

# What Do Establishments Do When Wages Increase? Evidence from Minimum Wages in the United States

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**Abstract:** I investigate how establishments adjust their production plans on various margins when wage rates increase. Exploiting state-by-year variation in minimum wage, I analyze U.S. manufacturing plants' responses over a 23-year period. Using instrumental variable method and Census restricted-use Microdata, I find that when the hourly wage of production workers increases by one percent, manufacturing plants reduce the total hours worked by production workers by 0.7 percent and increase capital expenditures on machinery and equipment by 2.7 percent. The reduction in total hours worked by production workers is driven by intensive-margin changes. My estimated elasticity of substitution between capital and labor is 0.85. Following the wage increases, no statistically significant changes emerge in revenue, materials or total factor productivity. Additionally, I find that when wage rates increase, establishments are more likely to exit the market. Finally, I provide evidence that when the minimum wage increases the wages of some of the establishments in a firm, the firm also increases the wages for its other establishments.

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Understanding establishments’ behaviors when wage rates change is fundamental for understanding the impact of policy or economic changes, such as income taxes, minimum wage laws, investment tax credits, technological changes, influx of immigrants or union activities. These changes can affect wages directly or indirectly. Without knowing how establishments react to wage changes, predicting the potential impact of the policies or economic changes is difficult. When wage increases relative to the price of other inputs, establishments may replace workers with machines; they may also increase output price, cut output, or exit the market. While all these responses are possible, investigating what establishments actually do remains a challenging task because of lack of data and clean identification strategy.

Despite the difficulties, researchers have been trying to understand establishments’ responses using U.S. data. Capital-labor substitution draws much attention ([Acemoglu and Restrepo, 2017](#); [Autor and Dorn, 2013](#); [Beaudry et al., 2010](#)). Changes on other margins, such as output prices ([Aaronson, 2001](#); [Ganapati and Weaver, 2017](#)) and firm exit ([Aaronson et al., 2018](#); [Luca and Luca, 2018](#)), have also been studied. These studies typically focus on one or two margins, but not much has been done to provide a full picture of establishments’ behavior. This is what this paper attempts to do.

In this paper, I study establishments’ responses to exogenous wage increases among low-wage manufacturing plants in the United States, with a focus on capital-labor substitution. To generate plausibly exogenous increases in wage rates, I exploit variation in federal and state minimum wage laws. Combining the policy variation with three restricted-access establishment-level datasets, I investigate how manufacturing establishments’ production changes in various margins: employment, hours of work, capital expenditures on machines, capital expenditures on structures, materials, energy, total revenue, profit margin, total factor productivity, and plant exit.<sup>1</sup>

I also estimate an important parameter: the elasticity of substitution between capital and labor, also known as  $\sigma$ . This parameter is a key to studies on trends in labor share ([Karabarbounis and Neiman, 2013](#)), income inequality ([Boushey et al., 2017](#); [Piketty, 2014](#)), non-neutral technical change ([Raval, 2019](#)), and labor or investment policies ([Hall and Jorgenson, 1967](#)). My estimation relies on the variation of the minimum wage and census data from the manufacturing industry, so it does not provide an estimate for the aggregate  $\sigma$ . It is, however, important in its own context and provides a benchmark for other estimates.<sup>2</sup> As [Arrow et al. \(1961\)](#) point out, “Technological alternatives are numerous and flexible in

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<sup>1</sup>An “establishment” refers to a single physical location at which a business is conducted or at which production takes place. In this paper, the terms “establishment” and “plant” have the same meaning and are thus used interchangeably.

<sup>2</sup>Specifically, I estimate the substitutability between machines and hours of work of low-wage production workers in the U.S. manufacturing industry.

some sectors, limited in others; and uniform substitutability is most unlikely.” After all, each establishment makes its own decision. The decision varies with the establishment’s input composition, output, prediction of competitors’ strategy, and so on. Heterogeneous responses suggest that an estimate for the aggregate  $\sigma$  is important, but estimates for context-specific  $\sigma$  is also informative.

To identify establishments’ responses and the  $\sigma$ , I use the interaction term of changes in the minimum wage and a measure of how binding the minimum wage is to each establishment as an instrument. The instrument picks up the differential responses of manufacturing plants that are bound by the minimum wage at different levels. To focus on more comparable establishments, the analysis includes only low-wage manufacturing plants. I provide supporting evidence for the exclusion restriction assumption of the instrument by testing parallel pre-trends among the low-wage manufacturing plants and testing the impact of the minimum wage on high-wage establishments (a falsification test).

The establishment-level data are from the Annual Survey of Manufactures (ASM), the Census of Manufactures (CM) and the Longitudinal Business Database (LBD) from 1991 to 2013. Combining the ASM and the CM, I construct a three-year panel starting in 1991 and four five-year panels of manufacturing establishments starting in 1994, 1999, 2004 and 2009. The ASM and the CM contain a rich set of variables. Among the variables, the most important ones are number of production workers, total hours of work and total payroll of these workers, capital expenditures on machinery and equipment, and capital expenditures on structures and buildings.<sup>3</sup> Dividing annual payroll of production workers by their total hours of work provides an average hourly wage for the production workers in a plant. I use the average hourly wage as the measure for the wage rate.<sup>4</sup>

The LBD provides information on establishments’ entries and exits. The information makes it possible to explore if establishments are more likely to exit when the wage increases. The LBD also allows me to link establishments to their parent firms to identify responses across establishments within firms: if an increase in the minimum wage increases the wages of some of the establishments within a firm, does the firm increase the wages for other establishments too?

This paper contributes to the literature that investigates firms’ responses to changes in input price that are linked to technology. For example, do firms substitute machines for

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<sup>3</sup>“Production workers” are the workers who are directly involved in production activities, up through the line-supervisor level. In this paper, I use the terms “capital expenditures on machinery and equipment” and “capital expenditures on machines” interchangeably. The latter is more widely used for brevity, but it includes both expenditures on machinery and equipment. Similarly, the term “capital expenditures on structures and buildings” is used interchangeably with “capital expenditures on structures.”

<sup>4</sup>The ASM and the CM do not provide information on the wage distribution within an establishment or the hourly wage of non-production workers.

labor when technology lowers the price of machines ([Autor and Dorn, 2013](#)) or the price of personal computers ([Beaudry et al., 2010](#)) relative to labor? Another relevant literature estimates the tax incidence of policies on inputs, such as the earned income tax credit ([Leigh, 2010](#); [Rothstein, 2010](#)) or corporate taxes ([Suarez Serrato and Zidar, 2016](#)). The welfare implications of these policies depend on the extent to which firms pass through changes in these policies onto workers or consumers, or, in the case of the earned income tax credit, the extent to which firms capture the benefits of the program. An understanding of firms' responses to exogenous wage changes will shed light on possible margins of adjustment that may occur following these policy changes.

This paper also adds to the literature investigating firms' responses to changes in the minimum wage.<sup>5</sup> Most of such analysis uses data from outside the United States. For example, using British firm-level administrative data, [Draca et al. \(2011\)](#) find that firms' profits will decrease as the minimum wage increases, and [Riley and Bondibene \(2017\)](#) find that firms respond by increasing productivity. [Acar et al. \(2019\)](#) find that firms in Turkey are more likely to exit formal markets after a minimum wage hike. [Harasztosi and Lindner \(2019\)](#) explore the impact of a change in the minimum wage on Hungarian firms on various margins using firm-level administrative data.

A growing body of literature studies whether U.S. firms substitute capital for labor when the minimum wage increases. Most of the studies provide indirect evidence. For instance, [Aaronson et al. \(2018\)](#) show that increases in the minimum wage increase the entry of capital-intensive restaurants and the exit of labor-intensive restaurants. [Lordan and Neumark \(2018\)](#) show that an increase in the minimum wage tends to reduce automatable employment, and [Aaronson and Phelan \(2017\)](#) show that minimum-wage hikes lead to declines in cognitively routine occupations relative to other occupations. While these studies find supportive evidence that firms replace capital for labor when the minimum wage increases, a recent study by [Gustafson and Kotter \(2018\)](#) find that increases in the minimum wage reduce capital investment among firms in retail, restaurant and entertainment industries relative to non-labor-intensive firms in other industries. The capital-labor substitution of manufacturing plants, however, are understudied. Manufacturing plants are of interest because they are different from restaurants on two aspects: first, manufacturing plants produces tradable goods. It is, therefore, more difficult for manufacturing plants to pass the increase in the labor costs onto consumers; second, compared to service workers, manufacturing workers are more likely to perform routine tasks, so they are more at risk when wages increase relative to the price of other inputs. Using detailed establishment-level data in the United States, I am able to explore U.S. manufacturing plants' responses on capital-labor substitution and other margins to increases in the wage rates.

