The Effect of Labor Cost on Innovation

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Abstract

Using minimum wage changes as an exogenous shock to the cost of low-skill labor, we show that corporate innovative output declines after the shock, especially in industries dependent on unskilled labor. The substitutability between technology and unskilled labor plays a key role in the response of innovative output to minimum wage shocks. We identify technology that reduces the demand for unskilled labor either through automation or due to capital-skill complementarity. We find that minimum wage shocks have a less deleterious impact on the innovative output of firms developing technology that reduces the demand for unskilled labor.

1. Introduction

The minimum wage is a central part of public policy debate. Originally introduced as a 'fair' wage to reduce exploitation of labor, the minimum wage has increasingly become synonymous with a 'living' wage – a wage necessary to help workers achieve self-sufficiency. Since 2014, the effective minimum wage has increased in 27 states. Several cities, such as Seattle and San Francisco, have adopted minimum wages above their states' minimum wage. Despite the recent political popularity of minimum wage legislation, economists remain skeptical about its effectiveness due to possible cut in jobs and work hours. Researchers have extensively examined the impact of minimum wage legislation on employment. Although the evidence varies depending on the sample and methodology employed, the weight of evidence from this literature indicates that an increase in minimum wages decreases employment.[1]

In this paper, we explore another unintended consequence of the minimum wage - a change in corporate innovative output. The link between labor cost and innovation is recognized in several strands of economics. Economic historians have long argued that high cost of labor can spur the development of labor-saving technology. For example, Habakkuk (1962) argues that innovation and mechanization was faster in the United States than in Britain during the nineteenth century due to labor shortages in the United States that resulted in high labor cost. Allen (2009) posits that the Industrial Revolution occurred in Britain and not elsewhere in the world due to the relatively high wages in Britain during the eighteenth century.

[1] For example, Card and Krueger (1994) examine the impact of an increase in New Jersey's minimum wage in 1992 on employment in fast-food restaurants and find no evidence of a decline in employment. Using a panel data on state minimum wage laws, Neumark and Wascher (1992) find a decline in employment among teenagers and young adults. Numerous other studies are surveyed in Brown, Gilroy, and Kohen (1982) and Neumark and Wascher (2008).

These arguments assume substitutability between labor and capital. If labor becomes more expensive, firms demand less of it and may adopt labor-saving technology instead.[2] However, labor and capital need not be substitutes. Some technology requires labor in the production process, in which case high wages can reduce the profitability of firms. In fact, in most macroeconomic models, labor and technology are complements, with the latter usually embedded within capital stock. In these models, high wages predict a slowdown in the adoption of new technology.[3] Acemoglu (2010) captures these competing arguments in an endogenous technology model. He demonstrates that when technology is labor complementary, meaning the technology increases the marginal product of labor, an increase in the cost of labor discourages technological advancement. If the technology is labor-saving, an increase in labor cost induces technological change.

Following this intuition, we argue that the impact of a minimum wage increase on innovative output will depend on whether the technology being developed by the firm increases or decreases the demand for *unskilled* labor. Technology that automates routine tasks or shifts demand away from low-skill workers toward skilled workers can become more attractive if the cost of low-skill labor increases. In contrast, innovation resulting in new products or equipment that necessitate hiring more factory workers can becomes less profitable if the cost of production workers increases. Our empirical analysis exploits the possibility that technology interacts differently with unskilled labor than with skilled labor. Our approach is motivated by a large literature on skill-biased technological change which argues that the elasticity of substitution

[2] Evidence supportive of this argument is found in Hannan and McDowell, J. (1984) who show that banks in higher wage areas are more likely to install ATM machines.

[3] In endogenous growth models, labor scarcity and high wages reduces the growth of technology and output. See for example, Romer (1986, 1990), Segerstrom, Anant, and Dinopoulos (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992). In semi-endogenous growth models, labor cost and scarcity reduce the level of technology and output. See for example, Jones (1995), Young (1998), and Howitt (1999).

between unskilled labor and capital equipment is higher than that between skilled labor and capital equipment (see, for example, Griliches, 1969; Berman et al., 1994; Berman et al., 1998; Krusell et al., 2000; Duffy et al., 2004).

We examine the impact of a minimum wage shock on firm-level innovative output conditional on the characteristics of the labor force in the firm's industry and the type of innovation the firm or its industry engages in. We identify 139 state-years that experience an increase in the effective minimum wage following federal- and state-level changes to the minimum wage between 1985 and 2010. We begin by verifying that the minimum wage is a binding wage floor by examining the change in average wage following an increase in a state's effective minimum wage. Using data from the Current Population Surveys (CPS) and Bureau of Labor Statistics (BLS) we confirm prior evidence that the average hourly wages increase after minimum wage shocks. This increase is driven by the lower end of the wage scale, with statistically significant increases observable below the 20th percentile.[4]

After confirming that the minimum wage shock has a significant impact on the average cost of labor, we examine the change in patents and citations per patent after the wage shock from two years before till two years after the minimum wage shock.[5] In multivariate analysis that controls for factors known to affect innovative output, we find a significant decline in patents and citations per patent after the wage shock. However, this decline could be due to other changes in the economy contemporaneous with the minimum wage shock. To identify the role of the minimum wage change, we exploit cross-industry variation in the share of wages paid to low-skill

[4] Our findings are consistent with prior evidence that increases in minimum wage do not spill over to workers higher up in the wage scale. See, for example, Card and Krueger (1995), and Neumark and Wascher (2007).

[5] For robustness, we also look at the input in the innovative process, namely research and development expense. See Section 6.

workers and the wage gap between the lowest paid workers and the median-wage earner. Using a variety of proxies, we provide robust evidence that the decline in innovation following minimum wage shocks is more pronounced in industries with more low-wage and low-skill workers. We use falsification tests to show that this decline in innovation in low-wage industries is observed only around minimum wage shocks and not around randomly selected years in our sample period. Moreover, multi-period regressions show that the decline in innovation in low-wage industries begins after the minimum wage shock, not before.

Having determined that the decline in innovation is driven by industries dependent on low-skill workers, we consider the type of innovation firms engage in. Firms developing technology that reduces the demand for unskilled labor are likely to be less affected by increases in the minimum wage. We use two approaches to ascertain whether a firm is likely to be engaged in innovation that reduces the demand for unskilled labor. In the first method, we machine-read patent descriptions for words such as automatic, mechanize, robotic and other words synonymous with automation. In our sample of more than 300,000 patents, about 20% contain one or more words indicative of automation technology. For each firm, we count the total number of appearances of words indicative of automation in patents held by the firm at the time of the shock. Using raw and scaled measures of this variable, we show that the decline in innovative activity is less pronounced for firms whose patent descriptions refer to automation more frequently. We interpret this find as follows. Firms whose patents do not refer to automation are more likely to be developing technology that requires production workers rather than replaces them. Therefore, an increase in the cost of production workers has a more adverse effect on the innovative output of these firms. Our finding is supportive of Acemoglu's (2010) argument that the response of innovative activity to labor cost depends on whether the technology increases or decreases the marginal product of labor.

To address concerns that the number of appearances of automation words captures other firm characteristics such as tendency to file more patents or to write longer patent descriptions, we conduct falsification tests. In the falsification tests, we use randomly selected words instead of words synonymous with automation. We find that appearance of the random set of words in patent description has no relation with the change in innovative output after the minimum wage shock. We also conduct falsification tests on the timing of the minimum wage shock by using randomly selected years as hypothetical shock years. We find that our automation measures have no correlation with change in innovation after the hypothetical event year.

For our second method of identifying firms more likely to be engaged in innovation that reduces demand for unskilled labor, we turn to the literature on capital-skill complementarity. This literature suggests that capital stock embodying advanced technology shifts demand away from unskilled labor toward skilled labor (see Griliches, 1969; Berman, Bound, and Griliches, 1994; Krusell et al., 2000). We follow this literature and estimate skilled labor share equations within each 2-digit SIC code. The elasticity of the share of wages of skilled workers with respect to capital intensity captures the complementarity between skilled labor and capital. The stronger the positive relation between capital intensity and wage share of skilled workers, the greater the shift in demand away from unskilled labor to skilled labor. We classify firms operating in industries with high (low) capital-skill complementarity as engaging in innovation that reduces (increases) demand for unskilled workers. We find that, following minimum wage shocks, the decline in innovation is greater in industries with low capital-skill complementarity. This result is robust to different proxies of skill and survives falsification tests that using randomly selected years as hypothetical shock years. Thus, both our automation measure and capital-skill complementarity measure point to the same conclusion. Minimum wage increases have a more deleterious effect on innovation if the technology firms rely on tends to increase the demand for unskilled labor.

Our paper provides new evidence on the impact of minimum wage shocks on corporate innovative output. We provide the first empirical evidence on how substitutability between technology and labor affects the sensitivity of corporate innovative output to wage shocks. Our findings contribute to a few distinct strands of literature. There exists a voluminous literature on the impact of the minimum wage on employment levels and wage.[6] A similarly large literature on innovation relates factors such as institutional ownership, capital structure, liquidity, conglomeration, and takeover defenses to corporate innovative output.[7] Relatively little evidence exists on the effects of labor cost on corporate innovative output despite strong theoretical arguments that labor cost matters for innovation.[8] Our paper provides new evidence that minimum wage shocks are followed by a decline in innovative output, especially in industries that employ more low-wage workers. We show that the decline in innovation depends on whether the firm is engaged in technology that increases or decreases the demand for unskilled labor. Thus, our paper also contributes to the growing literature on skill-biased technological change.

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[6] See for example, Card and Kreuger, 1995; DiNardo, Fortin, and Lemieux, 1996; Pettengill, 1981, Pettengill, 1981; Card and Krueger, 1995; Flinn, 2002; Denardo, Fortin, and Lemieux, 1996; Lee, 1999.

[7] See Aghion, Van Reenen, and Zingales (2013), Lerner, Sorensen, and Stromberg (2011), Ferreira, Manso, and Silva (2014), Atanassov (2013), Fang, Tian, and Tice (2014), and Seru (2014).

[8] One exception is Bena, Ortiz-Molina and Simintzi (2019) who examine the impact of labor dismissal costs on a firm's engagement in process innovation.

2. Related Literature

The national minimum wage was introduced as part of the Fair Labor Standards Act (FLSA) in 1938 despite controversy among economists about its merits. Some economists expressed concern that the minimum wage would reduce the employment of lower-skilled workers (Clark, 1913; Stigler, 1946). Others, such as Webb (1912) and Feline (1923) argued that the minimum wage prevents exploitation of labor and can have the added benefit of increasing consumer purchasing power, thereby helping aggregate demand.

