t*. NA_Pat and NA_Cite are similarly calculated measures of *non-automation* patents and citations. See Appendix C for definitions of the remaining control variables.

Panel B presents the differences-in-means of the same variables between two subsamples - the high (low) $\Delta MinWage$ subsample includes firms in states experiencing an above- (below-) median percentage increase in the minimum wage. $\Delta MinWage$ is described in Table 2.

Panel A: Full sample

	N	Mean	Median	SD	p10	p90
Automation patents (logs), *A_Pat*	16,153	0.010	0.000	0.049	0.000	0.017
Automation citations (logs), *A_Cite*	16,153	0.861	0.000	1.356	0.000	2.910
Non-automation patents (logs), *NA_Pat*	16,153	0.017	0.001	0.072	0.000	0.027
Non-automation citations (logs), *NA_Cite*	16,153	0.958	0.178	1.397	0.000	3.076
Size	16,153	5.883	5.782	2.255	2.981	8.958
R&D	16,153	0.059	0.026	0.084	0.000	0.153
Return on assets	16,153	0.091	0.122	0.181	-0.060	0.234
PPE	16,153	0.253	0.204	0.194	0.048	0.547
Leverage	16,153	0.163	0.095	0.190	0.000	0.440
Capex	16,153	0.055	0.042	0.050	0.011	0.111
Herfindahl index	16,153	0.285	0.229	0.201	0.084	0.582
Squared Herfindahl Index	16,153	0.122	0.052	0.178	0.007	0.338
Market-to-book	16,153	2.024	1.499	1.576	0.945	3.682
Years public (logs)	16,153	2.689	2.773	0.918	1.386	3.850

Panel B: Comparing subsamples experiencing a high vs. low percentage increase in the minimum wage

	Low $\Delta MinWage$ (Avg. = 0.091)	High $\Delta MinWage$ (Avg. = 0.168)	High - Low	p-value
Automation patents (logs), *A_Pat*	0.012	0.011	-0.001	[0.069]
Automation citations (logs), *A_Cite*	1.051	0.857	-0.194	[0.000]
Non-automation patents (logs), *NA_Pat*	0.016	0.019	0.002	[0.031]
Non-automation citations (logs), *NA_Cite*	1.071	0.956	-0.115	[0.000]
Size	6.160	5.957	-0.204	[0.000]
R&D	0.065	0.053	-0.013	[0.000]
Return on assets	0.077	0.094	0.017	[0.000]
PPE	0.197	0.262	0.065	[0.000]
Leverage	0.133	0.182	0.049	[0.000]
Capex	0.043	0.054	0.012	[0.000]
Herfindahl index	0.278	0.298	0.020	[0.000]
Squared Herfindahl Index	0.118	0.132	0.014	[0.000]
Market-to-book	2.040	1.937	-0.103	[0.000]
Years public (logs)	2.764	2.758	-0.006	[0.349]

Table 7: Change in automation patents after minimum wage increases

This table presents the change in automation patents and change in citations received by automation patents of treated firms after minimum wage increases. Analysis of the change in non-automation patents is also presented. The sample is described in Table 6. The dependent variables A_Pat, A_Cite, NA_Pat and NA_Cite are defined in Table 6. *ΔMinWage* is described in Table 2. The dummy variable *Before1* for a state-year is equal to one for the year *T-1* and zero otherwise. The dummy variable *After1* is equal to one for year *T+1* and zero otherwise. The dummy variable *After2* is equal to one for year *T+2* and zero otherwise. The control variables *Size*, *R&D, Return on assets*, *PPE*, *Leverage*, *Herfindahl, Herfindahl index squared*, *Market-to-book ratio,* and *Years public (logs)* are all described in Appendix C. All regressions include firm- and year-fixed effects with standard errors clustered by state. *t* statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

	AUTOMATION				NON-AUTOMATION			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patents	Citations	Patents	Citations	Patents	Citations	Patents	Citations
	A_Pat	*A_Cite*	*A_Pat*	*A_Cite*	*NA_Pat*	*NA_Cite*	*NA_Pat*	*NA_Cite*
Before1× Δ MinWage (β_1)	-0.0005	0.2540	0.0006	0.2809	-0.0024	0.1286	-0.0012	0.1497
	(-0.13)	(1.36)	(0.14)	(1.62)	(-0.33)	(0.55)	(-0.18)	(0.69)
After1× Δ MinWage (β_2)	0.0104***	0.3601	0.0114***	0.3853*	0.0093	-0.0818	0.0108	-0.0494
	(2.79)	(1.58)	(2.80)	(1.90)	(1.08)	(-0.37)	(1.15)	(-0.25)
After2× Δ MinWage (β_3)	0.0083	0.5883**	0.0099	0.6480***	0.0051	0.3019	0.0077	0.3672
	(1.26)	(2.53)	(1.55)	(3.33)	(0.65)	(0.78)	(0.95)	(1.08)
Before1	-0.0017	-0.1091*	-0.0024**	-0.1278**	-0.0027	-0.0434	-0.0042**	-0.0605
	(-1.46)	(-2.00)	(-2.04)	(-2.55)	(-1.43)	(-0.75)	(-2.60)	(-1.09)
After1	-0.0085**	-0.2715***	-0.0092***	-0.2724***	-0.0132***	-0.0940	-0.0153***	-0.0958
	(-2.58)	(-3.00)	(-3.27)	(-3.84)	(-3.20)	(-0.98)	(-4.54)	(-1.22)
After2	-0.0098**	-0.3126**	-0.0106***	-0.3130***	-0.0150**	-0.2108	-0.0174***	-0.2117*
	(-2.32)	(-2.32)	(-2.94)	(-2.92)	(-2.55)	(-1.54)	(-3.50)	(-1.85)
ΔMinWage	-0.0383**	-1.9247***	-0.0375**	-1.8301***	-0.0337	-1.7635***	-0.0319	-1.6394***
	(-2.17)	(-2.76)	(-2.28)	(-3.16)	(-1.25)	(-2.98)	(-1.43)	(-3.53)
Size			0.0034***	0.2285***			0.0069***	0.2457***
			(3.06)	(5.46)			(5.97)	(6.16)
R&D			-0.0003	0.4783***			0.0133*	0.8501***
			(-0.04)	(3.04)			(1.85)	(6.52)
Return on assets			-0.0057**	-0.3032***			-0.0061	-0.2574***
			(-2.33)	(-3.75)			(-1.59)	(-4.97)
PPE			0.0044	0.2877			0.0172	0.4794**
			(0.45)	(1.54)			(1.48)	(2.51)
Leverage			0.0059***	0.2638***			0.0106***	0.2422**
			(4.63)	(3.59)			(4.55)	(2.54)
Capex			0.0038	-0.3762			0.0031	-0.7963**
			(0.51)	(-1.12)			(0.22)	(-2.61)
Herfindahl Index			-0.0166	-0.2757			0.0010	0.0872
			(-1.00)	(-0.80)			(0.06)	(0.23)
Sq. Herfindahl Index			0.0112	0.3582			0.0068	-0.1558
			(0.88)	(0.81)			(0.34)	(-0.35)
Market-to-book			-0.0012***	-0.0529***			-0.0020***	-0.0624***
			(-2.86)	(-5.47)			(-5.25)	(-7.99)
Years public (logs)			0.0046***	0.1421***			0.0166***	0.1315***
			(2.78)	(4.15)			(3.82)	(3.52)
Constant	0.0200***	1.2543***	-0.0079	-0.4375*	0.0290***	1.2725***	-0.0587***	-0.5654**
	(5.26)	(9.25)	(-0.74)	(-1.92)	(5.39)	(11.27)	(-3.87)	(-2.07)
N	16153	16153	16153	16153	16153	16153	16153	16153
adj. R^2	0.83	0.72	0.83	0.73	0.80	0.76	0.81	0.77