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<sup>5</sup>Table (B1) summarizes the findings of the minimum wage literature.

Finally, this paper contributes to the literature that estimates the elasticity of substitution between capital and labor (Chirinko et al., 2011; Chirinko and Mallick, 2017; Oberfield and Raval, 2014; Raval, 2019). To the best of my knowledge, this paper provides the first estimate of the elasticity of substitution between capital and labor using the change in the minimum wage in the United States as an instrument. Using the minimum wage as an instrument identifies the substitutability between capital and low-skilled labor. The paper is thus also related to the literature that estimates the elasticity of substitution between high- and low-skilled labor by identifying closer substitutes for low-skilled labor. For example, Autor and Katz (1999) show that the elasticity between high- and low-skilled labor is 1.41. A lower estimate of elasticity of substitution between capital and labor will indicate that high-skilled workers are closer substitutes to low-skilled workers than capital is.

I find six sets of results. First, when the hourly wage of production workers increases by 10 percent, or equivalently \$0.90, plants reduce the total hours worked by these workers by 7.2 percent. Because of the reduction, annual payroll for a worker does not increase by a full 10 percent as the hourly wage, but rather by 2.8 percent, or equivalently, \$500. The increase in annual payroll costs an average plant \$63,000. By adjusting the hours, however, an average plant saves \$165,000. In addition, I find that the reduction in total production worker hours is driven by intensive-margin changes: average hours worked per production worker reduces by 4.5 percent and number of production workers reduces by 2.7 percent. On average, a plant employs 129 production workers, so 2.7 percent is equivalent to 3 production workers. The difference in the intensive- and extensive-margin changes imply that it is costlier for manufacturing plants to adjust overall employment levels than to adjust hours of work per worker.<sup>6</sup>

Second, when the hourly wage of production workers increases by 10 percent, the plants increase capital expenditures on machines by 27 percent, or equivalently, \$167,000. This magnitude is comparable to the money that a plant saves by adjusting total production worker hours.

Third, the estimated elasticity of substitution between capital and labor is 0.85, with a standard error of 0.177. The estimate is thus not statistically different from one. The implied confidence interval, however, rules out most estimates below 0.5.

Fourth, following an increase in the hourly wage of production workers, some establishments exit the market. Estimates show that a 10 percent increase in wage rates increases the probability of exiting by 3.2 percentage points. The probability of exit among establishments in low-wage industries is 11%, so 3.2 percentage points correspond to a change of 30

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<sup>6</sup>The conclusion may be different in other industries, such as accommodation and food services, because the turnover rate in the manufacturing industry is relatively low. See statistics from the Bureau of Labor Statistics: <https://www.bls.gov/news.release/pdf/jolts.pdf>

percent. This result is consistent with the findings of [Aaronson et al. \(2018\)](#) and [Luca and Luca \(2018\)](#).

Fifth, I do not detect statistically significant responses on other margins: overall employment, cost of materials, cost of energy, total revenue, or productivity. I find suggestive evidence that the profit margin decreases, but the result is not robust to the specifications and the samples I choose.

Finally, I explore how the results change when I separate the analysis for single-unit and multi-unit firms.<sup>7</sup> When I restrict the analysis to single-unit firms, the capital-labor substitution results still hold. In addition, I find that these firms increase the employment of non-production workers, suggesting complementarity between capital and high-skilled workers. When focusing on multi-unit firms, I find that when the wage is increased for some of the establishments in a firm, the firm will increase the wages for other establishments that are not directly affected.

The rest of the paper is organized as follows: Section 1 lays out the theoretical framework. Section 2 introduces the background and the data used in the estimation. Section 3 presents the empirical method and main estimation results, and Section 4 discusses the robustness of the empirical results. Section 5 and Section 6 show the results on plants exit and the results by single- and multi-unit firms. Section 7 concludes the paper.

# 1 Theoretical Framework

The empirical analysis of the paper focuses on manufacturing plants. A general purpose of the paper, however, is not just to understand how establishments in the manufacturing industry respond, but also to understand to what extent the results can be extend to other sectors. The model in this section explains how establishments' characteristics can affect establishments' decision in their demand for labor, one of the most important margins, when wage rate changes. In addition, this model also derives an analytical solution for the impact of the change in the wage rate on the change in the price of capital. Capital price is not observed in the data, and thus, I rely on the model to acquire intuition regarding how it may change.

## 1.1 The Baseline Model

Assume identical plants operate in a competitive market, and one can think of the competitive market as a single industry in a state. All the plants produce identical output.

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<sup>7</sup>If a firm has only one establishment operating at one single physical location, the firm is a single-unit firm; if a firm has multiple establishments, it is a multi-unit firm.

The plants use capital ( $K$ ), production worker hours ( $L$ ), and a composite input including materials ( $M$ ) to produce output ( $X$ ) following a production function

$$X = X(K, L, M).$$

Production worker hours are the total hours that production workers work in a plant. Plants pay an hourly wage of  $p_L$  for each production worker hour, so the total payroll for production workers is  $p_L L$ . Capital refers to machines used in the production; it is supplied to plants following a supply curve  $K = K(p_K)$ , where  $p_K$  is the price for one unit of capital. The composite input,  $M$ , includes materials, non-production workers, buildings, electricity and other necessary inputs.<sup>8</sup> This composite input is supplied perfectly elastically to plants at a price  $p_M$ . I follow [Fullerton and Heutel \(2007\)](#) to derive plants' optimal choices of input ratios as functions of Allen elasticities of substitution and cost shares:

$$\hat{K} - \hat{L} = (a_{KK} - a_{LK})\hat{p}_K + (a_{KL} - a_{LL})\hat{p}_L + (a_{KM} - a_{LM})\hat{p}_M + \delta_{KL}\hat{X}, \quad (1.1)$$

$$\hat{M} - \hat{L} = (a_{MK} - a_{LK})\hat{p}_K + (a_{ML} - a_{LL})\hat{p}_L + (a_{MM} - a_{LM})\hat{p}_M + \delta_{ML}\hat{X}. \quad (1.2)$$

The hat symbols denote percent changes.<sup>9</sup> For example,  $\hat{L} = dL/L$  represents percent changes of production worker hours. The term  $a_{ij} = \theta_j e_{ij}$  is the cost share of the input  $j$ ,  $\theta_j = p_j j / p_X X$ , times the Allen partial price elasticity  $e_{ij}$ , for  $i, j \in \{K, L, M\}$ . An Allen elasticity  $e_{ij}$  is

$$e_{ij} = \frac{1}{\theta_j} \frac{\partial \ln(i)}{\partial \ln(p_j)}.$$

This is the cross-price elasticity of input  $i$  with respect to the price of input  $j$ , and then divided by the cost share of input  $j$ . Note that the Allen elasticities are symmetric; that is,  $e_{ij} = e_{ji}$ . Additionally, at most one of  $e_{KL}$ ,  $e_{ML}$  and  $e_{KM}$  can be negative. Finally,  $\delta_{ij} = \partial \ln(i/j) / \partial \ln X$  are elasticities of changes in input ratios with respect to a change in the output.

Next, I set up a consumers' problem. Assume identical consumers who consume output  $X$  typically consume only two goods,  $X$  and  $Y$ . A good  $Y$  is supplied perfectly elastically at the price of  $p_Y$ . These consumers maximize the utility

$$U = U(X, Y),$$

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<sup>8</sup>This model could be developed with  $N$  inputs, to cover all possibilities such as machinery, structures, land, production workers, non-production workers, contract workers, energy, or other materials. Retaining such level of generality is cumbersome, however, so an example is developed here with three inputs ( $L$ ,  $K$ , and  $M$ ), which could be further generalized to any three of those inputs just listed. The point for the moment is that a model with at least three inputs allows any two of them to be complements or substitutes, or can allow different degrees of substitutability.