There exists a vast literature, both theoretical and empirical, on the impact of the minimum wage on employment, wages, income, poverty and skill-acquisition. We know from existing empirical evidence that changes in minimum wage have an economically and statistically significant impact on wages, not just those of minimum wage workers but also of other workers at the lower end of the wage scale (see Card and Kreuger, 1995; DiNardo, Fortin, and Lemieux, 1996; Pettengill, 1981). There are two reasons for this wage spillover to workers above the minimum wage. First, if relative wage is important for eliciting effort, then employers may raise wages of higher-skilled workers in response to an increase in the minimum wage (Grossman, 1983). Second, theoretical and empirical research suggests that following a minimum wage increase, employers substitute away from the lowest-skilled workers toward somewhat higher skilled labor, putting an upward pressure on the wages of the latter (see Pettengill, 1981; Card and Krueger, 1995; Flinn, 2002; Denardo, Fortin, and Lemieux, 1996; Lee, 1999). The impact of this exogenous imposed increase in cost of labor on employment and earnings has been extensively studied. Although the evidence tends to vary depending on methodology and sample, in a comprehensive review Neumark and Wascher (2010) conclude that the empirical evidence largely supports the view that a minimum wage increase reduces the employment of low skilled workers and lowers their earnings.[9]

Despite the contentious debate on this issue, it is not surprising that a change in the cost of labor affects how much labor firms use. Theory suggests that the availability and cost of labor also affects technological advancement. On the one hand, technology may be used to substitute for the more costly labor. This substitution effect could spur the development of labor-saving technology in the presence of labor-scarcity and high cost of labor. On the other hand, labor scarcity and high cost of labor reduces the size of the workforce that may use the new technology and also eats into firm's profitability. In commonly used models of endogenous technological development, the latter scale effect dominates, and technology is effectively labor-complementary.[10] These models would suggest that an increase in the cost of labor discourages innovation. Acemoglu (2010) captures these competing forces in a comprehensive, generalized model of endogenous technological advancement and identifies conditions under which labor scarcity encourages or impedes innovation. Although Acemoglu's analysis primarily focuses on the availability of labor, under the assumption of competitive labor markets, the same results hold for an exogenously imposed increase in the cost of labor, such as through minimum wage legislation. Acemoglu demonstrates that labor scarcity and, under most conditions, high cost of labor spur technological

[9] It is difficult to do justice to the large literature on the minimum wage. Research from the 1960s and 1970s is summarized in Brown, Gilroy and Cohen (1982). In late 1980s a number of states raised state-level minimum wages. This increase in state-level variation triggered another wave of research called new minimum wage research which is summarized in Neumark and Wascher (2010).

[10] A common feature of endogenous technology models is the scale effect, whereby a larger population (i.e. larger supply of labor) stimulates innovation because new inventions are more widely used when the population is larger and also because there are more inventors available to work in research sectors. For example, in Romer (1986, 1990), technology is nonrivalrous in the sense that once invented, its use in one activity does not preclude its use in another activity. This assumption creates a scale effect, whereby an increase in the size of the population translates into a larger profit for the inventor. In these models, technology is effectively labor-complementary, that is, it increases the marginal product of labor. Also see Grossman and Helpman (1991), Aghion and Howitt (1992).

advancement only if the new technology decreases the marginal product of labor.[11] When new technology is labor-complementary, that is, when new technology increases the marginal product of labor, an increase in the cost of labor discourages innovation. One of the implications of Acemoglu's work is that the link between labor scarcity and labor cost can vary across sectors and over time, depending on the type of technology being developed.

Whether technology increases or decreases the demand for labor can depend on the skill-level of labor. Literature on capital-skill complementarity argues that the elasticity of substitution between capital equipment and unskilled labor is greater than that between capital equipment and skilled labor (see for example, Griliches, 1969; Stokey, 1996; Krusell et al, 2000). An implication of this capital-skill complementarity is that technological development increases the demand for skilled labor, not unskilled labor. A few papers do find evidence that skill-biased technical change has reduced the demand for less-skilled workers in developed countries (Berman, Bound, and Griliches (1994) and Berman, Bound, and Machin (1998). However, evidence in favor of capital-skill complementarity is not unanimous. Duffy et al. (2004) find only weak evidence in favor of the capital-skill complementarity hypothesis in a cross-country dataset. The evidence is strongest when they use a low threshold to define skill – primary education only. Our paper adds to these different streams of literature by examining the impact of an exogenously imposed increase in wages on corporate innovation conditional on characteristics of the labor force (skilled or unskilled) and characteristics of the technology (whether it increases or decreases demand for unskilled labor)

[11] Zeira's (1998) model has this labor-saving feature as technology is designed to takeover tasks previously performed by labor.

The exogenous wage shock is important for our test design because, at the firm-level, innovation is known to affect wages. In panel of U.K. firms, Reenan (1996) finds that innovating firms pay higher average wages and concludes that workers share in the rents generated by innovation. Other researchers show that innovation increases demand for skilled labor and widens the wage gap between skilled and unskilled labor (Berman, Bound, and Griliches, 1994; Thoenig and Verdier, 2003; Allen, 2001; Bartel and Sicherman, 1999). These papers suggest that technological progress and the accompanying demand for skilled labor is one explanation for the rising income inequality.[12]

By exploring the change in innovation after an exogenously imposed change in labor cost, we sidestep this issue of reverse causality. In the 1980s, the federal minimum wage remained unchanged for an extended period of time leading several states to pass state-level minimum wage laws. This state-level activism accelerated in the 1990s and has resulted in greater variation in the minimum wage across states and over time. However, examining the change in corporate innovative output following minimum wage legislation presents its own set of challenges. Distribution of minimum wage policy across the United States is not random. High minimum wage states are concentrated in certain regions such as the Pacific Coast, the Northeast, and parts of the Midwest. This regional clustering of minimum wage legislation means that the industrial make-up of high minimum wage states could be different from that of low minimum wage states. Moreover, states with higher minimum wages tend to be Democratic-leaning and have greater unionization. Allegretto, Dube, Reich and Zipperer (2013) show that states with greater increases in minimum wage have experienced more severe economic downturns and faster growth in wage inequality in

[12] However, DiNardo, Fortin, and Lemieux (1996) show that the failure of the minimum wage to keep up with inflation is a major determinant of the rise in wage inequality.

the upper half of the wage spectrum. These structural and economic differences between high and low minimum wage states can generate a spurious correlation between minimum wages legislation and change in innovation. Our empirical analysis avoids these challenges by focusing only on states that are affected by changes in minimum wage legislation. We identify the impact of the minimum wage on innovation by exploiting cross-industry variation in labor-market characteristics.

3. Data and variables

In this section, we describe minimum wage shocks, the sample of affected firms, our measures of innovative output, and control variables used throughout the analysis. Variables capturing labor characteristics and our proxies for labor-saving technology are described later in Section 4.

3.1. Data sources and sample

We use state-level and federal minimum wage data obtained from the Department of Labor to identify minimum wage shocks. Many states have state-level minimum wage regulation. Employees who are subject to both state and federal minimum wage are entitled to the higher of the two. We call this the effective minimum wage in a given state-year and identify state-years in which the effective minimum wage increased due to changes in either the federal or the state minimum wage rate. If the effective minimum wage in a state increased more than once within a two-year period, we treat the first increase as the shock. Using this method, we have 139 state-years that experienced an increase in the effective minimum wage events but were not preceded by an increase in the previous two years. These minimum wage events are summarized in Table

1. Our analysis focuses on the change in firms' innovative output over the two years before and two years after a change in the effective minimum wage. The analysis is restricted to firms listed on U.S. exchanges. A firm is assumed to be affected by the minimum wage shock in state in which it is headquartered.

Most of the minimum wage events in our sample are due to three increase in the federal minimum wage that occurred in 1990, 1996, and 2007. Since changes in the macroeconomic environment can affect innovative output, our identification strategy is to exploit cross-industry variation in labor characteristics and type of technology being developed. In robustness tests, we confirm that our results are not driven by any one of these three federal-level shocks to the minimum wage.

An increase in the minimum wage serves as an exogenous shock to the cost of labor if the minimum wage is a binding price floor. Prior research shows that increases in the minimum wage are followed by increases in the average wage.[13] We confirm these findings in our sample by constructing a wage distribution using the CPS Merged Outgoing Rotation Groups database during the period 1980-2010. The CPS Outgoing Rotation Groups database includes wages of workers ages 16 to 64 with 0 to 39 years of potential experience in current employment. Unemployed and self-employed workers are excluded. All the wage data are transformed to 1982 dollars using CPI-U deflator. For each state affected by the minimum wage shock, we identify the hourly wage of the worker at the 10th, 20th, 50th, 80th, and 90th percentile during each of the two years before the wage shock and two years after the shock. Differences in means for this distribution before the shock and after the shock are presented in Table 2. The minimum wage increases by 14% on

[13] See Neumark and Wascher (2007) for a review of research on the effect of minimum wage on average wages and employment.

average after the minimum wage shock. We see a statistically significant increase of 3% at the 10th percentile of the wage scale. However, at the 20th percentile, the wage increase of 1.45% is not statistically significant. These findings are consistent with prior evidence of Card and Krueger (1995a) who show statistically significant increases in the wage distribution at the 5th percentile and 10th percentile, but no evidence at the 25th percentile. Our data confirm past evidence that the minimum wage is binding and that the wage increase spills over only to those earning near the minimum wage. The wage increase does not spill over to workers further up the wage scale. This suggests a tightening of the wage gap between those at the bottom of the wage scale and workers in the middle of the distribution.

3.2 Measuring innovation

As in prior studies, we measure innovative output with patenting activity (see Lerner, Sorensen, and Stromberg, 2011; Seru, 2014; Fang, Tian and Tice, 2015). Firm-level patent and citation data from 1985 - 2006 are obtained from National Bureau of Economic Research (NBER) Patent Data Project. Firm-level patent and citation data from 2007-2010 are obtained from Kogan et. al (2018). We use two measures of patenting activity – the number of patent applications filed in a year that are eventually granted and the number of non-self-citations a patent receives in future years. Both measures are adjusted for the truncation problem highlighted in Hall, Jaffe, and Trajtenberg (2001, 2005). Since the distribution of patents tends to be right-skewed, we follow prior literature and use the natural log of patent counts and patent citations. Since many firm-years have zero patents or citations per patent, we follow Fang, Tian and Tice (2015) and add one to the actual values before taking the natural logarithm. Table 2 provides sample statistics for Patents and citations per patent

3.3. Control variables

All regressions include the following control variables. Firm size, *SIZE*, measured by the natural logarithm of firm market capitalization; investment in innovation, *RDTA*, measured by R&D expenditures scaled by total assets; profitability, *ROA*, measured by return on assets; asset tangibility, *PPETA*, measured by net property, plant, and equipment scaled by total assets; leverage, *LEVERAGE*, measured by total debt-to-total assets; investment in fixed assets, *CAPEXTA*, measured by capital expenditures scaled by total assets; industry competitiveness, *HHI*, measured by the Herfindahl index based on annual sales; square of the Herfindahl index, *HHISQ*, included to mitigate the nonlinear effects of product market competition as per Aghion et al. (2005); growth opportunities, *Q*, measured by Tobin's *Q*; and firm age, *LNAGE*, measured by the natural logarithm of one plus the number of years the firm is listed on Compustat. Table 3 provides sample summary statistics of all control variables.