Table 8: Innovation in supplier industries and primary state of operations

In columns 1 through 4 of this table, we control for labor-saving innovation in supplier industries. We use the 1997-2012 U.S. Benchmark Input-Output Table to construct weights based on the share of outputs of 'using' industries that are due to the supply of inputs from originating industries. We assume that the same weights apply to the supply of innovations (Delgado and Mills 2017). We compute the supply of innovations as the weighted sum of the number of truncation-bias adjusted number of patents, *Ln (Supplier autom. patents*), or the truncation-bias adjusted number of citations for using industry, *Ln(Supplier autom. citations*). In columns 5 through 6, we restrict the sample to firms for which the headquarter state is also the primary state of operations as per Garcia and Norli (2012). All regressions include control variables, firm- and year-fixed effects with standard errors clustered by state. *t* statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

	Controlling for supplier innovation				Headquarter state is primary state of operations			
	Automation:		Non-automation:		Automation:		Non-automation:	
	Patents *(A_Pat)* (1)	Citations *(A_Cite)* (2)	Patents *(A_Pat)* (3)	Citations *(A_Cite)* (4)	Patents *(A_Pat)* (5)	Citations *(A_Cite)* (6)	Patents *(A_Pat)* (7)	Citations *(A_Cite)* (8)
Before1× Δ MinWage (β_1)	-0.0009	0.2841*	-0.0045	0.1268	-0.0045	0.2031	-0.0081	-0.1585
	(-0.19)	(1.70)	(-0.61)	(0.57)	(-0.77)	(0.85)	(-0.84)	(-0.54)
After1× Δ MinWage (β_2)	0.0096**	0.4046*	0.0101	0.0178	0.0130**	0.4147	0.0152	0.0047
	(2.47)	(1.89)	(1.20)	(0.09)	(2.04)	(1.26)	(1.64)	(0.01)
After2× Δ MinWage (β_3)	0.0053	0.5941***	0.0030	0.2388	0.0001	0.6609**	-0.0053	-0.0104
	(0.92)	(3.16)	(0.37)	(0.75)	(0.01)	(2.41)	(-0.41)	(-0.03)
Before1	-0.0021	-0.1262***	-0.0034*	-0.0580	-0.0031*	-0.1281**	-0.0038	-0.0026
	(-1.52)	(-2.90)	(-1.84)	(-1.07)	(-1.72)	(-2.49)	(-1.32)	(-0.04)
After1	-0.0090***	-0.2699***	-0.0149***	-0.1104	-0.0146***	-0.3453***	-0.0201***	-0.1199
	(-3.01)	(-4.67)	(-4.38)	(-1.46)	(-3.15)	(-3.54)	(-2.90)	(-1.23)
After2	-0.0097**	-0.2925***	-0.0160***	-0.1908*	-0.0153**	-0.4307***	-0.0204**	-0.1500
	(-2.53)	(-3.16)	(-3.41)	(-1.97)	(-2.66)	(-3.47)	(-2.34)	(-1.25)
ΔMinWage	-0.0348**	-1.9746***	-0.0348*	-1.8190***	-0.0298	-1.5004**	-0.0170	-1.9750***
	(-2.13)	(-4.01)	(-1.94)	(-4.35)	(-1.67)	(-2.35)	(-0.63)	(-4.18)
Ln (Supplier autom. patents)	0.0010		0.0072					
	(0.12)		(0.40)					
Ln(Supplier autom. citations)		0.0502		0.0492*				
		(1.48)		(1.94)				
Constant	-0.0041	-0.3704	-0.0502***	-0.5054	-0.0192**	-0.3401	-0.0587***	-0.4322*
	(-0.39)	(-1.36)	(-5.69)	(-1.55)	(-2.05)	(-1.47)	(-2.96)	(-1.70)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15193	15193	15193	15193	8347	8347	8347	8347
Adjusted R^2	0.83	0.73	0.81	0.77	0.82	0.75	0.82	0.79

Table 9: Falsification test using random search words

This table presents a falsification test in which we classify patents into two groups based on the appearance or absence in the patent descriptions of a set of randomly selected words. A detailed list of the randomly selected words used for the classification of patents into two groups is provided in Table A2 of Appendix A. The sample used is the same as in Table 7. Columns 1 through 4 focus on patents that contain at least one of the randomly selected words in the patent descriptions. We call these '*random-hit'* patents. In columns 1 and 3, the dependent variable is the number (in logs) of truncation-bias-adjusted 'random-hit' patents filed by firm i in year t. In columns (2) and (4) the dependent variable is the number (in logs) of truncation-bias-adjusted, non-self-citations received by firm i's 'random-hit' patents. Columns 5 through 8 focus on patents that do not contain any of the randomly selected words in the patent descriptions. We call these '*random-miss'* patents. In columns 5 and 7, the dependent variable is the number (in logs) of truncation-bias-adjusted 'random-miss' patents filed by firm i in year t. In columns 6 and 8, the dependent variable is the number (in logs) of truncation-bias-adjusted, non-self-citations received by firm i's 'random-miss' patents. The rest of the variables are as described in Table 7. All regressions include firm- and year-fixed effects with standard errors clustered by state. t statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

	Subsample with random words: 'Random-hit' patents				Subsample without random words: 'Random-miss' patents			
	(1) Patents	(2) Citations	(3) Patents	(4) Citations	(3) Patents	(4) Citations	(7) Patents	(8) Citations
Before1× Δ MinWage (γ_1)	-0.0083	-0.0395	-0.0060	0.0129	-0.0063	0.3101	-0.0049	0.3535**
	(-1.08)	(-0.16)	(-0.88)	(0.05)	(-0.84)	(1.57)	(-0.69)	(2.07)
After1× Δ MinWage (γ_2)	0.0040	-0.3796	0.0068	-0.3315	0.0004	-0.0102	0.0021	0.0315
	(0.46)	(-1.62)	(0.83)	(-1.50)	(0.04)	(-0.03)	(0.23)	(0.10)
After2× Δ MinWage (γ_3)	-0.0027	-0.1516	0.0023	-0.0325	-0.0081	0.1093	-0.0052	0.2015
	(-0.23)	(-0.48)	(0.23)	(-0.12)	(-0.75)	(0.34)	(-0.54)	(0.76)
Before1	-0.0004	-0.0376	-0.0019	-0.0602	-0.0014	-0.0900**	-0.0026*	-0.1126***
	(-0.18)	(-0.65)	(-1.00)	(-1.08)	(-0.79)	(-2.35)	(-1.71)	(-3.21)
After1	-0.0081**	-0.0617	-0.0101***	-0.0632	-0.0088***	-0.1210	-0.0102***	-0.1320*
	(-2.13)	(-0.72)	(-3.35)	(-0.96)	(-2.73)	(-1.45)	(-4.22)	(-1.88)
After2	-0.0082	-0.1136	-0.0107**	-0.1177	-0.0092*	-0.1930*	-0.0109***	-0.2072**
	(-1.49)	(-0.89)	(-2.33)	(-1.14)	(-1.99)	(-1.98)	(-3.02)	(-2.59)
ΔMinWage	-0.0552*	-1.7518**	-0.0525**	-1.6121***	-0.0321	-1.5703**	-0.0298	-1.4495**
	(-2.01)	(-2.62)	(-2.11)	(-2.98)	(-1.27)	(-2.31)	(-1.30)	(-2.53)
Constant	0.0289***	1.4103***	-0.0463**	-0.6265**	0.0212***	1.0618***	-0.0462***	-0.7220***
	(5.08)	(11.16)	(-2.50)	(-2.30)	(4.38)	(8.88)	(-3.71)	(-3.21)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16153	16153	16153	16153	16153	16153	16153	16153
adj. R^2	0.78	0.74	0.79	0.75	0.78	0.74	0.79	0.75