<sup>9</sup>Appendix A derives equation 1.1 and 1.2.

and are subject to a budget constraint  $p_X X + p_Y Y = \bar{I}$ , where  $\bar{I}$  is a fixed income. Assume that the utility function is differentiable and increasing in  $X$  and  $Y$ . The first order conditions (FOCs) of the consumers' problem imply that a higher price of  $X$  lowers the demand for it. Define the demand function for  $X$  as a function of the price of  $p_X$ :  $X = X(p_X)$ . Linearizing the definition of the demand elasticity of  $X$ , one can derive:

$$\hat{X} = -\varepsilon_X^D \hat{p}_X, \quad (1.3)$$

where  $\varepsilon_X^D \equiv -d \ln X / d \ln p_X > 0$  is the absolute value of the demand elasticity of  $X$ . The magnitude of  $\varepsilon_X^D$  is governed by how easily consumers can substitute between  $X$  and  $Y$ . Next, I discuss the system of linearized equations and analytical solutions of the model.

## 1.2 Linearization and Analytical Solutions

By totally differentiating the plants' production function, one can show that

$$\hat{X} = \theta_K \hat{K} + \theta_L \hat{L} + \theta_M \hat{M}. \quad (1.4)$$

Because output  $X$  is sold in the competitive market, the zero-profit condition of the plants is  $p_X X = p_K K + p_L L + p_M M$ . The total differentiation of this condition leads to:

$$\hat{p}_X + \hat{X} = \theta_K (\hat{p}_K + \hat{K}) + \theta_L (\hat{p}_L + \hat{L}) + \theta_M (\hat{p}_M + \hat{M}). \quad (1.5)$$

Finally, totally differentiating the capital supply curve shows that

$$\hat{K} = \varepsilon_K^S \hat{p}_K, \quad (1.6)$$

where  $\varepsilon_K^S = \partial \ln K / \partial \ln p_K$  is the elasticity of capital supply. I assume  $\varepsilon_K$  to be positive.

Because I assume that the supply of the composite input,  $M$ , is perfectly elastic,  $p_M$  can be normalized to be zero. Equations 1.1 - 1.6 form a system of 6 equations with 6 unknowns:  $p_K$ ,  $p_X$ ,  $K$ ,  $L$ ,  $M$ ,  $X$ . Then I solve the model analytically and derive the unknowns as functions of a change in  $p_L$  to investigate plants' responses to exogenous wage changes.

In this paper, I discuss two analytical solutions: the price of capital and the equilibrium quantity of production workers. Solving the model shows that

$$\hat{p}_K = \frac{\theta_L [-A + \theta_L (e_{KL} - e_{LL}) + \theta_M (e_{KL} - e_{ML})]}{\theta_K [A + (1/\theta_K) \varepsilon_K^S + \theta_L (e_{LK} - e_{KK}) + \theta_M (e_{MK} - e_{KK})]} \hat{p}_L, \quad (1.7)$$

where  $A = (1 + \theta_L \delta_{LK} - \theta_M \delta_{MK}) \varepsilon_X^D$ . The term  $A$  is likely to be and assumed to be positive.<sup>10</sup> Equation 1.7 reveals how the equilibrium price of capital will change when the wage rate

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<sup>10</sup>Plants' profit-maximization problem implies that the marginal cost of each input equals its marginal revenue product. For example,  $p_X (\partial X / \partial K) = p_K$ . Then  $1 + \theta_L \delta_{LK} - \theta_M \delta_{MK}$  can be rewritten as  $(1/\theta_K)(\theta_M + \theta_L - \theta_K)$ , which is positive according to the data (see summary statistics in Table 1). Because  $\varepsilon_X^D$  is assumed to be positive,  $A$  is positive.



changes. Starting with the denominator, because the cost shares ( $\theta$ s), the demand elasticity of output  $X$  ( $\varepsilon_K^S$ ) and  $A$  are positive, the sign of the denominator depends on the signs of  $e_{LK} - e_{KK}$  and  $e_{MK} - e_{KK}$ . Substituting the definition of Allen elasticities into those two terms, one can show

$$e_{LK} - e_{KK} = \frac{1}{\theta_K} \frac{\partial \ln(L/K)}{\partial \ln(p_K)},$$

and

$$e_{MK} - e_{KK} = \frac{1}{\theta_K} \frac{\partial \ln(M/K)}{\partial \ln(p_K)}.$$

Assuming that  $L$  and  $M$  are substitutes for  $K$ , it is easy to see that these two terms are positive. Yet, if, for example,  $M$  and  $K$  are complements, then the sign of  $e_{MK} - e_{KK}$  depends on the relative magnitude of the reduction in  $M$  and  $K$ , given an increase in the price of capital. Suppose establishments cut more capital than other inputs, then,  $e_{MK} - e_{KK}$  is positive. Throughout the analysis, I assume, for simplicity, that  $e_{LK} - e_{KK}$  and  $e_{MK} - e_{KK}$  are positive. Therefore, the denominator of equation 1.7 is positive.

The numerator of equation 1.7 includes three effects. First, the term  $-A$  shows that if establishments pass through the increases in the costs of production workers onto consumers, the demand for the output may decrease, which, in turn, will decrease the demand and the price of capital (an output effect). Second, the term  $e_{KL} - e_{LL}$  shows that if establishments substitute capital for labor, then the demand for capital will rise, and thus, the price of capital will go up (a substitution effect). Third, the term  $e_{KL} - e_{ML}$  is positive if capital is a closer substitute for production workers than other inputs are. The third term means that if plants can easily replace production workers with other inputs, then the upward pressure on the price of capital will be mitigated. The sign of the impact of an exogenous change in labor costs on capital price depends on the signs and the relative magnitudes of these three effects.

Next, I solve for the demand for production worker hours:

$$\hat{L} = -\theta_L [(e_{KL} - e_{LL}) + \delta_{LK}\varepsilon_X^D] \hat{p}_L + [\varepsilon_K^S + \theta_K (e_{LK} - e_{KK}) - \delta_{LK}\varepsilon_X^D] \hat{p}_K. \quad (1.8)$$

Substituting equation 1.7 into equation 1.8, one can solve for the change in the equilibrium production worker hours a plant uses as a function of a change in the wage rate. Equation 1.8 shows that the change in the labor demand  $\hat{L}$  can be affected through two channels: the change in the wage rate of production workers ( $\hat{p}_L$ ) and the change in the price of capital ( $\hat{p}_K$ ).

The wage rate has a direct effect on the demand for labor. A positive  $e_{KL} - e_{LL}$  means that an increase in the wage rate induces establishments to increase the capital-labor ratio, so this term represents a substitution effect. Holding the price of capital constant, if  $e_{KL} - e_{LL}$  is positive, then an increase in the wage rate reduces the demand for production worker hours

through capital-labor substitution. The term  $\delta_{LK}\varepsilon_X^D$  represents an output effect: if  $\delta_{LK}$  is positive, then a pass-through of input prices onto the output price will reduce the demand for the output, and thus the equilibrium production worker hours used in the production will decrease.<sup>11</sup>

Intuitively, this term reveals that for industries with different values of cost share of low-wage labor, the elasticity of substitution between capital and labor or output demand elasticities will have different labor demand elasticities. The generalization of an industry-level estimate to approximate a nation-wide estimate can be problematic. In the empirical analysis, I estimate low-wage manufacturing plants' responses to changes in the wages of production workers. If manufacturing production workers are more susceptible to replacement by machines than service workers, or if demand for the output of manufacturing plants is more elastic than the demand for restaurants or hotels, it is possible that my estimate of labor demand elasticity is higher than an estimate that uses data from a service industry would be.

The change in the price of capital also affects labor demand through a substitution and an output effect. The term  $\varepsilon_K^S + \theta_K (e_{LK} - e_{KK})$  is the substitution effect, and it is positive if capital and production workers are substitutes. The term  $-\delta_{LK}\varepsilon_X^D$  is the output effect. If  $\delta_{LK}$  is positive, then an increase in the price of capital can be passed onto consumers and reduce demand for  $L$ . Suppose that the substitution effect dominates the output effect and that the capital price increases following an exogenous increase in wage rates. Then the reduction in labor demand will be smaller than a counterfactual situation in which capital prices do not change. If this is the case, then not controlling for the prices of capital when estimating the impact of an exogenous wage increase on the change in labor demand will lead to an attenuated estimate for labor demand.