4. Labor characteristics

In this section, we first examine whether innovation as measured by patents and citations per patent changes after minimum wage shocks. In subsections 4.1 and 4.2 we explore how labor characteristics of an industry affect the change in innovation around minimum wage shocks.

In columns 1 and 2 of Table 4, we regress patents and citations per patent on a dummy variable POST, which is equal to one for the firm-years after the minimum wage shock and zero for the years before. The regression includes firm- and year-fixed effects but no control variables are included. The coefficient on POST is negative and statistically significant for both patent and citations. In columns 3 and 4 we include several control variables described in Section 3.3 above. The coefficient on POST remains negative and significant indicating that both patent count and citations per patent are lower after the minimum wage shock than before. In columns 5 and 6 we include the political party in power. The dummy variable DEMOCRATIC is equal to one if the Democratic candidate carried the state in the most recent presidential election and zero if the Republican candidate did. The coefficient on DEMOCRATIC indicates that innovative output is higher in states with the Republican party in power. However, the interaction of DEMOCRATIC with POST indicates that Republican states experience a bigger decline in innovative output after the minimum wage shock. Finally, in columns 7 and 8 of Table 4, we present placebo experiments in which each state is randomly assigned a hypothetical event year between 1985 and 2010. In these specifications, POST is a dummy variable that takes a value of zero for the two years before the hypothetical event year and one for the two years after. We see that POST is statistically indistinguishable from zero. Thus, the decline in innovation is observed around the minimum wage shocks but not at other randomly selected years in our sample period.

4.1 Unskilled or low-wage workers

The decline in innovative output could be due to other regulatory or economic changes that coincide with minimum wage shocks. To identify the impact of the minimum wage change on patents and citations per patent, we exploit cross-industry variation in the number of low-wage workers. Workers at the bottom of the wage scale are affected by the increase in minimum wage because the increase spills over to them directly in the form of higher wages. This implies a bigger increase in labor cost for industries that employ more low wage workers. We use three different variables to help identify industries that hire more low-wage or unskilled workers. The first measure following Berman, Bound, and Griliches, is calculated using data from the Census Bureau's Annual Survey of Manufacturers. It is the value of non-production workers' wages divided by the total wages paid to all employees in the industry. The Census Bureau distinguishes between production workers and other employees in white-collar type roles such as supervisory or management roles, sales and marketing, finance and legal, and other professional and technical employees.

The second variable is share of industry total wages paid to skilled workers. It is calculated using data from CPS Merged Outgoing Rotation Database as the value of wages paid to workers with at least some college education divided by the total wages in an industry. The third measure is the industry average hourly wage deflated to 1982 dollars obtained from the Bureau of Labor Statistics. Panel A of Table 5 provides summary statistics of these variables.

Using these measures, we create three classifications of low-wage or low-skill industries. *Blue-collar industry* is a dummy variable that equals 1 for industries with the share of production worker wages above the sample median and 0 otherwise. *Low-skill industry* is a dummy variable that equals 1 for industries with the share of skilled worker wages below the sample median and 0 otherwise. *Low-wage industry* is a dummy variable that equals 1 for the industries with average hourly wage rate in 1982 dollars below the sample median and 0 otherwise.

In Panel B of Table 5, we present regressions of patents and citations per patent on interaction between POST and the three indicator variables blue-collar industry, low-skill industry and low-wage industry. We see that in 5 of the 6 regressions presented in Panel B, the interaction term is negative and statistically significant. These results indicate that industries most likely to be affected by an increase in the minimum wage, i.e. industries that employ more low-wage workers or low-skill workers, experience a bigger decline in innovation after the minimum wage shock. We note that the regressions include all control variables and interactions of POST with the control variables, but for brevity, we do not tabulate coefficients on control variables and their interactions. Firm- and year-fixed effects are included, and standard errors are clustered by industry.

One critique of this result is that low-wage industries or industries employing unskilled workers may be experiencing a downward trend in innovativeness during our sample period due to reasons unrelated to the minimum wage. We conduct two tests to address this concern. In Panel C of Table 5, we present falsification experiments in which the same regressions are repeated with a randomly assigned year from our sample period serving as hypothetical event year. In this table, POST_RAN is a dummy variable equal to 1 for the two years after the randomly assigned year and zero for the two years before. The coefficients on the interactions of this POST_RAN variable with low-wage industry, low-skill industry and blue-collar industry are statistically insignificant.

In our second test shown in Panel D of Table 5, we present multi-period regressions as in Fang, Tian, and Tice (2014). In this test, we interact the dummy variables capturing low-wage or low-skill industry with each of the following indicator variables *Before_1* which is equal to 1 if the firm-year observation is from the one year preceding the year in which the minimum wage change occurred and zero otherwise, *After_1* which is equal to 1 if the firm-year observation is from year following the year in which the minimum wage shock occurred and 0 otherwise, and After_ 2 which is equal to 1 if the firm-year observation is from for the second year following the minimum wage shock and 0 otherwise. The omitted group (benchmark), therefore, is the observations from 2 years before the minimum wage shock. We see in Panel D that coefficients on the interactions with Before_1 are mostly insignificant and in the case of low-wage industry positive. Thus, there is no evidence that the decline in innovation existed prior to the minimum wage shock. Rather, the coefficients on the interaction with After_1 or After_2 tend to be negative and statistically significant, indicating that the decline in patents and citations per patent occurred after the minimum wage shock.

4.2 Measures of wage gap

In this subsection, we use the wage gap to identify industries more likely to be affected by the minimum wage shock. Industries with a small wage gap between the lowest paid employee and those higher up in the wage distribution, such as the median worker, are more reliant on low-wage workers. Labor cost in these industries would be more sensitive to minimum wage changes. We also classify industries with a low skill premium, meaning a small wage gap between skilled and unskilled workers, as more exposed to minimum wage shocks.

We calculate four main measures of wage gap. The first three are based on the CPS Merged Outgoing Rotation Groups database during the 1980-2010 period. We transform the wage data to 1982 dollars using CPI-U deflator and calculate a variable called *2010 Wage Gap* as the wage level at the 20^{th} percentile minus the wage level at the 10^{th} percentile. We also compute an alternative measure called *5010 Wage Gap*, computed as the wage level at the 50^{th} percentile minus the wage level at the $10^{th.}$ Table 6-Panel A presents summary statistics of these variables. *Skill wage gap (CPS)* is calculated as the hourly wage of skilled workers divided by hourly wage of unskilled workers, where skilled workers are those with at least some college education and unskilled are those with a high school diploma or less. The fourth key measure of wage gap, *Skill wage gap (ASM)*, is calculated using data from the Annual Survey of Manufacturers. It is the hourly wage of non-production workers divided by the hourly wage of production workers.

We define a dummy variable called *Low 2010 Wage Gap*, which takes a value of 1 for industries with 2010 Wage Gap below the sample median and 0 otherwise. *Low 5010 Wage Gap* takes a value of 1 for industries with 5010 Wage Gap below the sample median and 0 otherwise. *Low skill wage gap (CPS)* is a dummy variable that equals 1 for industries with Skill wage gap (CPS) below the sample median and 0 otherwise. *Low skill wage gap (ASM)* is a dummy variable that equals 1 for industries with Skill wage gap (ASM) below the sample median and 0 otherwise.

Panel B of Table 6 presents regressions of patents and citations per patent on interaction between POST and the four indicator variables Low 2010 Wage Gap, Low 5010 Wage Gap, Low skill wage gap (CPS), and Low skill wage gap (ASM). The regressions specifications are the same as in Panel B of Table 5. In columns 1 through 8 of Panel B, we see that the coefficients on the interaction terms are all negative and statistically significant in the patent regressions as well as in the citations per patent regressions. These results corroborate evidence presented in Section 4.1 above - industries that employ more low-wage workers, experience a bigger decline in innovation after the minimum wage shock.

One concern with using wage gap as a proxy for low-wage industry is that, in some industries, the lowest wage workers or the lowest skilled workers in the industry may earn significantly above the minimum wage. In such cases, a change in the minimum wage will not have a significant impact on labor cost. We explore how common such industries are by identifying industries in which the 10^{th} percentile wage is more than 25% greater than the minimum wage. In our sample, less than 3% (5%) of industries with low 2010 Wage Gap (5010 Wage Gap) have this characteristic. Dropping these industries does not qualitatively change the results in Table 6.

As a falsification test, we look at the wage gap between the median worker and the highest paid workers in the industry. We calculate a variable called *9050 Wage Gap* as the wage level at the 90^{th} percentile minus the wage level at the 50^{th} percentile. Prior literature shows that a change in the minimum wage does not spill over to the upper end of the wage scale. Thus, the 'upper' wage gap is less informative about the impact of minimum wage changes on an industry's labor cost. Not surprisingly, columns 9 and 10 in Panel B show that the interaction of POST with Low 9050 Wage Gap is insignificant.

In Panel C of Table 6, we present additional falsifications tests for the lower wage gap variables 2010 Wage Gap and 5010 Wage Gap. Patent and citation regressions are repeated with a randomly assigned year from our sample period. In Panel C, POST_RAN is a dummy variable equal to 1 for the two years after the randomly assigned year and zero for the two years before. The coefficients on the interactions of this POST_RAN variable with the 2010 wage gap, 5010 wage gap, Skill wage gap (CPS) and Skill wage gap (ASM) indicator variables are either statistically insignificant or positive. Panels B and C together show that the wage gap variables are associated with a decline in innovation only during the period surrounding the minimum wage shock.

Finally, we use multi-period regressions in Panel D of Table 6 to confirm that the decline in innovation observed in low wage gap industries was not already in progress before the minimum wage shock. The regression specification for the multi-period regressions is the same as described for Table 5-Panel D. The coefficients on the interactions with Before_1 are all insignificant. Thus, there is no evidence that the decline in innovation existed prior to the minimum wage shock. Rather, the coefficients on the interaction with After_1 or After_2 tend to be negative and statistically significant. Thus, the observed decline in patents and citations in low 2010 wage gap industries and low 5010 wag gap industries begins only after the minimum wage shock.