Table 10: Firms in contiguous counties

This table presents a difference-in-difference analysis of the change in automation patents and change in citations received by automation patents around minimum wage increases in the sample of treated firms and control firms in contiguous counties. The treated firms are those affected firms by a minimum wage event that can be matched to a neighboring county. The control firms are those headquartered in counties that are contiguous to (i.e., share a border with) treated firms but are themselves located in states that did not experience a minimum wage event at the time. The information on adjacent counties in the U.S. is obtained from U.S. Census Bureau: https://www.census.gov/geographies/reference-files/2010/geo/county-adjacency.html. In addition, the treated and control firm must have applied for at least one patent in the two years before or two years after the minimum wage event in question. The 142 state-years experiencing minimum wage events are described in Table 1.
The dependent variables relating to automation patents *A_Pat, A_Cite,* and the dependent variables relating to non-automation patents *NA_Pat, and NA_Cite* are defined in Table 6. The method of classifying automation patents is provided in Appendix A. All other variables are described in Table 7. All regressions include firm- and year-fixed effects with standard errors clustered by state. *t* statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

	AUTOMATION		NON-AUTOMATION	
	(1)	(2)	(3)	(4)
	Patents	Citations	Patents	Citations
	A_Pat	*A_Cite*	*NA_Pat*	*NA_Cite*
Before1 x Treated	0.0006	0.0384	-0.0000	-0.0557*
	(1.13)	(0.88)	(-0.00)	(-1.90)
After1 x Treated	0.0009*	0.1286***	0.0012	0.1017
	(1.97)	(4.02)	(0.94)	(1.39)
After2 x Treated	0.0014*	0.1563**	0.0001	0.0462
	(1.88)	(2.53)	(0.07)	(1.09)
Before1	-0.0001	-0.0348	0.0015	0.0763**
	(-0.76)	(-1.06)	(1.29)	(2.15)
After1	-0.0001	-0.0079	-0.0013	-0.1067*
	(-0.32)	(-0.16)	(-1.52)	(-1.95)
After2	-0.0002	0.0105	0.0004	-0.0604
	(-0.32)	(0.10)	(0.46)	(-1.01)
Treated	0.0007	0.0936	0.0021	0.0997
	(1.38)	(1.04)	(1.29)	(1.42)
Constant	-0.0040	-0.6819	-0.0105	-0.6480
	(-1.39)	(-1.68)	(-1.01)	(-1.65)
Controls	Yes	Yes	Yes	Yes
N	8736	8736	8736	8736
adj. R^2	0.99	0.79	0.95	0.82

Table 11: Subsample tests: percentage of low-wage workers and routine tasks

This table examines the change in automation patents patent in subsamples based on low-wage workers and routine tasks. The sample period and regression specification are the same as in column 3 of Table 7. In Panel A, column 1 (column 2) is restricted to the subsample of firms operating in industries with above-median (below-median) values of the percentage of minimum wage workers. Column 3 (column 4) is restricted to the subsample of firms headquartered in states with above-median (below-median) values of the binding wage percentile. See Appendix C for summary statistics on the state-level binding wage percentile. In Panel B, we look within subsamples of routine-task industries classified using task composition data from the Director of Occupational Titles (DOT). In Panel B, the sample in column 1 (column 2) is restricted to firms operating in routine-task (non-routine-task) industries using the FINGDEX and STS classification of routine tasks. In column 3 (column 4) the sample is restricted to firms operating in routine-task (non-routine-task) industries, using the DCP and MATH classification of routine tasks. Summary statistics of the DOT indices are presented in Appendix C. *t* statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

Panel A	(1)	(2)	(3)	(4)
Dependent variable: *A_Pat*	Industries w/ high pct. min. wage workers	Industries w/ low pct. min. wage workers	States w/ high binding wage percentile	States w/ low binding wage percentile
Before1× Δ MinWage (β_1)	0.0034	-0.0013	0.0106	0.0004
	(0.43)	(-0.36)	(1.65)	(0.08)
After1× Δ MinWage (β_2)	0.0126*	0.0066	0.0059	0.0072
	(1.71)	(1.45)	(0.73)	(1.58)
After2× Δ MinWage (β_3)	0.0159**	0.0022	0.0331***	0.0013
	(2.03)	(0.32)	(3.65)	(0.18)
Before1	-0.0041*	-0.0015	-0.0045***	-0.0008
	(-1.78)	(-1.29)	(-2.87)	(-0.54)
After1	-0.0142***	-0.0058*	-0.0075**	-0.0034
	(-2.88)	(-1.79)	(-2.69)	(-1.02)
After2	-0.0172**	-0.0067	-0.0135***	-0.0031
	(-2.53)	(-1.65)	(-3.20)	(-0.69)
ΔMinWage	-0.0634**	-0.0277*	-0.1085***	0.0140
	(-2.38)	(-1.70)	(-5.18)	(0.87)
Constant	-0.0061	0.0034	-0.0089**	-0.0016
	(-0.55)	(0.13)	(-2.27)	(-0.09)
N	8324	7829	7986	8165
adj. R^2	0.69	0.89	0.76	0.89

Panel B	FINGDEX+STS classification		DCP+MATH classification	
	Routine-task industries	Non-Routine-task industries	Routine-task industries	Non-Routine-task industries
Before1× Δ MinWage (β_1)	0.0034	-0.0003	0.0020	0.0013
	(0.61)	(-0.06)	(0.49)	(0.19)
After1× Δ MinWage (β_2)	0.0174**	0.0038	0.0192***	-0.0020
	(2.59)	(0.79)	(3.63)	(-0.25)
After2× Δ MinWage (β_3)	0.0161	-0.0007	0.0133*	-0.0033
	(1.64)	(-0.09)	(1.80)	(-0.36)
Before1	-0.0026***	-0.0024*	-0.0016*	-0.0032
	(-3.23)	(-1.83)	(-1.79)	(-1.58)
After1	-0.0088***	-0.0057*	-0.0071**	-0.0059
	(-3.00)	(-1.88)	(-2.45)	(-1.47)
After2	-0.0096***	-0.0072*	-0.0071**	-0.0081
	(-2.86)	(-1.80)	(-2.37)	(-1.41)
ΔMinWage	-0.0239	-0.0267**	-0.0212	-0.0307*
	(-1.43)	(-2.34)	(-1.45)	(-1.79)
Constant	-0.0363***	0.0199	-0.0337***	0.0259
	(-3.31)	(0.74)	(-3.40)	(0.82)
N	6497	6414	7680	5229
adj. R^2	0.79	0.88	0.78	0.88
Controls`	Yes	Yes	Yes	Yes