## 2 The Minimum Wage, the Manufacturing Industry and Data

This section first introduces the minimum wage laws in the United States. Since the analysis focuses on manufacturing industries, I also discuss the characteristics of these industries, which helps to explain the external validity of the empirical results. Then I introduce the datasets used in the estimation.

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<sup>11</sup>The term  $\delta_{LK}$  equals  $\partial \ln L / \partial \ln X - \partial \ln K / \partial \ln X$ . The term  $-\theta_L (\partial \ln L / \partial \ln X)$  implies that a reduction in the output will reduce the demand for labor. However, the term  $\theta_L (\partial \ln K / \partial \ln X)$  implies that this reduction in labor demand will be smaller if establishments are more likely to reduce capital when output is reduced.

## 2.1 The Minimum Wage

A minimum wage is the lowest hourly wage an employer must pay a worker. The minimum wage is determined by the federal government, but state and local governments can set higher minimum wages for their jurisdictions. In 2018, 29 states and the District of Columbia have a minimum wage higher than the federal minimum wage of \$7.25 per hour. Counting all the state-year changes, including the federal minimum wage hikes that increased state minimum wages, the minimum wage changed nearly 400 times between 1991 and 2013.<sup>12</sup> The average minimum wage increase is \$0.50, with the largest change of \$1.80 occurring in Michigan in October, 2006 and the smallest change of \$0.02 occurring in Connecticut in April, 1991. Figure 1a shows that a majority of states experienced 5 to 6 changes over the 23 years and that coastal states tend to experience more minimum wage hikes. Between 1991 and 2013, the minimum wage in Washington, Oregon, Florida and Vermont was indexed to inflation most of the time. These states, therefore, experienced more than 12 changes. Figure 1b shows the density of the magnitude of these changes, in percent terms. The average minimum wage increase is 9.2 percent, and most of the minimum wage increases are less than 15 percent.

The changes in the federal and state statutory minimum wage rates are used to generate exogenous variation in wages for establishments. In general, a minimum wage increase is implemented months or even years after announcement. A state sometimes announces a plan for a series of minimum wage hikes.<sup>13</sup> As a result, we may expect “anticipatory” behavior, in which firms respond before the actual implementation of minimum wage hikes. In Section 4.1, I explore the pre-treatment responses using leads and lags of the changes of the minimum wage. The minimum wage can change at any time during the course of a year.<sup>14</sup> In the analysis, I use the average minimum wage in a year in the main specification.<sup>15</sup>

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<sup>12</sup>The data are collected and organized by David Neumark and are available at <https://www.socsci.uci.edu/~dneumark/datasets.html>.

<sup>13</sup>For example, in August of 2006, California Governor Arnold Schwarzenegger announced that the state’s minimum wage would be raised from \$6.75 per hour to \$8 per hour over the next two years, with a \$0.75 increase in 2007 and another \$0.5 increase in 2008.

<sup>14</sup>Figure B1 shows that, in fact, only 32.1 percent of minimum wage changes took place in January; 47.8 percent of the changes took place between August and October, and another 12.9 percent took place in April. These five months account for 92.8 percent of all changes.

<sup>15</sup>This measure captures the immediate responses to changes in the minimum wage as well as part of anticipatory responses when a minimum wage is changed in the middle of the year. As a robustness check, I follow Autor et al. (2016) in using the minimum wage that is in place for the longest period of time in a year as the minimum wage for that year. Appendix Tables B4a and B4b show that the results are robust to the alternative measure.

## 2.2 Manufacturing Industries

The manufacturing industry is not the largest employer of workers, but it is the industry with the largest capital investment in machinery and equipment (\$187 billion). Pooling together publicly available data from the American Community Survey (ACS) and the Annual Capital Expenditure Survey (ACES) in 2016, Figure 2 shows the share of employment and capital expenditures on machinery and equipment for each industry group out of the national total. The manufacturing industry accounts for 10.7 percent of the total employment, but 20.1 percent of all capital expenditures on machinery and equipment nationwide.<sup>16</sup>

The manufacturing industry does not hire a large number of minimum wage workers. In 2013, only 10 percent of workers in manufacturing industry are minimum-wage earners, defined as workers who earn hourly wages below 1.2 times the state minimum wage. In contrast, 40.5 percent of workers in restaurants and hotels were minimum-wage earners.<sup>17</sup> As a result, previous research on the minimum wage has focused on restaurants or hotels.

The manufacturing industry is relevant for minimum wage, however, for two reasons. First, manufacturing is a tradable sector. Its output is sold in national or international markets. It is, therefore, hard for manufacturing plants to pass through increases in the input cost to consumers. In fact, two recent studies, Cengiz et al. (2019) and Harasztosi and Lindner (2019), find that the disemployment effect of the minimum wage is relatively large for the manufacturing industry. Cengiz et al. (2019) use U.S. data and find labor demand elasticity with respect to own wage to be -1.4 for the manufacturing industry, though the estimate is imprecise. Second, workers, especially production workers, in manufacturing are more likely to perform routine tasks. These workers are more vulnerable to being replaced by machines than service workers. In fact, Lordan and Neumark (2018) and Aaronson and Phelan (2017) find the minimum wage has larger impact on automatable and cognitively routine jobs than on other jobs, and manufacturing industry has a large share of these

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<sup>16</sup>Statistics from the ACES are calculated by the Census Bureau and reported in Table 4a of <https://www.census.gov/data/tables/2016/econ/aces/2016-aces-summary.html>. Statistics from the ACS are calculated using the individual-level data from IPUMS-USA (<https://usa.ipums.org/usa/>) and aggregated to industry groups as defined in the ACES. Following the design of ACES, these statistics are calculated excluding farms, whose North American Industry Classification System (NAICS) codes begin with 111 or 112, and public services, whose NAICS codes begin with nine.

<sup>17</sup>Author's calculation using IPUMS CPS-ASEC data. Among hourly wage earners, the numbers are different. Using CPS-ORG data and restricting the analysis to only hourly wage earners, 58.3 percent of workers in restaurant and hotel service industries earn the minimum wage, compared to 9.5 percent of manufacturing industry workers who earn the minimum wage. The hourly wage is calculated by dividing the total wage and salary income by the total hours worked. Manufacturing industries refer to the industries with Census 1990 industry codes between 100 and 392, and restaurant and hotel service industries refer to the industries with Census 1990 industry codes 641, 762 and 770.

jobs.<sup>18</sup>

## 2.3 Data

To measure establishments' behavior, I use three establishment-level datasets between 1991 and 2013 from the Census Bureau. Two of the datasets, the ASM and the CM, include only manufacturing establishments—with the North American Industry Classification System (NAICS) codes starting with 31–33. The third dataset, the LBD, includes almost all establishments in the private sector in the United States.

The CM is available every five years in the Economic Census years ending with two or seven. It surveys nearly all manufacturing establishments in the United States.<sup>19</sup> The ASM provides establishment-level data every year except for years ending with two or seven. Unlike the CM, the ASM includes a sub-sample of approximately 50,000 manufacturing plants each year. The sub-sample is based on the previous CM: two years after each Economic Census, the Census Bureau draws a stratified random sample among all manufacturing establishments identified in the previous CM and sends them the initial ASM survey. It then follows these establishments every year for another 4 years. In the years when Economic Census is conducted, the ASM survey is replaced by the CM survey. The ASM and CM data between 1991 and 2013, therefore, can be pooled together to form one short, three-year panel (1991–1993) and four five-year panels (1994–1998, 1999–2003, 2004–2008, and 2009–2013). The sampling criteria vary by year, but in general, the sampling probability of a plant is a function of the establishment's size and industry. Large plants that meet certain criteria are sampled with a probability of one. Therefore, although the short five-year sample is balanced, the pooled long panel is unbalanced; larger firms tend to have longer time series.<sup>20</sup> Because the ASM/CM over-samples large firms, one must be cautious when drawing inferences from the results.

In both surveys, establishments are asked to report their capital expenditures on ma-

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<sup>18</sup>For example, [Frey and Osborne \(2017\)](#) show that the probability of computerization for certain low-wage manufacturing occupations is above 97 percent. These occupations include hand sewing, textile bleaching and dyeing machine operators and tenders, and shoe machine operators and tenders.

<sup>19</sup>Exceptions are small manufacturing establishments that employ fewer than five employees or that have payrolls beneath certain industry-level thresholds.