5. Technology characteristics

In this section, we explore whether the type of technology a firm is developing affects the sensitivity of its innovative output to wage shocks. We employ two methods to identify firms that are engaged in developing technology that reduces the demand for unskilled labor. In the first method, we machine-read patent descriptions to identify automation technology. In the second method, we follow the capital-skill complementarity literature to estimate the elasticity of the share of skilled wages to capital growth. If growth in capital stock shifts demand from unskilled labor to skilled labor, the share of skilled-worker wages rise with capital stock. In this section, we use the term labor-saving technology to refer to technology that reduces the demand for *low-skill* labor.

5.1 Automation

We machine-read descriptions of all patents filed by firms 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 our search words is presented in Table 7. Of the 301,694 patents applied for by firms over the four-year period surrounding the minimum wage shock, 68,525 patents contained at least one occurrence of words synonymous with automation. These patents were filed by 1,382 unique firms. As is evident from Table 7, the most commonly appearing word is ‘automatically’, which appears in 46,355 distinct patents and is used a total of 167,019 times. Other frequently used words are “automatic”, “automation”, “robotic” and “robot”.

To measure a firm’s engagement in automation technology at the time of the minimum wage shock, we aggregate the total number of appearances of the words listed in Table 7 for each firm during the year of the minimum wage shock. We call this firm-level measure *auto_count*. We also create an alternative measure called *Proportion auto_count.* This variable is calculated as the number of appearances of words synonymous with automation in a patent divided by total number of words in that patent, averaged across all patents applied for by the firm in the year of the shock. Panel A of Table 8 summarizes Auto_count (in logs) and Proportion auto_count.

Using these measures of auto_count, we create indicator variables to capture whether firms are likely to be engaged in labor-saving technology, i.e. technology that reduces the demand for unskilled labor. The variable *Low Auto_count* takes a value of 1 for firms with below median values of log auto_count and zero otherwise. The variable *Low Proportion auto_count* takes a value of 1 for firms with below median values of this ratio and zero otherwise. In Panel B, we regress patents and citations per patent on these indicator variables. Regression specifications are the same as in prior tables. The control variables are not tabulated for brevity. We see that in the patent regressions, the coefficients on the interaction of POST with both measures of low auto_count are negative and statistically significant. That is, decline in patenting after the minimum wage increase is more evident in firms that are not developing labor-saving technology as compared with firms engaged in labor-saving technology. In the regressions of citations per patent, the coefficient on POST x Low Auto_count leads to a similar conclusion. It is negative and statistically significant indicating that citations per patent decline more firms whose technological innovation does not replace unskilled workers as compared to firms engaged in automation. In column 4, the coefficient on the interaction of POST with Proportion auto_count is negative but statistically insignificant. Thus, three of the four specifications presented in Panel B are supportive of the hypothesis that the change in innovation after minimum wage shocks depends on the type of innovation the firms are engaged in.

Next, we conduct falsification tests. In our first falsification test, we replace automation words with a set of 20 randomly selected words. The random words are selected using the following procedure. First, we randomly select 10% of patents from our full sample of more than 300,000 patents. We collect all unique words appearing in this subset of randomly selected patents other than proper nouns and commonly occurring stop words such as ‘is’, ‘an’, ‘the’ etc. From this set, we randomly select 20 words. Next, we create a variable called *random_count* equal to the number of appearances of these random words in our full sample of more than 300,000 patents during the year of the minimum wage shock. We regress patent and citations per patent on two indicator variables. Low Random_count is a dummy variable equal to one for firms with below median values of random_count and zero otherwise. Proportion random_count is a dummy variable equal to one for firms with below median values of average ratio of the random words to total words in the patent and zero otherwise. In Table 8 Panel C, we regress patents and citations per patent on these two indicator variables. Both are statistically insignificant in the patents regression and citations regressions.

Next, we run a falsification test using random years as hypothetical events. In Panel D of Table 8, we present regressions of patents and citations on the interaction of POST_RAN and the automation indicator variables. We see that the interaction terms are statistically insignificant in all the regressions. The results in Table 8 together indicate the decline in innovation following minimum wage shocks is less pronounced in firms that, based on our count of automation words, are classified as developing labor-saving technology as compared firms that do not. This difference relation between innovative output and our automation measures is not observed around randomly selected years.

5.2 Capital-Skill Complementarity

In this section, we use an alternative method of identifying firms using technology that reduces demand for unskilled workers. There exists a large literature on skill-biased technological change in which capital stock embodies superior technology and interacts differently with skilled labor than with unskilled labor. Specifically, skill-biased technology increases demand for skilled labor relative to that of unskilled labor (see, for example, Griliches, 1969; Berman et al., 1994; Berman et al., 1998; Krusell et al., 2000; Duffy et al., 2004). We follow Berman, Bound, and Griliches (1994) to estimate the wage share of skilled workers in an industry. Assuming the cost function has a translog form and returns to scale are constant, they estimate the share equation in the quasi-fixed form. Capital is treated as fixed factor. That is, it is assumed that, in the short-term, firms are constrained in their choice of the level of capital. Assuming that firms minimize costs in choosing inputs, the following 'share' equation can be derived in first differences for the change in the share of wages paid to skilled workers

$$\Delta Skill\_Share_{s_j} = \beta_0 + \beta_1 \Delta ln\left(\frac{W_{s_j}}{W_{u_j}}\right) + \beta_2 \Delta ln\left(\frac{K_j}{Y_j}\right) + \epsilon_j \tag{1}$$

In this equation, $Skill\_Share_{s_j}$ is the share of wages paid to skilled labor in industry j, $w_{s_j}$and w_{u_j} are the wages of skilled and unskilled workers respectively, and the ratio $w_{s_j}/\ w_{u_j}$is the relative wage or the wage gap between the skilled and unskilled workers. The ratio K_j / Y_j is the industry's capital intensity where K_j represents capital stock, and Y_j represents output. If capital has a greater elasticity of substitution with unskilled labor than with skilled labor, then an increase in capital intensity will increase the wage share of skilled labor. That is, if capital-skill complementarity exists, then $\beta_2 > 0$.

There exists a possible endogeneity bias when estimating (1). Factors that affect a firm's capital investment may also be correlated with the demand for skilled labor. Following existing literature on capital-skill complementarity, we use GMM estimation with lagged values of capital intensity as weakly exogenous internal instruments (see Duffy et. al ,2004 and Larrain, 2015). This identification assumes that capital stock does not adjust to future technological shocks.

We estimate β_2 for each 2-digit SIC code using annual data on a panel of all 4-digit SIC codes within each 2-digit SIC. For robustness, we use two different data sources to estimate equation (1) and obtain two separate estimates of β_2. First, we follow Berman et. al and use data from the Annual Survey of Manufacturers (ASM). The ASM provides annual data on each 4-digit SIC code on hourly wages and total wages of production workers and non-production workers. Using this data, we define skill share as the share of wages paid to non-production workers divided by total wage bill in the industry. We use hourly wages of non-production workers as a proxy for wages of skilled workers (w_{s_j}). For w_{u_j}, wages of unskilled workers, we use hourly wages of production workers. Capital intensity is total capital stock divided by the industry's total value of shipments. The estimate of β_2 obtained using this data is referred to as β_2_ASM.

Second, we repeat the estimation using a different measure of skill from the CPS Merged Outgoing Rotation Group database. The CPS Merged Rotation Group database is a household-level survey that includes education level and wages earned. Using this data we calculate $Skill\_Share_{s_j}$ for each 4-digit SIC code as the dollar value of wages paid to skilled workers in the industry divided by total wages in the industry, where skilled workers are those with at least some college education and unskilled workers are those with a high school diploma or less. This is the same as the skill share measure calculated in Section 4.1 above. From the same database, we calculate relative wage in an industry as the hourly wages of workers in that industry with at least some college education divided by hourly wage of workers with a high school diploma or less. All wages are deflated to 1982 dollars. We use capital intensity as a proxy for $\frac{K_j}{Y_j}$, where capital intensity for each industry is calculated as industry total assets divided total industry sales, with both numbers obtained from Compustat. The estimate of β_2 obtained using this data is called β_2_CPS

Summary statistics of both measures of capital-skill complementarity, β_2_ASM and β_2_CPS, are provided in Panel A of Table 9. In industries with higher values of β_2, growth in capital is more likely to shift demand away from unskilled labor to skilled labor. Assuming that innovation is embedded within capital growth, the innovative output of industries with high values of β_2 is less likely to be affected by an increase in the cost of low-skill labor. We test this hypothesis by regressing patents and citations per patent on the interaction terms POST x β_2_ASM and POST x β_2_CPS. In alternate specifications, we interact POST with indicator variables to identify industries with above median values of β_2_ASM and β_2_CPS.

Results are presented in Panel B of Table 9. In columns 1 and 2 of Panel B the coefficient on the interaction of POST and β_2_CPS is positive and statistically significant for both patents and citations per patent. That is, decline in innovative output after the minimum wage shock is greater for industries with lower values of β_2_CPS, that is for industries that are less likely to have capital-skill complementarity. In columns 3 and 4, we interact POST with the indicator variable Low β_2_CPS which takes a value of 1 for industries that have below median values of β_2_CPS and zero otherwise. This indicator variable identifies industries that technological advancement (as captured by the growth in capital stock) does not shift demand away from unskilled to skilled labor. Columns 3 and 4 of Panel B show that these industries experience a greater decline in innovative output after minimum wage shocks. The interaction of POST with Low β_2_CPS is negative and statistically significant for both patents and citations per patent. In columns 5 through 8, we see that the same results hold for β_2_ASM.

In Panel C of Table 9, we present falsification tests using random years as hypothetical events. Patents and citations per patent are regressed on the interaction of POST_RAN and the capital-skill complementarity measures. Recall that POST_RAN is a dummy variable equal to 1 for the two years after the randomly assigned year and zero for the two years before. The interactions of POST_RAN with β_2_ASM and with β_2_CPS are insignificant in all the regressions shown in Panel B. The interactions of POST_RAN with the indicator variables Low β_2_CPS and Low β_2_ASM are also insignificant. Thus, there is no relation between changes in innovation and the capital-skill complementarity measures around the randomly selected years.