Table 12: Industry and size subsamples

In all regressions, the sample period and regression specification are the same as in column 3 of Table 7. Panel A examines the change in automation patents after a minimum wage increase in specific industry subsamples. In column 1 the sample is restricted to firms in the manufacturing sector only. Column 2 is restricted to firms in the information industry. Panel B examines the change in automation patents in subsamples based on firm size. Small (large) firms are those with below-median (above-median) market capitalization. *t* statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

Panel A: Industry subsamples

	(1) Manufacturing only	(2) Information only
Before1× Δ MinWage (β_1)	0.0016	-0.0040
	(0.29)	(-0.36)
After1× Δ MinWage (β_2)	0.0142**	0.0346***
	(2.63)	(3.54)
After2× Δ MinWage (β_3)	0.0125*	0.0221*
	(1.72)	(1.76)
Before1	-0.0029**	-0.0041
	(-2.49)	(-1.05)
After1	-0.0111***	-0.0213*
	(-3.95)	(-1.91)
After2	-0.0125***	-0.0231*
	(-3.55)	(-1.79)
ΔMinWage	-0.0305	-0.0702*
	(-1.56)	(-1.82)
Constant	-0.0357***	0.0179
	(-3.94)	(0.71)
Controls	Yes	Yes
N	11301	4628
adj. R^2	0.75	0.83

Panel B: Size subsamples

	All industries		Manufacturing		Information	
	(1) Small firms	(2) Large firms	(3) Small firms	(4) Large firms	(5) Small firms	(6) Large firms
Before1× Δ MinWage (β_1)	-0.0051	0.0017	-0.0096	0.0029***	-0.0578**	0.0055*
	(-0.62)	(1.50)	(-0.86)	(2.82)	(-2.29)	(1.82)
After1× Δ MinWage (β_2)	0.0207***	0.0009	0.0255**	0.0009	0.0705**	0.0015
	(2.81)	(0.82)	(2.36)	(0.79)	(2.32)	(0.56)
After2× Δ MinWage (β_3)	0.0138	0.0008	0.0143	0.0002	0.0336	0.0011
	(1.29)	(0.49)	(1.04)	(0.12)	(1.28)	(0.41)
Before1	-0.0032*	-0.0001	-0.0031	-0.0004**	-0.0013	-0.0008
	(-1.76)	(-0.65)	(-1.42)	(-2.10)	(-0.19)	(-1.67)
After1	-0.0167***	-0.0001	-0.0202***	-0.0002	-0.0519**	-0.0003
	(-3.32)	(-0.56)	(-3.49)	(-0.64)	(-2.11)	(-0.68)
After2	-0.0189***	-0.0001	-0.0221***	-0.0001	-0.0547*	-0.0004
	(-2.89)	(-0.34)	(-3.05)	(-0.29)	(-1.95)	(-0.72)
ΔMinWage	-0.0575**	-0.0024	-0.0388	-0.0033*	-0.0805	-0.0039
	(-2.27)	(-1.23)	(-1.24)	(-1.72)	(-1.00)	(-1.17)
Constant	-0.0483	-0.0003	-0.1277***	-0.0012*	0.0109	-0.0000
	(-1.66)	(-0.69)	(-5.34)	(-1.88)	(0.19)	(-0.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	8077	8076	5277	6024	2086	2542
adj. R^2	0.82	0.55	0.74	0.50	0.82	0.56

Table 13. Summary statistics of routine-tasks, the employment and wage share of unskilled workers

Panel A presents summary statistics of the employment share of unskilled workers between the years 1985 to 2019. The employment share of unskilled workers in industry *i* in state *s* in a given year is calculated using the Current Population Survey (CPS) Merged Outgoing Rotation Group as the number of workers without any college education divided by the total number of workers in industry *i* in state *s* in that year. Descriptive statistics are presented separately for routine-task industries and non-routine-task industries. Two classifications of routine-task industries based on task composition data from the Director of Occupational Titles (DOT) are used. In the first classification, routine-task jobs are those with above-median values of the sum of two DOT indices, FINGDEX and STS while non-routine-task industries are those with below-median values of FINGDEX and STS. In the second classification, routine-task jobs are defined as jobs with below-median values of the sum of DCP and MATH and non-routine-task industries are those with above-median values of DCP and MATH. Summary statistics of the DOT indices are presented in Appendix C. Panel B presents summary statistics of the wage share of unskilled workers between the years 1985 to 2019. The wage share of skilled workers in industry *i* in state *s* in a given year is calculated as the total earnings of unskilled workers in that year divided by the total earnings of all workers in industry *i* in state *s* in that year. Earnings of unskilled and skilled workers are calculated using the Current Population Survey (CPS) Merged Outgoing Rotation Group as hourly wage rate times the number of hours worked. Skilled workers are defined as those with at least some college education and unskilled workers are those with a high school diploma or less. Statistics are presented separately for routine-task industries and non-routine-task industries

Panel A: Descriptive statistics of unskilled employment share (Emp_share)

	N	Mean	Median	SD	p10	p90
Classification 1: Using FINGDEX and STS to classify routine-task industries						
Routine	4323	0.474	0.494	0.153	0.271	0.657
Non-routine	4148	0.368	0.360	0.176	0.139	0.618
Classification 2: Using DCP and MATH to classify routine-task industries						
Routine	4635	0.506	0.521	0.141	0.316	0.683
Non-routine	3836	0.320	0.311	0.153	0.117	0.534

Panel B: Descriptive statistics of unskilled wage share (Wage_share)

	N	Mean	Median	SD	p10	p90
Classification 1: Using FINGDEX and STS to classify routine-task industries						
Routine	4427	0.354	0.378	0.161	0.142	0.558
Non-routine	4225	0.281	0.258	0.171	0.077	0.529
Classification 2: Using DCP and MATH to classify routine-task industries						
Routine	4753	0.395	0.412	0.155	0.173	0.586
Non-routine	3899	0.225	0.195	0.139	0.064	0.435

Table 14. Automation patents and the employment share of unskilled workers

Panels A and B present regressions of the employment share (Emp_share) of unskilled workers on automation patents applications and citations in the period following minimum wage increases. The analysis is conducted at the industry-state-year level. In all regressions, the dependent variable is the employment share of unskilled workers in industry, *i*, in a state, *s*, during the two years before and two years after the state experiences a minimum wage event. The minimum wage events spanning the period 1987 through 2017 are listed in Table 1. The analysis is conducted separately for routine-task industries and non-routine-task industries. In Panel A, routine-task jobs are based on FINGDEX and STS. See Table 13 for more information on the classification of routine task industries. Columns 1 and 2 of Panel A focus on routine-task industries while columns 3 and 4 focus on non-routine-task industries. In Panel B, routine-task jobs are based on DCP and MATH. Columns 1 and 2 of Panel B focus on routine-task industries while columns 3 and 4 focus on non-routine-task industries. The explanatory variables are as follows. *IndAuto_Pat* is the total number of truncation-bias-adjusted automation patents (in logs) applied for by firms in industry *j* in state *s* in year *t*. *IndAuto_Cite* is the total number (in logs) of truncation-bias-adjusted, non-self forward citations received by automation patents of firms in industry *j* in state *s*. The dummy variable *Before1, After1*, and *After2* are as described in Table 7. All regressions include industry-fixed effects, state-fixed effects, and year-fixed effects. Standard errors are clustered at the state level. *t*-statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

Panel A: Routine-task industries defined as those having above-median values of FINGDEX+ STS