<sup>20</sup>New establishments can be added after a random sample is drawn. When constructing the 23-year panel, I merge all the five-year panels and drop the establishments that do not show up in all years within the five-year panel. Therefore, those short panels are balanced. When analyzing establishment exit, however, establishments that dropped out of each short five-year (or three-year) panels are included.

chines or equipment and on buildings or structures, separately.<sup>21</sup> These variables allow me to estimate firms’ capital-labor substitution behaviors. The empirical analysis focuses on capital expenditures on machines. The ASM/CM panel also has other variables including employment, total hours worked and total payroll for production workers, total employment of both production and non-production workers, total value of shipment (TVS), costs of materials, and costs of energy in a plant. Production workers are workers, up through the line-supervisor level, who are directly involved in production processes. I calculate the hourly wage of production workers by dividing the total payroll paid to production workers by the total hours worked. The average wage of production workers at each plant is the measure for wage rates in the analysis.

Foster et al. (2016) construct measures for the real costs of energy, materials and real output for each establishment year. The real costs of energy in a plant year is the sum of the total cost of purchased electricity and purchased fuel deflated by an industry-level energy price deflator. The costs of materials include the cost of materials and parts, resales and contracted work, and the real costs are the nominal costs deflated by an industry-level material price deflator. These two measures for real costs are used in the analysis. I use the TVS as the measure for total revenue. Foster et al. (2016) construct a “real output,” which is the real value of inventory-adjusted TVS. Because this variable is deflated using industry-level price indices, I consider this variable to be a measure of real total revenue, rather than a measure of quantity of output. Both the TVS and the real total revenue are used in the analysis.

Another variable used in the analysis is the total factor productivity (TFP); it is a measure of plant productivity. The TFP, constructed in Foster et al. (2016), is the difference between the log of the real value of revenue and the weighted sum of the logs of the real value of the inputs: capital stock on machines, capital stock on structures, materials, energy and labor. The weight for each input is the industry-level cost share of the corresponding input.

Finally, I also attempt to estimate the impact of the change in the hourly wage of production workers on profit margin. A plant’s profit is constructed by subtracting all the costs—labor, capital expenditures, energy use, and materials—from its TVS. The profit is then divided by the TVS to acquire the measure of the profit margin. A more detailed discussion about the variables is in Appendix B.

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<sup>21</sup>Capital expenditures on machines refer to reported expenditures on automobiles, computers and peripheral data-processing equipment and other machinery and equipment, such as lathes or punch presses. Capital expenditures on structures include expenditures on the construction or maintenance of structures such as blast furnaces, brick kilns, fractionating towers and the usual factory offices and warehouses, as well as their integral parts (such as overhead traveling cranes and ventilating shafts); it also includes capitalized site improvements such as roads, fences, parking lots, or docks.

Panel A of Table 1 provides summary statistics of the full sample. On average, establishments employ 93 workers, 66 of them as production workers. Average hourly wages for these production workers are \$13.5 (in 1997 dollars). Establishments spend roughly \$2 million (in 1997 dollars) to pay their production workers. This accounts for 63.4 percent of the total payroll. The fact that production workers account for 71 percent of all workers but receive only 63 percent of the total payroll indicates that the annual salaries of non-production workers is slightly higher. This makes sense because all well-paid administrative workers are categorized as non-production workers. Establishments spend an average of \$0.76 million (in 1997 dollars) on used and new machines each year. Figure 3 shows that among all the inputs, materials represent the largest category in terms of the cost share (77 percent), followed by payroll (17 percent), capital expenditures (4 percent) and energy (2 percent). The average profit margin in the full sample is 17 percent. On average, the establishments are observed six times between 1991 and 2013.

The third dataset I use is the LBD. Each year, information is collected on employment, payroll and industry type from a variety of sources, including IRS administrative records.<sup>22</sup> Most importantly, the dataset includes the first and last years that a given firm is in business. I use the last year an establishment is in operation to examine manufacturing plants' exit decisions in the wake of hourly wage increases. The LBD also provides the link between multi-unit establishments and their parent firms.<sup>23</sup> I use the link to identify the within-firm-across-establishments responses.

The datasets used in this paper have several advantages over the firm-level data used in previous minimum wage literature. First, unlike the British administrative data use by [Draca et al. \(2011\)](#) and [Riley and Bondibene \(2017\)](#), which rely on annual payroll data, the U.S. data used for this study provide variables that allow me to calculate hourly wages of production workers. The U.S. data sources provide finer-grained measures to identify establishments that are bound by the minimum wage. Second, unlike many tax record data that have information only on the number of employees, the ASM and CM data indicate the average hours of work per production worker and the number of production workers in each manufacturing plant separately. The distinction between the two observations turns out to be crucial for understanding firms' substitution behavior. Third, the ASM and CM ask manufacturing plants to report capital expenditures on machines separately from capital expenditures on structures. Having measures of capital expenditures on both machines and structures is useful for understanding establishments' responses at these two different

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<sup>22</sup>[Jarmin and Miranda \(2002\)](#) provide a more detailed discussion on the sources.

<sup>23</sup>The information for the link was first collected in the 1972 economic censuses; then, two follow-up surveys in November 1972 and January 1973 covered entities that were not included in the 1972 censuses. Starting from 1974, the linkage was maintained and updated through the Company Organization Survey. [Kreps et al. \(1979\)](#) provides more details.



margins.

Despite their advantages, these datasets also have limitations. Most importantly, the ASM and CM only survey manufacturing firms, so the estimated response, especially regarding the elasticity of substitution between capital and labor, is specific to the manufacturing industry. In addition, I only observe average hourly wages of production workers in a plant, as opposed to average hourly wages of all workers; this paper, therefore, provides no information regarding how plants respond to the change in hourly wages of non-production workers. Finally, I do not observe the wage distribution of production workers, so it is not possible to identify the workers work at minimum wage. I take the average wage of production workers in a plant as a good measure for distinguishing between possible bound and unbound plants.

### 3 Identification Strategy and Empirical Results

#### 3.1 Identification Strategy

I start the analysis by investigating the correlation between the hourly wage of production workers and the key outcome variables using a first-difference ordinary least square (OLS) specification. The estimation equation is

$$\Delta y_{est} = \beta_0 + \beta_1 \Delta w_{est} + \Delta \varepsilon_{est}, \quad (3.1)$$

where  $\Delta y_{est}$  is the change of the log of the outcome variables from year  $t - 1$  to  $t$  of establishment  $e$ , in state  $s$ . For outcome variables that contain zeros, I use inverse hyperbolic sine (IHS) transformation that incorporates both intensive and extensive-margin changes.<sup>24</sup> The independent variable,  $\Delta w_{est}$ , is the one-year change in the log hourly wage of production workers. The coefficient of interest is  $\beta_1$ , which represents the correlation between the change in the wage and the change in the outcome variables. The constant term  $\beta_0$  in this first-difference model is a linear time trend in a model using the level of dependent and independent variables. The error term is  $\Delta \varepsilon_{est}$ . Taking the first difference controls for the time-invariant establishment characteristics. Throughout the analysis, I cluster standard errors by states.

An OLS estimate of  $\beta_1$  does not provide a causal interpretation if a factor that affects the change in both the wage and the outcome variables is not included in the equation. For example, if wages and capital expenditures increase at the same time, it does not necessarily mean that the increase in wages induce firms to invest in capital. Alternatively, it could be

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<sup>24</sup>In practice, the variables that use log transformation throughout the analysis are the hourly wage, the total production worker hours, capital stock on machines, TVS, the number of production workers, the average hours per production worker, and capital stock on machines/total production worker hour. When outcome variables are profit margin or TFP, they are not log transformed.



that a reduction in the output price increases the demand for the output, which increases the price for labor and investment in capital. In addition, classical measurement error of the hourly wage will bias the estimates for  $\beta_1$  toward 0.