6. Robustness issues

In this section, we briefly discuss alternative explanations and robustness tests. First, we explore the role of financial constraints. An increase in factor costs reduces profits and can cause firms to scale back on financial resources devoted to innovation. If this is a valid explanation for the observed decline in innovation after minimum wage shocks, the decline would be more observable in cash constrained firms. We use four proxies for financial constraints – leverage, KZ index, free cash flow (FCF), and cash over total assets (CA_TA). We classify cash constrained firms as those with above median values of leverage and KZ index and below-median values of free cash flow and cash over total assets. Table10 presents regressions in which POST is interacted with dummy variables *High Leverage*, *High KZ*, *Low FCF*, and *Low CA_TA*. Most of the interaction terms are statistically insignificant. In one patent count regression (column 7), the interaction term is negative and statistically significant at the 10% level, indicating that the decline in patenting activity after the shock is more pronounced in firms with low values of cash over total assets. In one citations per patent regression (column 6), the interaction term is negative and statistically significant at the 10% level, indicating that the decline in citations after the shock is more pronounced in firms with low free cash flow. To summarize, 2 of the 8 specifications provide weak support of the financial constraints' hypothesis.

Our primary analysis focus on innovative output, as measured by patents and citations per patent. We also explore whether the input into the innovative process is affected by the minimum wage shocks. We calculate innovative input as R&D expenditure divided by industry total assets.

In untabulated tests, we find that R&D expense declines more for industries with a higher wage share of production workers and for industries with a higher wage share of unskilled workers, where skill is defined as having at least some college education. Industries with a tighter lower wage gap as measured by the 2010 wage gap and the 5010 wage gap experience larger declines in R&D expense. Thus, we find some evidence of a greater decline in R&D after minimum wage shocks in industries more reliant on unskilled workers or lower-wage workers. R&D expense does not have a robust relation with our automation or capital-skill complementarity measures.

5. Conclusion

Several strands of economic theory argue that the cost of labor affects corporate innovative output. Economic historians argue that the high cost of labor propels firms to develop labor-saving technology. For this reason, they posit that labor scarcity was the driving factor behind the technological advancement in the U.K. and U.S.A in the 18th and 19th centuries respectively. On the other hand, in neoclassical macroeconomic models and endogenous growth models, technology increases the marginal product of labor. These models imply that high cost of labor depresses technological development. Acemoglu (2010) captures these competing effects in a generalized framework and argues that a higher labor cost induces (discourages) innovation if the new technology is labor-saving (labor-complementary).

We apply this intuition to the impact of minimum wage increases on innovation. We hypothesize that the innovative output of firms engaged in technology that tends to increase the demand for unskilled labor will be more adversely affected by minimum wage increases. We use state-level and federal-level minimum wage changes in the United States as exogenous shocks to the cost of labor and, first document statistically significant declines in corporate innovative output, especially in industries that depend on unskilled workers. Next, we create firm-level and industry-level measures of technology that reduces demand for unskilled labor. Our firm-level measure is created by machine-reading patent descriptions for words synonymous with automation. Our industry-level measure is drawn from the capital-skill complementarity literature and captures the shift in demand from skilled to unskilled labor due to growth in capital stock. Both measures provide robust evidence that minimum wage shocks have a more negative effect on the innovative output of firms whose technology tends to increase the demand for unskilled labor.

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Table 1. Minimum wage shocks

This table presents the distribution of minimum wage events across fifty U.S. states and years. The sample period runs from 1985 to 2010. The minimum wage data is obtained from the Department of Labor: https://www.dol.gov/whd/state/stateMinWageHis.htm. The minimum wage events are selected as follows: A state-year is selected as a "minimum wage event" if the effective minimum wage in a state increases in the current years but experience no changes in the past three years. The effective minimum wage in a state is defined as the maximum of state-level minimum wage or federal-level minimum wage. For state-years without an applicable state-level minimum wage, the federal minimum wage applies. The last column shows the total number of events experienced by each state. The last row of the table shows the total number of events by each year.

	87	88	89	90	91	92	93	94	95	96	97	98	99	00	01	02	03	04	05	06	07	Total
Alabama				1						1											1	3
Alaska				1						1						1						3
Arizona				1						1											1	3
Arkansas				1						1										1		3
California		1								1											1	3
Colorado				1						1											1	3
Connecticut	1									1												2
Delaware				1						1											1	3
Florida				1						1										1		3
Georgia				1						1											1	3
Hawaii		1														1						2
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	3
Massachusetts										1											1	2
Michigan				1						1										1		3
Minnesota		1								1									1			3
Mississippi				1						1											1	3
Missouri				1						1											1	3
Montana				1						1											1	3
Nebraska				1						1											1	3
Nevada				1						1										1		3
New Hampshire	1									1											1	3
New Jersey				1							1								1			3
New Mexico				1						1											1	3
New York				1						1									1			3
North Carolina				1						1											1	3
North Dakota			1							1											1	3
Ohio				1						1											1	3
Oklahoma				1						1											1	3
Oregon			1								1						1					3
Pennsylvania			1							1											1	3
Rhode Island										1								1				2
South Carolina				1						1											1	3
South Dakota				1						1											1	3
Tennessee				1						1											1	3
Texas				1						1											1	3
Utah				1						1											1	3
Vermont									1													1
Virginia				1						1											1	3
Washington			1					1														2
West Virginia				1																1		2
Wisconsin			1							1									1			3
Wyoming																					1	1
Total	2	3	5	35	0	0	0	1	1	43	2	0	0	0	0	3	1	2	4	5	32	139

Table 2. Change in wages after minimum wage shocks

This table presents the changes in hourly wages after the minimum wage shock. Minimum wage shocks are described in Table 1. The wage distribution is computed using the CPS Merged Outgoing Rotation Groups database during the period 1980-2010. This household survey includes weekly hours and earnings of workers ages 16 to 64 with 0 to 39 years, excluding unemployed workers and self-employed workers. Following Hirsh and Shumacher 2004, the sample only uses the non-imputed weekly wages or hourly wages. The wage data are transformed to hourly wages and are deflated to 1982 dollars using CPI-U deflator. The pre-event period is defined as the two years preceding the year in which the minimum wage change occurred, and post-event period is defined as two years following the event year. The year of the shock is excluded.

Distribution of hourly wages before and after minimum wage shock

	Minimum Wage	P10	P20	P50	P80	P90	Obs
Before Event	2.807	3.461	4.217	6.719	11.268	14.599	139
After Event	3.203	3.568	4.279	6.835	11.457	14.831	139
After - Before	0.396***	0.107***	0.061	0.117	0.189	0.232	139
P-Value	[0.000]	[0.000]	[0.162]	[0.144]	[0.216]	[0.250]	
Percentage increase	14.11%	3.09%	1.45%	1.74%	1.68%	1.59%	

Table 3. Summary statistics of dependent and independent variables

This table summarizes the two dependent variable, *Patents* and *Citations*, and several control variables used throughout the paper. Patents is defined as natural logarithm of one plus firm *j*'s total number of patents filed in the year *t*. Citations is defined as logarithm of one plus firm j's non-self-citations received on firm *j*'s patents filed in year *t*, corrected for truncation bias following Hall, Jaffe, and Trajtenberg (2001,2005). Firm-level patent and citation data from 1985 - 2006 are obtained from National Bureau of Economic Research (NBER) Patent Data Project. Firm-level patent and citation data from 2007-2010 are obtained from Kogan, Papanikolaou, Seru and Stoffman (2018): https://iu.app.box.com/v/patents. The following firm-level characteristics are from COMPUSTAT. *SIZE* is the logarithm of firm j's market capitalization; RDTA is research and development expenditures divided by the book value of assets (0 if missing); ROA is the return on assets computed as operating income before depreciation divided by book value of assets; PPETA is the property, plant and equipment divided by book value of total assets; LEVERAGE is the book value of long term debt divided by book value of total assets; CAPEXTA is total capital expenditures divided by the book value of total assets; HHI is the sum of squares of market shares of all firms in an industry, with industry defined at 3 digit NAICS code; HHISQ is the square of HHI. Q is firm j's market to book ratio; LNAGE is the logarithm of the firm age since listing on a U.S. exchange.

	Mean	Median	Min	Max	N	SD
PATENTS	0.493	0.000	0.000	8.231	29644	1.109
CITATIONS	0.900	0.000	0.000	11.553	29644	1.932
SIZE	5.559	5.464	0.840	10.249	29644	2.048
RDTA	0.038	0.000	0.000	0.537	29644	0.082
ROA	0.100	0.119	-0.926	0.456	29644	0.164
PPETA	0.291	0.225	0.000	0.912	29644	0.245
LEVERAGE	0.200	0.127	0.000	0.867	29644	0.216
CAPEXTA	0.060	0.042	0.000	0.376	29644	0.064
HHI	0.284	0.212	0.014	1.000	29644	0.213
HHISQ	0.126	0.045	0.000	1.000	29644	0.198
Q	1.858	1.368	0.585	10.328	29644	1.458
LNAGE	2.422	2.565	0.000	4.159	29644	1.026

Table 4. Change in innovation after wage shock

This table analyzes the change in innovative output after minimum wage shocks from 1985 to 2010. Columns 1 through 6 include all firms-years in states affected by minimum wage shocks from two years before the shock till two years after the shock, but excluding the year of shock itself. Wage shocks are described in Table 1. The dependent variables Patents and Citations and all control variables are described in Table 3. The explanatory variable of interest is a dummy variable called POST that is equal to 1 for the two years after the wage shock and 0 for the two years before the shock. Ordinary least squares regressions including firm- and year-fixed effects are presented with standard errors clustered by industry. Columns 5 and 6 include a dummy variable equal to one if the state was carried by the Democratic candidate in the most recent presidential election and zero if it was won by a Republican candidate. All regressions include interactions between the control variables and POST but these coefficients are not tabulated for brevity. Columns 6 and 7 present falsification tests with a randomly selected 'event' year during which the state does not experience a minimum wage shock. In these regressions, POST_RAN All is equal to 1 for the two years after the randomly selected year and 0 for the two years before the random year. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