Dependent variable:	Routine-task Industries		Non-routine Industries	
Employment share of unskilled workers	(1)	(2)	(3)	(4)
Before1 x IndAuto_Pat (δ_1)	0.0136		0.0118	
	(0.35)		(1.13)	
After1 x IndAuto_Pat (δ_2)	-0.0864		0.0188**	
	(-1.41)		(2.58)	
After2 x IndAuto_Pat (δ_3)	-0.1706**		0.0102	
	(-2.35)		(0.99)	
Before1 x IndAuto_Cite (δ_1)		0.0017		0.0028**
		(1.60)		(2.08)
After1 x IndAuto_Cite (δ_2)		-0.0008		0.0020
		(-0.52)		(1.66)
After2 x IndAuto_Cite (δ_3)		-0.0079***		0.0003
		(-4.65)		(0.18)
Constant	0.5065***	0.5072***	0.4021***	0.4021***
	(37.87)	(38.78)	(20.36)	(19.80)
Observations	3478	3478	2883	2883
Adjusted R^2	0.82	0.82	0.81	0.81

Panel B: Routine-task industries defined as those having below-median values of DCP + MATH

Dependent variable:	Routine Industries		Non-routine Industries	
Employment share of unskilled workers	(1)	(2)	(3)	(4)
Before1 x IndAuto_Pat (δ_1)	0.0360		0.0097	
	(0.71)		(1.29)	
After1 x IndAuto_Pat (δ_2)	-0.0165		0.0070	
	(-0.36)		(0.77)	
After2 x IndAuto_Pat (δ_3)	-0.2490***		0.0160	
	(-5.85)		(1.21)	
Before1 x IndAuto_Cite (δ_1)		0.0020*		0.0022*
		(1.71)		(1.88)
After1 x IndAuto_Cite (δ_2)		0.0009		0.0002
		(0.57)		(0.19)
After2 x IndAuto_Cite (δ_3)		-0.0066***		-0.0007
		(-4.02)		(-0.43)
Constant	0.5423***	0.5456***	0.3567***	0.3544***
	(34.55)	(34.79)	(18.91)	(18.51)
Observations	3726	3726	2633	2633
Adjusted R^2	0.77	0.77	0.76	0.77

Table 15. Automation patents and the wage share of unskilled workers

Panels A and B present regressions of the wage share of unskilled workers on automation patents applications and citations in the period following minimum wage increases. The analysis is conducted at the industry-state-year level. In all regressions, the dependent variable is the wage share of unskilled workers in industry *j* in a state, *s*, during the two years before and two years after the state experiences a minimum wage event. The minimum wage events spanning the period 1987 through 2017 are listed in Table 1. The analysis is conducted separately for routine-task industries and non-routine-task industries. In Panel A, routine-task jobs are based on FINGDEX and STS. See Table 13 for more information on the classification of routine task industries Columns 1 and 2 of Panel A focus on routine-task industries while columns 3 and 4 focus on non-routine-task industries. In Panel B, routine-task jobs are based on DCP and MATH. Columns 1 and 2 of Panel B focus on routine-task industries while columns 3 and 4 focus on non-routine-task industries. All explanatory variables are as described in Table 14 and regression specifications are the same as described in Table 14. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

Panel A: Routine-task industries defined as those having above-median values of FINGDEX+ STS

Dependent variable:	Routine-task industries		Non-routine-task industries	
Wage share of unskilled workers	(1)	(2)	(3)	(4)
Before1 x IndAuto_Pat (δ_1)	0.0056		0.0195	
	(0.18)		(1.31)	
After1 x IndAuto_Pat (δ_2)	-0.2634***		0.0057	
	(-3.83)		(0.63)	
After2 x IndAuto_Pat (δ_3)	-0.1224*		0.0062	
	(-1.72)		(0.61)	
Before1 x IndAuto_Cite (δ_1)		0.0018		0.0029
		(1.17)		(1.44)
After1 x IndAuto_Cite (δ_2)		-0.0039**		-0.0009
		(-2.24)		(-0.55)
After2 x IndAuto_Cite (δ_3)		-0.0034**		0.0001
		(-2.03)		(0.05)
Constant	0.3682***	0.3726***	0.3262***	0.3256***
	(26.34)	(26.70)	(17.87)	(17.55)
Observations	3582	3582	2968	2968
Adjusted R^2	0.80	0.80	0.78	0.78

Panel B: Routine-task industries defined as those having below-median values of DCP + MATH

Dependent variable:	Routine-task industries		Non-routine-task industries	
Wage share of unskilled workers	(1)	(2)	(3)	(4)
Before1 x IndAuto_Pat (δ_1)	0.0273		0.0217*	
	(0.76)		(1.68)	
After1 x IndAuto_Pat (δ_2)	-0.2676***		0.0112	
	(-3.67)		(1.22)	
After2 x IndAuto_Pat (δ_3)	-0.2422***		0.0298	
	(-6.37)		(1.40)	
Before1 x IndAuto_Cite (δ_1)		0.0025		0.0023
		(1.25)		(1.18)
After1 x IndAuto_Cite (δ_2)		-0.0055***		0.0001
		(-2.75)		(0.09)
After2 x IndAuto_Cite (δ_3)		-0.0048**		0.0014
		(-2.58)		(0.73)
Constant	0.4159***	0.4211***	0.2670***	0.2656***
	(28.55)	(28.71)	(14.75)	(13.98)
Observations	3844	3844	2704	2704
Adjusted R^2	0.76	0.76	0.73	0.73

INTERNET APPENDIX

A. Bindingness of the minimum wage

An increase in the minimum wage serves as a positive shock to the cost of labor if the minimum wage is a binding floor. Prior research shows that increases in the minimum wage have a positive effect on the lower end of the wage scale.[1] We confirm these findings in our sample by constructing a wage distribution using the Current Population Survey (CPS) Merged Outgoing Rotation Groups database. The CPS database includes wages of workers aged 16 to 64 with 0 to 39 years of potential experience in their current employment. We drop unemployed and self-employed workers from the sample. All the wage data are transformed to 1982 dollars using the CPI-U deflator. For each state-year between 1985 and 2019, we identify the hourly wage of the worker at the 10th, 20th, 50th, 80th, and 90th percentiles.[2] Next, for each of our 142 minimum wage events, we calculate the pre-event and post-event hourly wage at each of the percentiles as follows. For a minimum wage event occurring in state s in year t, the pre-event wage at the p^{th} percentile is the average of the wages at the p^{th} percentile in that state two years before the event. Similarly, the post-event wage at the p^{th} percentile is the average of the wages at the pth percentile in state s two years after the event.

Table A1 presents the average values across the 142 events of the pre-event and post-event wage at each percentile. Differences in means at each percentile are also presented. We see a statistically significant increase of 2.2% at the 10th percentile of the wage scale. However, at the 20th percentile and above, the change in wages is not statistically significant. These findings are consistent with prior evidence from Card and Krueger (1995) who show statistically significant increases in the wage distribution at the 5th percentile and 10th percentile, but no evidence at the 25th percentile or higher. Our data confirm prior evidence that minimum wage increases spill over to earnings at the lower end of the wage scale.