### 3.1.1 Instrumental Variable and 2SLS Regression

A valid instrumental variable can address both the endogeneity and the measurement error problem. If the changes in state minimum wages are random, then a 2-stage-least-square (2SLS) regression using the changes in the minimum wage as an instrument for hourly wages will be sufficient. [Allegretto et al. \(2013\)](#) show, however, that the minimum wage is higher in states that experience more severe economic downturns and have higher wage inequality. Using state-year variation in the minimum wage might, therefore, pick up spurious correlations between the change in the state minimum wage and the average change of the outcome variables. To overcome this challenge, I restrict the analysis to low-wage plants, and then estimate their differential responses depending how binding the minimum wage is to the plant. Low-wage plants are likely to be comparable: comparing a shoe manufacturer with a seafood manufacturer is more reasonable than comparing a shoe manufacturer with a car manufacturer. Estimating the differential responses of low-wage plants uses the plants with relatively high wage as a control group and makes it possible to account for state-specific changes that are not observed by researchers.

To implement this method, I first calculate the distance between the average hourly wage of production workers in each plant-year and the minimum wage of that state-year, denoted as  $dminw_{est}$ . This distance measures how binding the minimum wage is to an establishment in a given year. The smaller the distance, the more binding the state minimum wage is to that plant. Then, for each year, I rank establishments using  $dminw_{est}$  to construct a national distribution.<sup>25</sup> Each establishment-year is attached to a centile measure  $pct_{est}$  based on its position in the national distribution.

The idea is that, if in the lagged year, an establishment A is ranked lower than another establishment B, then we will expect that an increase in the minimum wage from year  $t-1$  to year  $t$  will have larger impact on establishment A than on establishment B. Figure 4 illustrates the idea using the ASM/CM data. The figure plots the coefficients of 17 bivariate regressions in which I regress the change in the log of hourly wage of production workers on the change in the log of minimum wage. Each regression uses a different sample of establishments with similar  $pct_{es(t-1)}$ : in the bottom 3 percentiles, between 4 and 6 percentiles, between 7 and 9 percentiles, ..., and up to the 51st percentile. The lower bound of each interval is labeled by the  $x$ -axis. The figure shows explicitly that increases in the minimum wage have larger

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<sup>25</sup>Sampling weights are used when constructing the national distribution  $dminw_{est}$ .

impact on more bound establishments, and this differential effect fades out at approximately the 20th percentile.

Motivated by Figure 4, I restrict the analysis to establishment-year observations satisfying  $pct_{es(t-1)} < 20$ . This restriction is designed to pick up the establishments that are similar, though differentially treated by the minimum wage. If the cut-off is too low, then all establishments tend to be treated and the estimated responses will be attenuated. The cut-off cannot be too high either, because a higher cut-off will select less comparable establishments into the sample. Despite these considerations, the cut-off at the 20th percentile is still arbitrary. In Section 4.3, I perform a sensitivity analysis on the chosen cut-off. Finally, I define a treatment variable as a function of  $pct_{es(t-1)}$ :  $T_{es(t-1)} = 1 - pct_{es(t-1)}/20$ . This treatment variable reverses the order of the centile measure and transforms it to be between zero and one. Larger values of the treatment variable mean that the minimum wage is more binding to the establishment.

One concern for the treatment variable is that it may not measure the extent to which an establishment is treated accurately because only the average wage, rather than a full distribution of hourly wages, is observed. For example, imagine two plants in state  $S$ , both of which have four workers with an average wage of \$9 in the current year. The state plans to increase the minimum wage from \$7 to \$8 in the next year. Suppose plant A has three workers, who earn \$7 per hour, and one worker who earns \$15 per hour; by contrast, all four workers in plant B earn \$9 per hour. Assuming no spillover effect, the increase in the minimum wage should have a larger impact on plant A, but the constructed instrument is not able to distinguish such differences between these two plants. This type of measurement error is hard to identify and fix with the current data. Note, however, that this type of measurement error is most likely to attenuate the estimates.<sup>26</sup>

The interaction term between the treatment variable and the change in log of the state minimum wage,  $\Delta minw_{st}$ , serves as an instrument. The baseline 2SLS regression is:

$$\Delta y_{est} = \beta_0 + \beta_1 \widehat{\Delta w_{est}} + \beta_2 \Delta minw_{st} + \beta_3 T_{es(t-1)} + \Delta \varepsilon_{est}, \quad (3.2)$$

where

$$\widehat{\Delta w_{est}} = \hat{\delta}_0 + \hat{\delta}_1 \Delta minw_{st} \times T_{es(t-1)} + \hat{\delta}_2 \Delta minw_{st} + \hat{\delta}_3 T_{es(t-1)}. \quad (3.3)$$

The definitions of  $\Delta y_{est}$ ,  $\Delta w_{est}$  and  $\Delta \varepsilon_{est}$  follow from equation 3.1. The instrumented variable is  $\widehat{\Delta w_{est}}$ . In the 2SLS regression, I control for  $\Delta minw_{st}$  and  $T_{es(t-1)}$  to single out the

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<sup>26</sup>For simplicity, consider a case where establishments are categorized into only two groups: treatment and control. Then if treated plants are mistakenly categorized to the control group, the estimated response of the control group will be larger than the true response. On the other hand, if untreated plants are mislabeled as treated, the estimated response of the treatment group will be smaller than the actual response. In both cases, miscategorization reduces the difference between the bound and unbound establishments. Therefore, the 2SLS results should be interpreted as conservative estimates of the true effect.

differential impact of the change in the minimum wage across plants that are bound by the minimum wage at different levels. Equation 3.3 is the first stage of the 2SLS regression. The  $\delta$ s with a hat above them represent estimated coefficients.

The instrument is valid if it satisfies two conditions. First, the instrument must have a strong predictive power for the change in the hourly wage of production workers. Second, it must satisfy the exclusion restriction assumption. The exclusion restriction assumption is that conditional on  $\Delta minw_{st}$  and  $T_{es(t-1)}$ , the instrument is not correlated with  $\Delta \varepsilon_{est}$ . In other words, the changes in the minimum wage affect the outcome variables of establishments bound by the minimum wage at different levels differently only through the fact that the changes in the minimum wage affect the wage of these establishments differently.

The exclusion restriction assumption cannot be tested directly, but I discuss several circumstances under which the assumption can be violated and the way to test it. Using capital-labor substitution as an example, the exclusion restriction assumption can be violated in the following ways.

(1) Minimum wages are more likely to increase in states that are more likely to substitute capital for labor. One advantage of exploiting additional variation within state-year is that I can add state-by-year fixed effects to demean the data within state-year. I find that including state-by-year fixed effects have limited impact on the results, indicating that the results are not likely driven by this concern.

(2) Some other policies, that affect capital investment positively and use of labor negatively, change at the same time when state minimum wages increase. In particular, if these policies have larger impacts on lower wage firms, then the estimates can pick up the impact of these policies. In Appendix Table B2, I show that state-by-year minimum wage changes are not correlated with several investment policies that can potentially drive capital-labor substitution.

(3) Very-low-wage establishments are more likely to substitute capital for labor than low-wage establishments in the absence of a minimum wage change. If this is true, we will observe this differential substitution prior to the change in the minimum wage. In Section 4.1, I present pre-treatment trends across the low-wage establishments to show this is not the case.

(4) An increase in the minimum wage differentially affects establishments' outcome variables through channels other than its differential impact on the hourly wage. In this case, the exclusion restriction is violated even if the change in the minimum wage is exogenous to low-wage establishments. I address this concern by estimating the reduced-form regressions, that is, regressing the outcome variables on instruments directly. The reduced-form estimation does not rely on the assumption that the differential change in the hourly wage

is the only channel. Table B3 show the reduced-form results, and they are consistent with the 2SLS results.

The differential impact of the minimum wage is only expected to affect low-wage establishments. If we find that the minimum wage also differentially affects high-wage firms, then it is likely that some unobserved state characteristics are driving the result. In section 4.2, I present a falsification test to show that this is not a concern.

### 3.1.2 Summary Statistics of the Main Sample

After making the sample restriction described above, I further drop the observations that employ zero workers or zero production workers or whose total production worker hours are zero. This sample is referred to as the *main* sample. Table 1 Panel B shows the summary statistics for the main sample.<sup>27</sup> Because the main sample includes only low-wage plants, the average hourly wage, \$8.86 (in 1997 dollars), is lower than the full sample wage. Other than paying lower wages, low-wage plants employ more workers and have higher revenues, but at the same time, they have lower capital stock. Because of the sample restriction, an average establishment in the main sample is observed only three times (three changes). These distinctions mean that the analysis does not represent an average establishment.<sup>28</sup> I discuss the external validity of the results in Section 7.