							Falsification Test	
	(1) Patents	(2) Citations	(3) Patents	(4) Citations	(5) Patents	(6) Citations	(7) Patents	(8) Citations
POST	-0.1051***	-0.1782***	-0.4987***	-0.6854***	-0.5728***	-0.7847***		
	(-2.62)	(-2.84)	(-3.67)	(-3.94)	(-3.74)	(-3.98)		
POST_RAN							-0.0249	0.0533
							(-0.48)	(0.59)
SIZE			0.0729***	0.1299***	0.0743***	0.1309***	0.0850***	0.1425***
			(4.15)	(4.71)	(4.15)	(4.69)	(4.09)	(4.30)
RDTA			-0.0051	1.0819***	0.0251	1.1239***	0.5782***	1.8403***
			(-0.03)	(4.94)	(0.14)	(5.00)	(3.92)	(4.14)
ROA			-0.2714***	-0.3466***	-0.2756***	-0.3523***	-0.1470***	0.0353
			(-2.88)	(-2.64)	(-2.89)	(-2.65)	(-3.55)	(0.25)
PPETA			0.2802**	0.6294***	0.2618**	0.6013***	0.0129	0.0752
			(2.52)	(2.72)	(2.49)	(2.70)	(0.16)	(0.57)
LEVERAGE			0.0809	0.0459	0.0803	0.0435	0.1398***	0.2202***
			(1.62)	(0.41)	(1.62)	(0.39)	(3.08)	(3.00)
CAPEXTA			0.0036	0.2730	-0.0136	0.2612	-0.1608	-0.3744
			(0.03)	(0.88)	(-0.10)	(0.87)	(-1.06)	(-1.34)
HHI			0.2373	0.7711	0.2295	0.7648	0.1381	0.4034
			(0.93)	(1.31)	(0.91)	(1.31)	(0.53)	(0.81)
HHISQ			-0.1807	-0.5481	-0.1789	-0.5478	-0.0657	-0.2686
			(-0.83)	(-1.06)	(-0.83)	(-1.07)	(-0.25)	(-0.61)
Q			-0.0199***	-0.0258***	-0.0196***	-0.0252***	-0.0187**	-0.0374**
			(-3.06)	(-2.96)	(-3.05)	(-2.93)	(-2.48)	(-2.19)
LNAGE			0.1272***	0.3204***	0.1274***	0.3194***	0.0314*	0.1394***
			(3.38)	(3.80)	(3.40)	(3.81)	(1.67)	(3.02)
DEMOCRATIC					-0.0958**	-0.2166***		
					(-2.27)	(-2.71)		
POST x DEMOCRATIC					0.1318***	0.1675**		
					(2.72)	(2.56)		
N	29644	29644	29644	29644	29644	29644	22288	22288
adj. R^2	0.76	0.70	0.78	0.71	0.78	0.71	0.87	0.80

Table 5. Low-skill industries and change in innovation

This table presents the change in innovation after minimum wage shocks from 1985 to 2010 conditional on the labor characteristics of an industry. Wage shocks are described in Table 1.

Panel A summarizes three measures of industry labor characteristics. The first is the dollar value of wages paid to production workers divided by total payroll in the industry. These data from the Annual Survey of Manufacturers. The second variable is the dollar value of wages paid to skilled workers divided by total industry wages, where skilled workers are those with at least some college education. These data are from the CPS Merged Rotation Database. The third measure is the average hourly wage rate in the industry obtained from the Bureau of Labor Statistics Quarterly Census of Employment and Wages. All three measures are calculated prior to the minimum wage shock.

Panel B presents regressions of patents and citations on the interaction between POST and three indicator variables based on the labor characteristics summarized in Panel A. The dependent variables *Patents* and *Citations* are described in Table 3. POST is a dummy variable equal to 1 for the two years after the wage shock and 0 for the two years before the shock. *Blue-collar industry* is a dummy variable that equals 1 for industries with the share of production worker wages above the sample median and 0 otherwise. *Low-skill industry* is a dummy variable that equals 1 for industries with the share of skilled worker wages below the sample median and 0 otherwise. *Low-wage industry* is a dummy variable that equals 1 for the industries with average hourly wage rate in 1982 dollars below the sample median and 0 otherwise.

Panel C presents falsifications tests with a randomly selected 'event' year during which the state does not experience a minimum wage shock. In Panel C, POST_RAN is equal to one for the two years following the hypothetical event year and zero for the two years prior to the hypothetical event year. All other variables are the same as in Panel B.

Panel D presents multi-period regressions. *Before_1* which is equal to 1 if the firm-year observation is from the one year preceding the year in which the minimum wage change occurred and zero otherwise, *After_1* which is equal to 1 if the firm-year observation is from year following the year in which the minimum wage shock occurred and 0 otherwise, and After_ 2 which is equal to 1 if the firm-year observation is from for the second year following the minimum wage shock and 0 otherwise.

The set of control variables included in all regressions but not shown in the tables is the same as in Table 4. All regressions include the interactions between POST or POST_RAN and each control variable. All regressions include firm- and year-fixed effects with standard errors clustered by industry. *t* statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

Panel A: Summary Statistics of industry labor characteristics

	Mean	Median	Min	Max	SD
Production worker wages /Total industry payroll (ASM)	0.504	0.512	0.256	0.814	0.075
Skilled worker wages/Total wages in industry (CPS)	0.687	0.683	0.247	0.993	0.163
Log (Average hourly wage)	2.476	2.503	1.725	2.874	0.207

Panel B: Change in innovation after wage shock

	(1) Patents	(2) Citations	(3) Patents	(4) Citations	(5) Patents	(6) Citations
POST x Blue-collar industry	-0.0508**	-0.0532				
	(-2.05)	(-1.22)				
POST x Low-skill industry			-0.1100**	-0.1398**		
			(-2.38)	(-2.12)		
POST x Low-wage industry					-0.0292**	-0.0484**
					(-2.09)	(-2.01)
POST	-0.4912***	-0.6716***	-0.4499***	-0.5669***	-0.4953***	-0.6822***
	(-3.69)	(-4.00)	(-4.01)	(-3.39)	(-3.68)	(-3.94)
Blue-collar industry	0.0296	-0.0366				
	(0.74)	(-0.50)				
Low-skill industry			0.0437	0.2517		
			(0.55)	(1.17)		
Low-wage industry					-0.0363	-0.1338
					(-0.86)	(-1.46)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29564	29564	18468	18468	29644	29644
Adjusted R^2	0.78	0.71	0.77	0.69	0.78	0.71

Panel C: Change in innovation after random year (Falsification test)

	(1) Patents	(2) Citations	(3) Patents	(4) Citations	(5) Patents	(6) Citations
POST_RAN x Blue-collar industry	0.0060	-0.0283				
	(0.48)	(-0.86)				
POST_RAN x Low-skill industry			0.0129	0.0572		
			(0.83)	(1.56)		
POST_RAN x Low-wage industry					0.0126	0.0564
					(1.20)	(1.61)
POST	-0.0360	0.0499	0.0509	0.2969**	-0.0287	0.0368
	(-0.71)	(0.54)	(0.97)	(2.52)	(-0.55)	(0.41)
Blue-collar industry	0.0918***	0.1048				
	(3.07)	(1.65)				
Low-skill industry			-0.0374	-0.1393		
			(-1.17)	(-1.21)		
Low-wage industry					0.0004	-0.0141
					(0.01)	(-0.21)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22252	22252	13972	13972	22288	22288
Adjusted R^2	0.87	0.80	0.88	0.80	0.87	0.80

Panel D: Change in innovation after wage shock: multiperiod regressions

	(1) Patents	(2) Citations	(3) Patents	(4) Citations	(5) Patents	(6) Citations
Before_1 x Blue-collar industry	0.0249	0.0063				
	(1.45)	(0.21)				
After_1 x Blue-collar industry	-0.0747**	-0.0934*				
	(-2.56)	(-1.89)				
After_2 x Blue-collar industry	-0.1298***	-0.1581***				
	(-3.79)	(-3.11)				
Blue-collar industry	0.1298***	0.3078***				
	(3.05)	(3.95)				
Before_1 x Low-skill industry			-0.0205	-0.0504		
			(-0.97)	(-1.36)		
After_1 x Low-skill industry			-0.0981***	-0.1346**		
			(-2.98)	(-2.54)		
After_2 x Low-skill industry			-0.1327***	-0.1566**		
			(-3.13)	(-2.37)		
Low-skill industry			0.0361	0.1805		
			(0.41)	(0.71)		
Before_1 x Low wage industry					0.0513***	0.0784***
					(4.46)	(3.46)
After _1 x Low wage industry					-0.0200	0.0006
					(-0.95)	(0.02)
After_2 x Low wage industry					-0.0790**	-0.1059**
					(-2.53)	(-2.38)
Low wage industry					0.1556***	0.4465***
					(4.55)	(5.46)
Before_1	0.1107***	0.2256***	0.1806***	0.3056***	0.0945***	0.1852**
	(4.05)	(3.14)	(4.18)	(2.80)	(3.40)	(2.58)
After_1	-0.0616	0.2013	-0.0328	0.4326**	-0.0828	0.1451
	(-0.64)	(1.53)	(-0.37)	(2.29)	(-0.88)	(1.13)
After_2	-0.1279	0.1604	-0.0425	0.5012***	-0.1444	0.1190
	(-1.27)	(1.45)	(-0.43)	(2.92)	(-1.47)	(1.10)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29564	29564	18468	18468	29644	29644
Adjusted R^2	0.75	0.68	0.74	0.65	0.75	0.68

Table 6. Wage gap and change in innovation

This table presents the change in innovation after minimum wage shocks from 1985 to 2010 conditional on the labor characteristics of an industry. Wage shocks are described in Table 1.

Panel A summarizes three measures of the wage gap in an industry. The *2010 Wage gap* is computed as the wage level at the 20th percentile minus the wage level at the 10th percentile. The *5010 Wage gap* is computed as the wage level at the 50th percentile minus the wage level at the 10th percentile. The *9050 Wage gap* is computed as the wage level at the 90th percentile minus the wage level at the 50th percentile. *Skill wage gap (CPS)* is calculated as the hourly wage of skilled workers divided by hourly wage of unskilled workers, where skilled workers are those with at least some college education and unskilled are those with a high school diploma or less. All four of these measures are obtained from the CPS Merged Outgoing Rotation Groups database during the 1980-2010 period. *Skill wage gap (ASM)* is calculated as the hourly wage of non-production workers divided by the hourly wage of production workers, with the data obtained from the Annual Survey of Manufacturers. All five measures of wage gap are calculated prior to the minimum wage shock.

Panel B presents regressions of patents and citations on the interaction between POST and five indicator variables based on the wage gap variables summarized in Panel A. The dependent variables patents and citations are described in Table 3. POST is a dummy variable equal to 1 for the two years after the wage shock and 0 for the two years before the shock. *Low 2010 wage gap* is a dummy variable that equals 1 for industries with 2010 wage gap below the sample median and 0 otherwise. *Low 5010 wage gap* is a dummy variable that equals 1 for industries with 5010 wage gap below the sample median and 0 otherwise. *Low 9050 wage gap* is a dummy variable that equals 1 for industries with 9050 wage gap below the sample median and 0 otherwise. *Low skill wage gap (CPS)* is a dummy variable that equals 1 for industries with Skill wage gap (CPS) below the sample median and 0 otherwise. *Low skill wage gap (ASM)* is a dummy variable that equals 1 for industries with Skill wage gap (ASM) below the sample median and 0 otherwise.

Panel C presents falsifications tests with a randomly selected 'event' year during which the state does not experience a minimum wage shock. In Panel C, POST_RAN is equal to one for the two years following the hypothetical event year and zero for the two years prior to the hypothetical event year. All other variables are the same as in Panel B.