We also note that the 'bindingness' of the minimum wage varies by state. There is significant variation across states in the maximum percentile of the wage distribution at which the state minimum wage or federal minimum wage binds. For example, in 1990, the federal minimum wage increased from \$3.30 to \$3.80. Based on the CPS data, in the preceding year, 2.9% of workers in Illinois earned below \$3.80, while in Mississippi 7.7% of workers earned below \$3.80. The maximum binding percentile also varies over time. For example, in 2004, the state of Illinois increased the minimum wage above the federal level of \$5.15 to \$5.50. In the preceding year, fewer than 1% of workers in Illinois were earning below \$5.50. This variation in the bindingness of the minimum wage is attributable primarily to cross-state differences in wage levels. In the later years of our sample, differences in the statutory state-level minimum wages also contribute to variation in the maximum binding percentile. In Section

[1] See Card and Krueger (1995) and Lee (1999). Also see Neumark and Wascher (2007) for a review of research on the effect of the minimum wage on average wage levels and employment.
[2] Since our first (last) minimum wage event is in 1987 (2017), we need data on wages from 1985 through 2019 to capture the pre-event and post-event wage percentiles for all events.

4.5 of the paper, we exploit the variation by state in the bindingness of the minimum wage to identify the effect of the minimum wage on corporate innovation.

Table A1: Descriptive statistics for bindingness of the effective minimum wage

This table provides descriptive statistics of the average binding wage percentile across the 142 minimum wage events in our sample. For each state *s* experiencing a minimum wage event in year *T*, we calculate the maximum percentile at which the new minimum wage binds in years *T-2* and *T-1* and take an average of the two values. This average binding percentile captures the fraction of workers in the state earning below the new minimum wage during the period leading up to the minimum wage increase. The binding wage percentile is used to create above- and below-median subsamples that are used in columns 3 and 4 of Table 11 Panel A.

		Percentage of workers below the new minimum wage				
Period	N	Mean	Median	SD	Min	Max
All	142	0.033	0.029	0.017	0.007	0.084
1987-1990	42	0.050	0.050	0.016	0.017	0.084
1991-2000	45	0.032	0.029	0.011	0.014	0.054
2001-2010	40	0.018	0.017	0.009	0.007	0.047
2011-2017	15	0.028	0.026	0.010	0.017	0.055

B. Automation patent examples

Example 1: US Patent # 5046844 - Apparatus For Inspecting And Hangering Shirts
Assignee: Cintas Corporation
Abstract
An apparatus for inspecting and hangering an open-necked garment such as a shirt comprises an inspection station having a garment form in the shape of the shoulders of a shirt, and lighting fixtures positioned beneath the garment form so that when a shirt is placed on the garment form the lighting fixtures shine light from the interior of the shirt through the shirt to permit visual inspection of tears, holes, stains and other defects. Hangers are automatically fed to the inspection station immediately adjacent the garment form with the hook portion of the hanger extending through the open neck of the shirt. Once the inspection operation is completed, an automatic hanger take-away device removes the hanger, and the shirt draped over the hanger and garment form, from the inspection station for further processing.
Excerpt from patent background and summary
A problem with the prior art method of inspecting shirts described above is that the worker has to perform the visual and touch inspection operations separately, and this increases the time required to completely inspect a shirt. To visually inspect a shirt, workers have had to grasp the shirt by hand and turn it from front to back so that the buttons, buttonholes, shirt pocket, collar and other areas of the shirts can be fully viewed. After this visual inspection, the worker then performs a touch inspection before placing the shirt on a hanger. The method and apparatus of this invention is predicated upon the concept of permitting visual and touch inspection of a garment such as a shirt, both on its interior and exterior surfaces, at an inspection station wherein the garment is also automatically hangered and taken away to another processing location. The garment form hangs the shirt in a position for convenient visual and touch inspection. In addition, the lights beneath the garment form shine light through the shirt to permit visual inspection thereof. Automatic hangering of the shirt is also performed efficiently at the inspection-hangering station. The hangers are automatically fed in position against the garment form before the shoulder portion of a shirt is draped over the garment form for inspection. The inspected shirt is then automatically taken away to another location by removing the hanger from the garment form and carrying the shirt along with it. The number of **manual operations required** to perform the inspection and hangering operation with the apparatus herein are therefore significantly **reduced** which increases the overall speed and efficiency of processing the shirts while ensuring that a thorough, accurate inspection is performed.

Example 2: US Patent # 7603299 - Automated Receiving System
Assignee: Target Brands
Abstract
An automated receiving system for a distribution facility having at least one automated receiving door and at least one manual receiving door. The automated receiving system includes a scheduler and a transport system. The scheduler is configured to receive electronic shipment data representative of an incoming shipment of packages, to determine an unload score for the incoming shipment based on the electronic shipment data, and to cause the incoming shipment to be directed to either the at least one automated receiving door or the at least one manual receiving door based on the unload score. The transport system is configured to successively receive each package from the incoming shipment and to transport each package within the distribution facility.
Excerpt from patent background and summary
Large retailers typically utilize centralized warehouses, or distribution centers, to supply goods to multiple retail stores. Shipments of goods are generally hauled by carriers, who typically deliver the goods to the distribution centers by truck. Trucks having relatively homogenous loads, such as trucks carrying a single type of product from a single manufacturer, can generally be unloaded and have their contents verified relatively quickly. However, trucks having mixed loads containing a wide variety of products from multiple manufacturers, such as trucks carrying loads from consolidators or import warehouses, can be difficult and time consuming to unload as each package, or carton, must be individually evaluated by distribution center personnel to identify its contents and

determine how it is to be distributed. Such a time-consuming receiving process is costly and can result in undesirable delays in delivering goods to retail stores having inventory needs.
One embodiment of the present invention relates to an automated receiving system for a distribution facility having at least one automated receiving door and at least one manual receiving door. The automated receiving system includes a scheduler and a transport system. The scheduler is configured to receive electronic shipment data representative of an incoming shipment of packages, to determine an unload score for the incoming shipment based on the electronic shipment data, and to cause the incoming shipment to be directed to either the at least one automated receiving door or the at least one manual receiving door based on the unload score. The transport system is configured to successively receive each package of the incoming shipment and to transport each package within the distribution facility. By automatically identifying packages as they are unloaded from a shipment and distributing identified packages within the distribution facility based on retail outlet inventory needs, automated receiving system 10 according to the present invention reduces the time required to process shipments. As a result, automated receiving system 10 **reduces labor costs** and reduces the time required to supply the inventory needs of associated retail outlets. Furthermore, the time-saving benefits of automated receiving system 10 are optimized by evaluating shipment characteristics prior to their arrival so that only those shipments most likely to result in the largest time savings are processed by automated receiving system 10.

Example 3: US Patent # 5146842 - Rotisserie
Assignee: Brinker International
Abstract
A rotisserie for use in cooking meat on a spit. The spit is releasably coupled to a spit retainer which is rotatably mounted on a central post. A drive mechanism is mounted on the spit retainer and imparts rotational motion thereto. The central post is pivotally mounted whereby the spit can be rotated between a first position in which the meat can be removed from the spit and a second position in which the spit is in a cooking position.
Excerpt from patent background and summary
Rotisseries are well known in the restaurant industry and are commonly used for slow-roasting poultry, beef, and pork. A common rotisserie includes one or more spits mounted horizontally across the width of a heat source. The spits are rotated by a motor which is connected to the spits through a series of gears and/or chains. In order to place a spit over the heat source to initiate cooking, or in order to remove a spit from the rotisserie, **it is necessary for the rotisserie operator to stop the rotation of rotisserie**. Next, the operator must reach over the heat source in order to mount/remove the spit from the rotisserie. This process is both cumbersome and hazardous for the operator due to his/her proximity to the heat source.
This invention relates to a rotisserie constructed to permit removal of a spit **without the need for interrupting the operation of the rotisserie** and, more particularly, to a rotisserie providing for the pivotal mounting of a plurality of spits.