Table 2 lists the industries with the largest share of low-wage establishments (out of all the establishments in an industry). In this table, an establishment is considered as low wage if it is below the 10th percentile of the national distribution of  $dminw_{est}$ . I use the four-digit 2002 NAICS codes to define industries.<sup>29</sup> The top 10 low-wage industries are concentrated in the textile, apparel and food manufacturing industries. These industries are known to be labor-intensive and tend to hire a large number of workers who perform routine tasks.

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<sup>27</sup>The main sample accounts for 13 percent of the full sample, not 20%, mainly because the analysis uses the first difference, and the observations of the first year of each short panels drop out.

<sup>28</sup>Additionally, because the ASM samples large establishments with higher probability than small establishments, my estimates tend to pick up the responses of large, low-wage establishments.

<sup>29</sup>These statistics are calculated by pooling data from 1991 to 2013. For each year and industry, I calculate the percent of establishments that are below the 10th percentile. Sampling weight is used. Then I average the percent across years. The challenge for the calculation is that there was a major change of the industry classification system in 1997. The Standard Industrial Classification (SIC) system was changed to the NAICS. To maintain a consistent measure of industries over time, I use the NAICS 2002 code assigned to all establishments in the LBD in Fort and Klimek (2016).

## 3.2 Empirical Results

### 3.2.1 OLS Results

Panel A of Table 3 reports the OLS results of equation 3.1 using the main sample. The results show that a one percent increase in the hourly wage of production workers is associated with a 0.5 percent decrease in total production worker hours (Column 1), a 0.004 percent (insignificant; Column 2) decrease in capital expenditures and a 0.03 percent increase in nominal and real total revenue (Columns 5 and 6). The negative association between hourly wages and production worker hours is consistent with a negative slope on the labor demand curve. The estimated elasticity of substitution between capital and labor is 0.5 (Column 3). The results also show that a one percent increase in the hourly wages of production worker is correlated with the decrease in total employment (0.16 percent), and an increase of the real costs of energy (0.02 percent) and materials (0.03 percent). Higher wages are also associated with higher total factor productivity (Column 10). The OLS results, however, do not imply causal relationship between the hourly wage of production workers and the outcome variables. Adding state-by-year fixed effects (Panel B) and establishment fixed effects (Panel C) to the OLS regression may account for some, but not all the endogeneity.

### 3.2.2 2SLS Results – First Stage

Column 1 of Table 4 shows the estimates for  $\delta$ s in equation 3.3. The first stage F-statistic is 35, indicating a strong first stage. The coefficient of  $\Delta \text{Log}(\text{Min. Wage})$  shows that the change in the minimum wage has no effect on the wage of the establishments at the 20th percentile. The coefficient of the interaction term shows that the impact of the minimum wage on the hourly wage of production workers increases in  $T_{es(t-1)}$ . The interpretation of the magnitude of the coefficient depends on  $T_{es(t-1)}$ . For example, for an establishment at the 10th percentile, a one-percent increase in the minimum wage will increase the hourly wage of production workers by 0.25 percent.

To visualize the interpretation of the coefficient on the interaction term, Panel (a) of Figure 5 plots the impact of a one-percent increase in the minimum wage by percentiles, using the estimates in Column 1. The figure shows that the instrument captures the fact that the impact of a change in the minimum wage is larger for more bound establishments than for less bound ones.

### 3.2.3 2SLS Results – Production Workers

Panel A of Table 5a reports the results where the dependent variables are the change in the log of the total hours worked by production workers (Columns 1–4), average hours

per production worker (Columns 5–8), and number of production workers (Columns 9–12). Since this is a log-log specification, the coefficient, -0.977, in Column 1 means that when the hourly wage increases by one percent, an average establishment reduces the total production worker hours by 0.977 percent.

One concern of the baseline regression in equation 3.2 is that a state with large average minimum wage increases will also have large decline in total production worker hours for reasons not observed by researchers. The concern can be addressed by demeaning all variables using state-by-year fixed effects (FEs). Including state-by-year fixed effects will avoid the comparison of average changes in the total production worker hours between, for example, a state-year that had large minimum wage changes during the sample period and a state-year that had small minimum wage changes. The result with state-by-year fixed effects is reported in Column 2. The coefficient changes little, suggesting that the estimate in Column 1 is not driven by cross-state comparisons.

In Column 3, I further control for establishment fixed effects.<sup>30</sup> If one worries that a manufacturing plant that is always in the 5th percentile is more likely to reduce labor demand than a manufacturing plant that is always in the 15th percentile without minimum wage changes, then  $\beta_1$  will be negatively biased away from zero. Establishment fixed effects rule out such comparisons. Including establishment fixed effects reduces the magnitude of the coefficient, but not by much. The fact that state-by-year fixed effects and establishment fixed effects have limited impacts on estimates provides confidence that the minimum wage is exogenous to the manufacturing plant in the sample, and that the estimated coefficients can be interpreted causally.

To capture the potential nonlinear responses of establishments, I add an interaction term between the change in the minimum wage and the square of  $T_{es(t-1)}$  to the instrument. This quadratic version of the instrument will allow the highly bound establishments to be more responsive. Panel (b) of Figure 5 demonstrates the fit of the quadratic instruments. Comparing this figure with the figure in Panel (a), it is clear that the quadratic instruments fit the data better. This specification is, therefore, my preferred specification, and the coefficients estimated with this specification are used to interpret the results. The result of this specification is report in Column 4. The smaller standard error of this estimate also suggests that this specification fits better. The first-stage regression results are reported in Table 4. In all four cases, the first-stage F-statistics are above 20.

If all production workers in a plant are paid the average hourly wage, then the estimates in Columns 1–4 are essentially labor demand elasticity. The estimate of -0.724 is comparable

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<sup>30</sup>Note that the number of observations drops when establishment fixed effects are included. The drop is driven by the establishments that appear only once in the main sample, because they are not identified in this specification.

to the previous literature; in a survey of 105 studies, [Lichter et al. \(2015\)](#) show that the average own-wage elasticity of labor demand is -0.508, with standard deviation (*s.d.*) 0.774. The survey also shows estimates by data or specification: -0.728 (*s.d.* = 0.445) using panel data with fixed effects; -0.212 (*s.d.* = 0.409) in the short-run; and -0.539 (*s.d.* = 0.499) in the manufacturing industry.

The labor demand elasticity of -0.724 indicates that when the hourly wage of production workers increases by one percent, the annual total payroll for these workers increases by only 0.276 percent, or equivalently, \$6,300; that is an increase of \$50 per production worker. In a hypothetical situation where establishments are not allowed to adjust labor demand, a one percent increase in the hourly wage will increase the annual wage bill by \$22,800. In other words, an average plant saves approximately \$16,500 by adjusting the number of working hours for their production workers.

In the rest of columns, I decompose the total changes by intensive-margin (average hours per worker) and extensive-margin changes (number of workers). The coefficient of -0.511 in Column 5 means that a one percent increase in the hourly wage reduces average hours worked by 0.511 percent. The change in the results when adding state-by-year fixed effects (Column 6) and establishment fixed effects (Column 7) or using the quadratic instrument (Column 8) are small. Compared to the intensive-margin changes, estimates for extensive-margin changes are smaller and are statistically insignificant. Using the estimate in Column 12, a one percent increase in the hourly wage will lead an establishment to lay off 0.27 percent of its production workers, that is less than one worker based on the sample average. The finding that manufacturing plants are more responsive in adjusting hours than employment indicates that the cost of firing workers is higher than the cost of adjusting hours, as discussed in Section [A.3](#), and is consistent with the results of [Horton \(2017\)](#) and [Jardim et al. \(2017\)](#).<sup>31</sup>

### 3.2.4 2SLS Results – Capital Expenditures on Machines and the Elasticity of Substitution Between Capital and Labor

Panel B of Table [5a](#) shows how manufacturing plants adjust capital expenditures on machines. The outcome variable in Columns 1–4 is real capital expenditures on machines. I use inverse hyperbolic sine transformation to incorporate zeroes and then take the first difference. Column 1 reports the estimated coefficient  $\beta_1$  of the regression Equation [3.2](#).