Panel D presents multi-period regressions. *Before_1* which is equal to 1 if the firm-year observation is from the one year preceding the year in which the minimum wage change occurred and zero otherwise, *After_1* which is equal to 1 if the firm-year observation is from year following the year in which the minimum wage shock occurred and 0 otherwise, and After_ 2 which is equal to 1 if the firm-year observation is from for the second year following the minimum wage shock and 0 otherwise.

The set of control variables included in all regressions but not shown in the tables is the same as in Table 4. All regressions include the interactions between POST or POST_RAN and each control variable. All regressions include firm- and year-fixed effects with standard errors clustered by industry. *t* statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

Panel A: Summary statistics of wage gap measures

	Mean	Median	Min	Max	SD
2010 Wage gap	1.054	0.992	0.000	4.520	0.506
5010 Wage gap	4.023	3.790	0.583	10.650	1.644
9050 Wage gap	8.523	8.482	2.180	18.952	2.878
Skill wage gap (CPS)	1.533	1.504	1.000	4.350	0.233
Skill wage gap (ASM)	1.015	1.021	0.304	2.928	0.566

Panel B: Pre-shock wage gap and change in innovation after minimum wage shock

	(1) Patents	(2) Citations	(3) Patents	(4) Citations	(5) Patents	(6) Citations	(7) Patents	(8) Citations	(9) Patents	(10) Citations
POST x Low 2010 wage gap	-0.1063***	-0.1196**								
	(-2.88)	(-2.10)								
POST x Low 5010 wage gap			-0.0971**	-0.1256**						
			(-2.40)	(-2.15)						
POST x Low skill wage gap (CPS)					-0.0890*	-0.1182*				
					(-1.69)	(-1.74)				
POST x Low skill wage gap (ASM)							-0.1721**	-0.3050***		
							(-2.73)	(-3.93)		
POST x Low 9050 wage gap									-0.0093	-0.0242
									(-0.30)	(-0.51)
POST	-0.4122***	-0.5537***	-0.4163***	-0.5443***	-0.4295***	-0.5471***	-0.3223**	-0.4690**	-0.4582***	-0.5983***
	(-3.69)	(-3.72)	(-3.77)	(-3.76)	(-3.70)	(-3.21)	(-2.34)	(-2.55)	(-3.66)	(-3.56)
2010 wage gap	0.0887**	0.2603***								
	(2.58)	(2.73)								
5010 wage gap			0.1035**	0.1894**						
			(2.50)	(2.20)						
Skill wage gap (CPS)					0.1029	0.2217				
					(1.63)	(1.63)				
Skill wage gap (ASM)							0.0384	0.0754		
							(1.05)	(0.72)		
9050 wage gap									0.0134	0.0048
									(0.23)	(0.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27076	27076	27076	27076	18468	18468	10931	10931	27076	27076
Adjusted R^2	0.78	0.72	0.78	0.72	0.77	0.69	0.79	0.73	0.78	0.72

Panel C: Wage gap and change in innovation after random year (Falsification test)

	(1) Patents	(2) Citations	(3) Patents	(4) Citations	(5) Patents	(6) Citations	(7) Patents	(8) Citations	(9) Patents	(10) Citations
POST_RAN x Low 2010 wage gap	0.0194	0.0311								
	(1.58)	(1.10)								
POST_RAN x Low 5010 wage gap			0.0142	0.0547*						
			(1.10)	(1.69)						
POST_RAN x Low skill wage gap (CPS)					0.0392*	0.1412***				
					(1.92)	(2.98)				
POST_RAN x Low skill wage gap (ASM)							0.0076	0.0854*		
							(0.34)	(1.80)		
POST_RAN x Low 9050 wage gap									0.0155	0.0296
									(1.16)	(0.85)
POST_RAN	-0.0332	0.0411	-0.0278	0.0377	0.0217	0.2342**	-0.0439	-0.0024	-0.0013	0.1029
	(-0.61)	(0.47)	(-0.55)	(0.43)	(0.42)	(2.07)	(-0.49)	(-0.02)	(-0.02)	(1.17)
2010 wage gap	0.0037	0.0382								
	(0.14)	(0.71)								
5010 wage gap			-0.0312	0.0120						
			(-0.72)	(0.17)						
Skill wage gap (CPS)					0.0073	-0.0605				
					(0.23)	(-1.13)				
Skill wage gap (ASM)							-0.0586	-0.2832**		
							(-1.10)	(-2.18)		
9050 wage gap									-0.0174	-0.0505
									(-0.52)	(-0.61)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21296	21296	21296	21296	13952	13952	10222	10222	20748	20748
Adjusted R^2	0.87	0.80	0.87	0.80	0.88	0.80	0.87	0.79	0.87	0.80

Panel D: Wage gap and change in innovation: Multiperiod regressions

	(1) Patents	(2) Citations	(3) Patents	(4) Citations	(5) Patents	(6) Citations	(7) Patents	(8) Citations	(9) Patents	(10) Citations
Before_1 x Low 2010 Wage gap	0.0258	0.0058								
	(0.76)	(0.13)								
After_1 x Low 2010 Wage gap	-0.0834***	-0.1213**								
	(-2.82)	(-2.31)								
After_2 x Low 2010 Wage gap	-0.0797***	-0.0776								
	(-2.86)	(-1.64)								
Low 2010 Wage gap	0.0651	0.2323								
	(1.43)	(1.53)								
Before_1 x Low 5010 Wage gap			0.0141	-0.0028						
			(0.56)	(-0.10)						
After_1 x Low 5010 Wage gap			-0.0713***	-0.1047**						
			(-2.70)	(-2.24)						
After_2 x Low 5010 Wage gap			-0.0760**	-0.0958*						
			(-2.45)	(-1.83)						
Low 5010 Wage gap			0.0912*	0.1841						
			(1.74)	(1.42)						
Before_1 x Low skill wage gap (CPS)					0.0235	-0.0100				
					(0.91)	(-0.36)				
After_1 x Low skill wage gap (CPS)					-0.0890**	-0.1505**				
					(-2.15)	(-2.30)				
After_2 x Low skill wage gap (CPS)					-0.1136**	-0.1303**				
					(-2.35)	(-2.03)				
Low skill wage gap (CPS)					0.1027	0.2450*				
					(1.51)	(1.70)				
Before_1 x Low skill wage gap (ASM)							0.0329	-0.0119		
							(0.72)	(-0.20)		
After_1 x Low skill wage gap (ASM)							-0.1330	-0.2856**		
							(-1.62)	(-2.73)		
After_2 x Low skill wage gap (ASM)							-0.1219	-0.2614		
							(-0.93)	(-1.50)		
Low skill wage gap (ASM)							-0.0389	-0.1039		
							(-0.75)	(-0.59)		
Before_1 x Low 9050 Wage gap									-0.0012	-0.0258
									(-0.10)	(-0.93)
After_1 x Low 9050 Wage gap									0.0191	0.0235
									(0.88)	(0.60)
After_2 x Low 9050 Wage gap									0.0014	-0.0212
									(0.06)	(-0.56)
Low Wage gap									-0.0107	-0.0630
									(-0.12)	(-0.27)
Before_1	0.0829**	0.2042**	0.0876**	0.2061**	0.1733***	0.3056***	0.1140	0.4554**	0.0947***	0.2097***
	(2.23)	(2.47)	(2.51)	(2.63)	(4.11)	(2.83)	(1.10)	(2.29)	(3.04)	(2.75)
After_1	-0.0751	0.2396*	-0.0803	0.2290*	-0.0085	0.4716**	0.3675***	1.1659***	-0.1137	0.1790
	(-1.00)	(1.98)	(-1.06)	(1.85)	(-0.09)	(2.46)	(3.58)	(8.39)	(-1.47)	(1.43)
After_2	-0.1086	0.2304**	-0.1108	0.2339**	-0.0137	0.5345***	0.2931**	1.0013***	-0.1435	0.1942*
	(-1.25)	(2.25)	(-1.29)	(2.30)	(-0.14)	(3.08)	(2.21)	(7.16)	(-1.52)	(1.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27076	27076	27076	27076	18468	18468	10932	10932	27076	27076
Adjusted R^2	0.76	0.69	0.76	0.68	0.74	0.65	0.74	0.67	0.76	0.68

Table 7. Identification of automation technology

This table shows the occurrence of words indicative of labor-saving technology in patents filed by firms headquartered in states experiencing minimum wage shocks. Of 301,694 patents filed during the two years before and two years after the minimum wage shock, 68,525 patents filed by 6,846 firms contained at least one of the words listed below. Column 1 shows the number of patents in which the word appeared at least once and column 2 shows the total number of appearances of the word across all 68,525 patents.

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Appearances of words synonymous with automation in patent descriptions

	1	2
Word indicative of labor-saving technology	Patents containing word	Total appearances of word
automatically	46,355	167,019
automatic	32,564	124,808
automation	5,871	14,971
robotic	3,165	17,859
robot	3,000	34,150
automate	1,927	2,398
self-	424	538
mechanization	287	500
mechanize	57	65
labor-saving	13	17
robotization	8	8
robotize	4	4

Table 8. Automation and change in innovation

This table presents the change in innovation after minimum wage shocks from 1985 to 2010 conditional on a firm's engagement in automation technology. Wage shocks are described in Table 1.

Panel A shows summary statistics of two firm-level measures of automation. The variable *Auto_count* is the total number of appearances of any of the words synonymous with automation shown in Table 7 across all patents applied for by a firm in the year the minimum wage shock occurs. *Proportion auto_count* is the number of appearances of words synonymous with automation in a patent divided by total number of words in that patent, averaged across all patents applied for by the firm in the year of the shock.

Panel B presents regressions of patents and citations on the interaction between POST and two indicator variables based on the automation variables summarized in Panel A. The dependent variables patents and citations are described in Table 3. POST is a dummy variable equal to 1 for the two years after the wage shock and 0 for the two years before the shock. *Low Auto_count* is a dummy variable equal to 1 if log (Auto_count) is below the sample median and zero otherwise. *Low Proportion auto_count* is a dummy variable equal to 1 if Proportion auto_count is below the sample median and zero otherwise.

Panel C presents falsification tests in which patents and citations per patent are regressed on the interaction between POST and two indicator variables based the appearance of 20 randomly selected words in patent descriptions. We create variables Random_count and Proportion random_count using these randomly selected words instead of words synonymous with automation. In Panel C, the dummy variable *Low random_count* is a dummy variable equal to 1 for below median values of log(Random_count) and zero otherwise. *Low Proportion random_count* is a dummy variable equal to 1 for below median values of Proportion random_count and zero otherwise

Panel D presents falsifications tests with a randomly selected 'event' year during which the state does not experience a minimum wage shock. In Panel D, POST_RAN is equal to one for the two years following the hypothetical event year and zero for the two years prior to the hypothetical event year. All other variables are the same as in Panel B.