Example 4: US Patent # 10426667 - Cap Actuator For Opening And Closing A Container
Assignee: Abbott Laboratories
Abstract
The present invention is a method for opening and closing a cap pivotally mounted on a container for storing reagents for use in an automated analytical instrument. The cap has one end for sealing the container and a tab extending from the other end for pivoting the cap. The method comprises the steps of positioning a closed container adjacent an actuating device mounted on the analytical system. The method further comprises the steps of projecting the actuating device against the top of the tab to pivotally open the cap to a position sufficiently vertical for aspirating reagent from the container, and retracting the actuating device from the cap to a position above the pivotal mounting thereof. The method comprises the final step of causing relative motion between the cap and the actuating device so that the actuating device drags along the top of the cap pivotally closing the
Excerpt from patent background and summary
Although various known clinical analyzers for chemical, immunochemical and biological testing of samples are available, clinical technology is rapidly changing due to increasing demands in the clinical laboratory to provide new levels of service. These new levels of service must be more cost effective to **decrease the operating**

expenditures such as labor cost and the like, and must provide shorter turnaround time of test results to reduce the patient's length of stay in the hospital as well as improve efficiency of outpatient treatment. Modernization of analytical apparatus and procedure demands consolidation of work stations to meet the growing challenge placed on clinical laboratories.

Example 5: US Patent # 5005597 - Street Cleaning Device For Collecting Leaves And Debris

Assignee: Deere & Company

Abstract

Leaves and other debris arranged in piles along a roadway are lifted by a flail-type rotary cutting device towed centrally behind a tractor. The device includes a containment hood having a forwardly opening throat which is adjustable to conform generally to the size of the piles for receiving the piles and restricting the material from being thrown forwardly from under the hood particularly at the end of a pile. The lifted material is delivered into a receptacle towed behind the cutting device. The rotary cutting device can handle leaves and other debris in states ranging from dry and fluffy to frozen and snow-covered. The tractor and/or additional brushes may be used for preliminary piles sizing and positioning. Brushes may also be added to the machine for additional cleaning action and to help part wide piles.

Excerpt from patent background and summary

The present invention relates generally to street cleaning devices and, more specifically, to a device for picking up leaves and other debris from along streets and roads. In many municipalities, leaf burning has been banned, and leaves must be collected by street crews in the fall. In a typical situation, property owners deposit leaves in large piles of varying sizes adjacent the street curb. Thereafter, the street crews use one of numerous methods to remove the leaves from the street. Present methods are slow, expensive and labor and equipment intensive. Rain and snow present problems especially when attempts are made to vacuum wet material. At low temperatures, the vacuum tubes clog with ice because of the low pressure-high velocity air through the system. Baling and bagging require special handling, and, as with most common methods, large crews are necessary to keep up with the autumn disposal of leaves. It is therefore an object of the present invention to provide an improved method and apparatus for picking up leaves and debris from along streets, roadways and the like. It is a further object to provide such a method and apparatus which **reduce** the time, expense, **labor**, and equipment requirements for handling the leaves and debris. It is still another object of the present invention to provide an improved method and apparatus for picking up leaves and debris even when rain, ice and snow may be present. It is a further object to provide such a method and apparatus which **reduce** the time and **manpower** required to pick up leaves and debris.

Example 6: US Patent # 5163083 - Automation Of Telephone Operator Assistance Calls

Assignee: AT&T Bell Laboratories

Abstract

This invention relates to methods and apparatus for automatically processing operator assistance calls. A caller is connected to an automated operator position. The automated position has speech recognition facilities to **replace those of an operator**, has announcement capabilities to **replace those of an operator**, and has control apparatus for transmitting and receiving the same set of messages transmitted and received by an operator position. Advantageously, the operator assistance switch has the same interface to an automated position as to an operator position and interacts with the two identically. Since the capabilities of the automated position are limited by its program, the automated position switches a call to an automated position when a situation occurs for which it has not been programmed. Advantageously, a switch need not be specially programmed to communicate with an automated position. Advantageously, new operator assistance services can be provided automatically without rewriting the complex control software of the switch.

C. List of randomly selected words for placebo test in Table 9

This table contains a list the random words used in the analysis presented in Section 4.3 of the paper. From our main sample of more than half a million patents, we randomly select 10% of the patents and extract the text descriptions of this random subsample of patents. We tokenize all the text descriptions of this random subsample and drop frequently occurring 'stopwords' such as *the*, *of*, *patent,* etc. From the remaining tokenized list of words, we randomly select 25 words, which are tabulated below.

inbreeding	combustor	heritably	radiation
braid	farthest	mitral	racetrack
serves	staggered	biomolecules	thrombi
cooked	vocal	revision	desorbing
anonymized	container	spike	
suberic	straight	threadably	
wide	cleaved	sticks	

D. Robustness tests

D1. Alternative measures of automation patents

In this section, we discuss the robustness of our main findings in Table 7 of the paper. We first present robustness of our findings to two alternative methods of classifying automation patents. The first alternative is a modification of our own method. The second alternative is the automation classification of Mann and Püttmann (2018). In the main classification used in the paper, we classify patents as automation patents based on the appearance of specific keywords in the description of the patent. The list of keywords is presented in Main Appendix A1 of the paper and the frequency of occurrence of these keywords in our sample is presented in Table A1 of the Main Appendix. We see that the words *automatic* or *automatically* occur in more than 150,000 patents. The word '*self-*' appears in almost 70,000 patent descriptions that also contain words such as machine, equipment, apparatus etc. To allow for the possibility that just one appearance of these frequently occurring words is not a sufficient indication of automation technology, we develop an alternative specification, called *Auto Class 2*, that makes the following changes to the main classification: (i) require three or more occurrences of the words *automatic* or *automatically* to classify a patent as an automation patent (ii) require three or more appearances of the word '*self-*' in patent descriptions that also contain the words machine, equipment, apparatus etc. The remaining criteria remain unchanged. A detailed description of Auto Class 2 is as follows:

Alternate classification of automation patents (Auto Class 2)

A patent is classified as an automation patent if it meets any one of the following five criteria:

1. Three or more appearances of the words automatic or automatically
2. One or more appearances of the following words:
   - automate, automation, or automatization
   - mechanize or mechanization
   - robot, robotic, robotize, or robotization
   - labor-saving

3. To identify computer-assisted manufacturing: One or more appearances of the following bulleted list of words **and** the word *machine*, *manufacturing*, *equipment*, or *apparatus*
   - computer aided or computer-aided
   - computer assisted or computer-assisted
   - computer supported or computer-supported

4. To identify computer numerical control (cnc) patents which indicate automated control of machine tools: One or more appearances of the following words
   - numerically controlled or numerically-controlled
   - numeric control or numeric-control
   - cnc

5. To identify self-operated equipment: Three or more appearances of the word 'self-' **and** the word *machine*, *manufacturing*, *equipment*, or *apparatus*

In columns 1 and 2 of Table D1 below, we estimate equation 1 using Auto Class 2 to identify automation patents. In column 1, the dependent variable is the number of automation patents applied for by a firm. The coefficient β_2 is positive and statistically significant at the 5% level while β_3 is positive and significant at the 10% level. Thus, larger minimum wage increases are associated with bigger increases in the number of automation patent applications. In column 2, where the dependent variable is the number of non-automation patent applications, we see that β_2 and β_3 are both statistically insignificant. Thus, the percentage change in the minimum wage has no impact on non-automation patents. These results are qualitatively similar to the evidence in the baseline specification presented in Table 7.

Classification of Mann and Püttmann (2018)

We also check the robustness of our results to the automation patent classification of Mann and Püttmann (2018). They manually classify a few hundred randomly drawn patents based on patent text descriptions and then use a training algorithm to classify the rest of the patents in their sample. We match our data to their patent classification data and present the results in columns 3 and 4 of Table D1 below. The coefficient β_2 is positive and statistically significant at the 5% level for automation patents in column 3. Both β_2 and β_3 are both statistically insignificant for non-automation patents in column 4. These results are qualitatively similar to the evidence in the base specification presented in Table 7. Thus, our key result is robust to using Mann and Püttmann's (2018) classification of automation patents.

D2. Including SIC 283

The second issue we address is the exclusion of the drug industry (SIC 283) from our main sample. We exclude drug manufacturers from our main sample because many patents filed by the drug industry relate to the chemical composition of new drugs. In these patent descriptions, words such as automatic could be used in a context other than labor-saving technology. However, prior evidence shows significant robot penetration in the chemical industry (see, for example, Acemoglu and Restrepo, 2020). By dropping the drug industry from our sample, we miss out on possible robotization of the drug-production process. Therefore, we re-run our analysis including SIC 283 in the sample. When testing robustness to the inclusion of drug manufacturers, we use the primary automation classification employed in all our main tests (and described in detail in Main Appendix A1). In columns 5 and 6 of Table D1 below, we estimate equation 1 using a sample that includes firms in SIC 283 while employing our primary classification of automation patents. The results are qualitatively the same. In column 5, automation patents are higher after larger minimum wage increases while in column 6, the change in non-automation patents has no relation with the change in the minimum wage.

D3. Truncation bias

The third issue we discuss here is the well-recognized truncation bias in the patent data that occurs because of the gap between the patent application date and the grant date. Since it can take a few years for patents to be granted, a significant number of patents that are applied for near the end of the sample period are missing from the database. In our primary analysis, we addressed this truncation bias by dividing each patent for each firm-year by the mean number of patents of all firms for that year. In this section, we exclude the last five years of the sample period and estimate equation 1 using patent data from 1985 till 2014. The findings are presented in columns 7 and 8 of Table D1 below. In column 7, the dependent variable is the number of automation patents applied for by a firm. The coefficient β_2 is positive and statistically significant at the 1% level. In column 8, where the dependent variable is the number of non-automation patent applications, we see that β_2 and β_3 are both statistically insignificant. Thus, our key finding is robust if we drop the last few years of our sample period to adjust for the truncation bias.

D4. Location of firms' headquarters.

Finally, we consider the location of a firm's headquarters. Our main analysis uses the current headquarters of a firm obtained from Compustat. Any change of headquarters during our sample period would introduce noise in our analysis. To address this concern, we obtain historical data on headquarter locations and re-estimate equation 1.[3] In column 9 of Table D1 below, the dependent variable is automation patents. The coefficient β_2 is positive and statistically significant at the 1% level. Thus, larger minimum wage increases are associated with bigger increases in the number of automation patent applications. In column 10 of Table D1, where the dependent variable is the number of non-automation patent applications, we see that β_2 and β_3 are both statistically insignificant.

[3] The data on historical headquarters is obtained from Gao, Leung, and Qiu (2021).

Table D1: Robustness tests

This table presents the change in automation patents of treated firms after minimum wage increases. Analysis of the change in non-automation patents is also presented. The regressions are the same as the baseline specifications in columns 3 and 7 of Table 7 with the following modifications: in columns 1 and 2, the classification of automation patents is based on Auto Class 2 described in Internet Appendix D; in columns 3 and 4, the classification of automation patents is based on Mann and Püttmann (2018); in columns 5 and 6, automation patents are classified using our primary automation classification described in Main Appendix A1 but the sample includes firms in SIC code 283; in columns 7 and 8, automation patents are classified using our primary automation classification described in Main Appendix A1 but excluding events after 2014; in columns 9 and 10, automation patents are classified using our primary automation classification described in Main Appendix A1 but the historical state of headquarters is used as the firm's location. All regressions include control variables, firm- and year-fixed effects with standard errors clustered by state. *t* statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Auto Class2		MP automation measure		Including SIC 283		Dropping years after 2014		Historical headquarters	
	A_Pat	*NA_Pat*	*A_Pat*	*NA_Pat*	*A_Pat*	*NA_Pat*	*A_Pat*	*NA_Pat*	*A_Pat*	*NA_Pat*
Before1× Δ MinWage (β_1)	0.0016	-0.0017	-0.0067	-0.0003	0.0009	0.0018	0.0022	-0.0006	-0.0024	0.0003
	(0.41)	(-0.25)	(-1.00)	(-0.04)	(0.24)	(0.27)	(0.57)	(-0.10)	(-0.56)	(0.05)
After1× Δ MinWage (β_2)	0.0103**	0.0121	0.0175**	0.0023	0.0113***	0.0106	0.0116***	0.0111	0.0095**	0.0096
	(2.66)	(1.25)	(2.34)	(0.21)	(2.87)	(1.02)	(2.86)	(1.17)	(2.20)	(1.07)
After2× Δ MinWage (β_3)	0.0096*	0.0085	0.0032	0.0099	0.0097*	0.0085	0.0111	0.0076	0.0080	0.0074
	(1.69)	(0.99)	(0.33)	(1.18)	(1.74)	(1.23)	(1.67)	(0.93)	(1.35)	(1.17)
Before1	-0.0016	-0.0048***	-0.0021	-0.0035	-0.0021*	-0.0050***	-0.0030**	-0.0045**	-0.0008	-0.0026
	(-1.56)	(-2.75)	(-1.28)	(-1.66)	(-1.93)	(-2.92)	(-2.43)	(-2.55)	(-0.60)	(-1.60)
After1	-0.0065***	-0.0172***	-0.0127***	-0.0104***	-0.0080***	-0.0157***	-0.0095***	-0.0155***	-0.0063**	-0.0113**
	(-2.84)	(-4.52)	(-3.36)	(-3.42)	(-3.15)	(-4.64)	(-3.21)	(-4.40)	(-2.10)	(-2.62)
After2	-0.0075**	-0.0197***	-0.0122**	-0.0133***	-0.0090***	-0.0180***	-0.0112***	-0.0173***	-0.0071*	-0.0131**
	(-2.54)	(-3.56)	(-2.67)	(-2.91)	(-2.73)	(-3.76)	(-2.78)	(-3.36)	(-1.84)	(-2.27)
ΔMinWage	-0.0304**	-0.0398	-0.0419**	0.0066	-0.0355**	-0.0308	-0.0384**	-0.0318	-0.0326*	-0.0284
	(-2.46)	(-1.56)	(-2.36)	(0.37)	(-2.33)	(-1.47)	(-2.25)	(-1.36)	(-1.91)	(-1.11)
Constant	0.0004	-0.0627***	-0.0458***	-0.0835***	-0.0057	-0.0545***	-0.0078	-0.0593***	-0.0162**	-0.0659***
	(0.04)	(-3.88)	(-2.87)	(-4.11)	(-0.62)	(-3.95)	(-0.70)	(-3.74)	(-2.24)	(-3.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16153	16153	16153	16153	18199	18199	15869	15869	17127	17127
adj. R^2	0.81	0.82	0.73	0.70	0.82	0.80	0.83	0.81	0.81	0.81