The set of control variables included in all regressions but not shown in the tables is the same as in Table 4. All regressions include the interactions between POST or POST_RAN and each control variable. All regressions include firm- and year-fixed effects with standard errors clustered by industry. *t* statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

Panel A: Summary stats of automation measures

	mean	p50	min	max	sd
Auto_count (in logs)	1.545	1.098	0.000	8.831	1.767
Proportion auto_count (x 100)	0.038	0.016	0.000	1.939	0.078

Panel B: Automation words and change in innovation after minimum wage shock

	(1) Patents	(2) Citations	(3) Patents	(4) Citations
POST x Low auto_count	-0.0960***	-0.1093**		
	(-3.65)	(-2.21)		
POST x Low Proportion auto_count			-0.0689***	-0.0619
			(-2.66)	(-1.26)
POST	-0.4269**	-0.5308**	-0.5026***	-0.6336**
	(-2.28)	(-2.00)	(-2.97)	(-2.47)
Low auto_count	-0.5206***	-0.7206***		
	(-17.75)	(-13.59)		
Low Proportion auto_count			-0.3985***	-0.5868***
			(-15.60)	(-14.16)
Controls	Yes	Yes	Yes	Yes
Observations	6635	6635	6635	6635
Adjusted R^2	0.84	0.80	0.83	0.80

Panel C: Random words and change in innovation after minimum wage shock (Falsification test)

	(1) Patents	(2) Citations	(3) Patents	(4) Citations
POST x Low random_count	-0.0453	-0.0331		
	(-1.34)	(-0.61)		
POST x Low Proportion random_count			-0.0345	-0.0054
			(-0.85)	(-0.09)
POST	-0.5999***	-0.7757***	-0.6106***	-0.7945***
	(-3.08)	(-2.92)	(-3.81)	(-3.44)
Low random_count	-0.6170***	-0.8183***		
	(-19.23)	(-20.54)		
Low Proportion random_count			-0.3253***	-0.4270***
			(-9.58)	(-10.13)
Controls	Yes	Yes	Yes	Yes
Observations	6635	6635	6635	6635
Adjusted R^2	0.84	0.81	0.83	0.79

Panel D: Automation words and change in innovation after random year (Falsification test)

	(1) Patents	(2) Citations	(3) Patents	(4) Citations
POST_RAN x Low auto_count	0.0317	0.0264		
	(0.77)	(0.46)		
POST_RAN x Low Proportion auto_count			0.0317	0.0264
			(0.77)	(0.46)
POST_RAN	-0.2302**	-0.2462*	-0.2302**	-0.2462*
	(-2.41)	(-1.83)	(-2.41)	(-1.83)
Low auto_count	-0.2805***	-0.4830***		
	(-9.38)	(-9.83)		
Low Proportion auto_count			-0.2805***	-0.4830***
			(-9.38)	(-9.83)
Observations	5575	5575	5575	5575
Adjusted R^2	0.88	0.80	0.88	0.80

Table 9. Capital skill complementary and change in innovation

This table presents the change in innovation after minimum wage shocks from 1985 to 2010 conditional on industry-level estimates of capital-skill complementarity. Wage shocks are described in Table 1.

Panel A shows summary statistics of two estimates of capital-skill complementarity. β_2_CPS is a capital-skill complementarity index estimated from skilled labor share equation using data from the CPS Outgoing Rotation Group database. Workers with at least some college education are skilled and those with high school diploma or less are classified as unskilled. β_2_ASM is a capital-skill complementarity index estimated from skilled labor share equation using data from Annual Survey of Manufacturers. In this measure, non-production workers are considered skilled and production workers are classified as unskilled.

Panel B presents regressions of patents and citations on the interaction between POST and two capital skill complementarity measures β_2_CPS and β_2_ASM as well as with indicator variables based on the capital-skill complementarity measures. *Low* β_2_CPS is a dummy variable equal to 1 if β_2_CPS is below the sample median and zero otherwise. *Low* β_2_ASM is a dummy variable equal to 1 if β_2_ASM is below the sample median and zero otherwise. The dependent variables, patents and citations, are described in Table 3. POST is a dummy variable equal to 1 for the two years after the wage shock and 0 for the two years before the shock.

Panel C presents falsifications tests with a randomly selected 'event' year during which the state does not experience a minimum wage shock. In Panel C, POST_RAN is equal to one for the two years following the hypothetical event year and zero for the two years prior to the hypothetical event year. All other variables are the same as in Panel B.

The set of control variables included in all regressions but not shown in the tables is the same as in Table 4. All regressions include the interactions between POST or POST_RAN and each control variable. All regressions include firm- and year-fixed effects with standard errors clustered by industry. *t* statistics are in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively

Panel A: Summary statistics of capital skill complementary

	mean	p50	min	max	sd
β_2_CPS	0.0198	0.0152	-0.4956	0.4852	0.0803
β_2_ASM	0.0134	0.0005	-0.5101	0.6500	0.3029

Panel B: Capital skill complementary and change in innovation after minimum wage shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patents	Citations	Patents	Citations	Patents	Citations	Patents	Citations
POST x β_2_CPS	0.6345***	0.9447***						
	(3.04)	(3.42)						
POST x Low β_2_CPS			-0.0607*	-0.1222***				
			(-1.95)	(-2.88)				
POST x β_2_ASM					0.3838***	0.6405***		
					(5.97)	(6.95)		
POST x Low β_2_ASM							-0.1047*	-0.1530*
							(-2.03)	(-1.73)
POST	-0.4285***	-0.4983***	-0.3942***	-0.4413***	-0.3948***	-0.5914***	-0.2855**	-0.4213**
	(-3.82)	(-3.24)	(-3.56)	(-2.88)	(-2.99)	(-3.26)	(-2.22)	(-2.43)
Low β_2_CPS			0.0131	-0.0078				
			(0.13)	(-0.03)				
Low β_2_ASM							-0.0836	-0.1654
							(-1.58)	(-1.50)
Observations	16024	16024	16024	16024	10931	10931	10931	10931
Adjusted R^2	0.79	0.72	0.78	0.72	0.79	0.73	0.79	0.73

Panel C: Capital skill complementary and change in innovation after random year (Falsification test)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patents	Citations	Patents	Citations	Patents	Citations	Patents	Citations
POST x β_2_CPS	-0.0504	-0.1220						
	(-0.76)	(-0.78)						
POST x Low β_2_CPS			0.0084	0.0072				
			(0.60)	(0.20)				
POST x β_2_ASM					-0.0365	-0.0914		
					(-0.61)	(-0.88)		
POST x Low β_2_ASM							0.0079	-0.0263
							(0.37)	(-0.48)
POST	-0.0283	0.0500	-0.0311	0.0445	-0.0505	0.0097	-0.0580	0.0057
	(-0.51)	(0.53)	(-0.54)	(0.44)	(-0.54)	(0.06)	(-0.69)	(0.04)
Low β_2_CPS			0.1274	0.1042				
			(1.34)	(0.87)				
Low β_2_ASM							-0.2960*	-0.3802*
							(-1.97)	(-2.02)
Observations	20492	20492	20492	20492	10414	10414	10414	10414
Adjusted R^2	0.87	0.79	0.87	0.79	0.87	0.79	0.87	0.79

Table 10. Financial Constraints and change in innovation

This table presents the change in innovation after minimum wage shocks from 1985 to 2010. Wage shocks are described in Table 1. The sample includes firms-years in states affected by minimum wage shocks from two years before the shock till two years after the shock. The dependent variables *Patents* and *Citations* are described in Table 3. POST is a dummy variable that that equals 1 for the two years after the wage shock and 0 for the two years before the shock. The explanatory variables of interest are the interactions between POST and dummy variables capturing financially constrained firms. Proxies of financial constraints are as follows: *High Leverage* is a dummy variable equal to one if the firm's leverage is above median. Leverage is long-term debt plus short-term debt divided by total assets minus common equity plus market equity, where market equity is price as of calendar year-end following IPO times shares outstanding; High *KZ Index* is a dummy variable equal to 1 for firm's with above-median values of the KZ index calculated using the ordered logit coefficients from Kaplan and Zingales (1997) as
*-1.002*Free Cash Flow - 39.368*Dividends/Total Assets -1.315 * CA_TA + 3.139*Book Leverage + 0.283*Tobin's Q,* where book leverage is long term-debt and short-term debt divided by total assets. *Low FCF* is a dummy variable equal to 1 for firm's with below-median free cash flow. Free cash flow measured as operating income before depreciation less interest, taxes and capital expenditures divided by total assets; *Low CA_TA* is a dummy variable equal to 1 for firm's with below-median values of cash over total assets calculated as cash and cash equivalents divided by total assets. The set of control variables included in all regressions but not shown in the table is the same as in Table 4. Regressions also include the interactions between POST and each control variable. All regressions include firm- and year-fixed effects. Panel B presents placebo tests with a randomly selected 'event' year during which the state does not experience a minimum wage shock. In Panel B, POST is equal to one for the two years following the hypothetical event year and zero for the two years prior to the hypothetical event year. Standard errors are clustered by industry. *t* statistics in parentheses. ***, **, * indicate significance at 1%, 5% and 10% level respectively.

	(1) Patents	(2) Citations	(3) Patents	(4) Citations	(5) Patents	(6) Citations	(7) Patents	(8) Citations
POST x High Leverage	-0.0030	0.0077						
	(-0.12)	(0.16)						
POST x High KZ			0.0259	0.0525				
			(1.15)	(1.36)				
POST x Low FCF					0.0040	-0.0642*		
					(0.23)	(-1.78)		
POST x Low CA_TA							-0.0668*	-0.0709
							(-1.79)	(-1.24)
POST	-0.4266***	-0.6255***	-0.4354***	-0.6443***	-0.4285***	-0.5854***	-0.4153***	-0.6142***
	(-3.73)	(-4.16)	(-3.62)	(-4.07)	(-3.71)	(-3.84)	(-3.74)	(-4.15)
High Leverage	-0.0086	-0.0539						
	(-0.50)	(-1.20)						
High KZ			-0.0555**	-0.0812				
			(-2.41)	(-1.52)				
Low FCF					0.0381**	0.1136***		
					(2.31)	(3.68)		
Low CA_TA							0.0589***	0.0806***
							(3.81)	(3.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25312	25312	25312	25312	25312	25312	25312	25312
Adjusted R^2	0.79	0.72	0.79	0.72	0.79	0.72	0.79	0.72