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<sup>31</sup>The adjustment of the hours, as opposed to the employment, that a plant uses hinges on the assumption that production workers are paid by the hour or that the annual payroll to each worker is a function of their predetermined hours of work. In 2013, 59 percent of workers in the manufacturing industries were paid by the hour, compared to 79 percent of workers in the hotel and restaurant sectors, and 50 percent of workers in other industries (calculated using data from the IPUMS-CPS). The share of hourly wage earners in manufacturing industries is not small, which means that adjusting hours is a reasonable way for a plant to reduce its wage bill.



Including state-by-year fixed effects and establishment fixed effects or using the quadratic version of the instrument do not make statistically different changes to the estimates. The point estimate of 2.7 in Column 4 indicates that a one percent increase in the hourly wage increases the capital expenditures on machines by 2.7 percent. Using the mean of capital expenditures on machines of \$618,300, a manufacturing establishment is expected to increase its investment in machines by approximately \$16,700. The increase in capital expenditures on machines is roughly the same as the annual cost of payroll saved by adjusting production worker hours, \$16,500, suggesting that establishments use up their savings from adjusting working hours to upgrade their machines.

Columns 7–8 report the regression results on extensive-margin changes. I define a dummy variable that equals one when an establishment has positive capital expenditures on machines. The dependent variable is the one-year change of the dummy variable, and it takes three values: -1, 0, and 1. On average, 84.2 percent of establishment-year observations in the main sample have positive capital expenditures on machines. The estimated coefficient of 0.46 means that when the hourly wage increases by one percent, the probability of positive capital expenditures on machines increases by approximately 0.46 percentage points, or 0.55 percent. If the hourly wage increases by 10 percent, around 90 percent of the establishments are expected to have positive capital expenditures on machines. This is a sizable effect, indicating that when wage costs increase, manufacturing plants start to purchase machines to replace labor.

Columns 9–12 in Panel B of Table 5a report the estimated elasticity of substitution between capital and labor. The estimation uses production worker hours and capital stock on machines. I focus on the substitutability between production workers and machines for three reasons. First, the hourly wage provides a better measure than the total payroll for the unit price of labor and also helps to identify how bound the minimum wage is to each establishment. Unfortunately, the hourly wage is observed only for production workers, making it hard to measure the hourly wage for all workers in a plant. Second, I observe total hours of work by production workers; it is an ideal measure for quantity of labor because it captures both intensive- and extensive-margin adjustments. Last, but not least, in a manufacturing plant, production workers as a group are more homogeneous than the group of all workers, which include occupations such as managers, salespersons, production workers, and janitors. Thus, the elasticity of substitution between capital and labor is more clearly defined.



I use the real capital stock measure constructed by [Foster et al. \(2016\)](#).<sup>32</sup> When calculating the capital stock, they use the standard perpetual inventory method, in which the current period’s capital stock equals the capital stock in the previous period minus the capital depreciation plus new investments. The method requires three components at the plant level: investments in each period, capital depreciation rates, and initial capital stock. The investments are observed in the data as capital expenditures. The industry-level depreciation rate from the Bureau of Labor Statistics (BLS) is used to approximate plants’ capital depreciation. They initialize the capital stock for each plant using the earliest possible reported book value of fixed assets for structures and machines separately. The book value is adjusted to be in real terms using the industry-level ratio of real to book value of capital from the data from the Bureau of Economic Analysis (BEA). Finally, the calculated capital stock in each year is deflated using the industry-level investment price deflators from the BLS.<sup>33</sup>

Column 9 shows that the estimate of the elasticity is 1.3 when no fixed effects are included. Comparing the estimates in Column 9 and Column 11, we see that the inclusion of state-by-year fixed effects and establishment fixed effects reduces the point estimate by 27 percent, but the difference is not statistically significant. Using the preferred estimate in Column 12, the estimated elasticity of substitution between capital and labor is 0.85, with a 95% confidence interval (0.5, 1.2). The number 0.85 means that when the hourly wage increases by one percent relative to the cost of capital, an average plant will use 0.85 percent more capital relative to labor.<sup>34</sup> This estimate is larger than the estimate of 0.5 by [Raval \(2019\)](#) when using the 1987 CM and the cross-sectional variation across commuting zones. However,

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<sup>32</sup>The measure has been revised and extended to 2014. I use the extended version in the analysis. When estimating the elasticity of substitution, I use the capital stock, as opposed to capital expenditures. Consider a simple model that distinguishes capital flows and capital stock. To simplify the discussion, I assume that plants use only two inputs: capital and labor. Following the notation in Section 1, but adding a year subscription, in year  $t$ , the firm’s production function is:  $X_t = X_t(K_t, L_t)$ . In the production function,  $K_t$  is the capital that a plant uses in the production. Thus this is the capital stock. The elasticity of substitution between capital and labor is then

$$\Delta K_t - \Delta L_t = \sigma(\Delta w_t - \Delta r_t),$$

where  $\Delta$  denotes the change from year  $t - 1$  to  $t$ . Therefore, the  $\sigma$  is estimated using the relative change of the capital stock to the labor hour. On the other hand, consider the dynamics of the capital stock:  $K_{t+1} = (1 - \delta)K_t + I_{t+1}$ , where  $\delta$  is a time-invariant depreciation rate of the capital, and  $I_{t+1}$  is the investment to be made in period  $t + 1$ . In each period, given the prices of inputs ( $r_t$ ,  $w_t$ ) and the price of the output ( $p_X$ ), firms choose  $L_t$  and  $I_{t+1}$  to maximize profit. The capital flow,  $I_{t+1}$ , is the choice variable, so when estimating firms’ responses to change in wages, I use the change in  $I_{t+1}$  as the outcome variable.

<sup>33</sup>The industry-level price deflators they use are from the BLS and are at the two-digit SIC level before 1997 and the three-digit NAICS level afterwards. [Foster et al. \(2016\)](#) provides more details on the initialization of the capital stock.

<sup>34</sup>Ideally, to estimate substitutability along an isoquant curve, one would control for the change in the quantity of output. The output, however, is not observed in the data, and is not controlled in the estimation. It remains possible to control for a proxy for the output, the real revenue. After controlling for the change in the log of real revenue, the estimate for  $\sigma$  is 0.884, with standard error 0.158.

my estimate perfectly lines up with his industry-level estimates. As shown in Table 2, my estimate picks up industries such as apparel, leather, food products and textile industries, which all have estimated elasticities of substitution above 0.5 in Raval (2019). Another point worth mentioning is that although my point estimate is below one, it is not statistically significantly different from one. This implies that my estimate cannot rule out a Cobb-Douglas production function.

### 3.2.5 2SLS Results – Other Outcomes

Table 5b reports manufacturing plants’ responses to the change of the hourly wage on other margins. State-by-year fixed effects and establishment fixed effects are included in all the regressions. Results using a linear instrument are reported in the odd columns, and results using the quadratic version of the instrument are in the even columns. Columns 1–2 are the estimates for the employment of all workers. Using my preferred specification, the coefficient shows that total employment will drop by 0.16 percent, or equivalently 0.26 workers, when the hourly wage of production workers increases by one percent. The estimate is statistically insignificant. Results in columns 3–4 show that an increase in the hourly wage of production workers has a weak and insignificant positive effect on the number of non-production workers, suggesting complementarity between machines and non-production workers.

Columns 6 and 8 show that when the hourly wage increases by one percent, capital expenditures on structures increase by 1.17 percent (statistically insignificant), and total capital expenditures increase by 2.43 percent. This result indicates that the increase in total capital expenditures is driven by the increase in capital expenditures on machines. The magnitude of 2.43 indicates that the total capital expenditures of an average plant will increase by \$17,600 when the hourly wage increases by one percent.

Columns 10 and 12 report the coefficients when the outcome variables are two measures of revenue: the TVS and the real value of revenue. Results from these two measures are almost the same: a one-percent increase in the hourly wage of production workers increases total revenue by 0.2 percent (statistically insignificant). The industry-level price indices used when constructing real revenue are, however, too crude for drawing conclusions on establishments’ responses in output prices and output separately. It is possible that the observed small responses of revenue could be a result of two offsetting effects—an increase in price and a decrease in output.

The result in Column 14 indicates that the costs of electricity and fuel reduce by 0.01 percent when the hourly wage of production workers increases by one percent. This effect is small and statistically insignificant. Columns 16 and 18 report the results in which the out-

come variables are materials and profit margin. The signs of these coefficients are consistent with the previous literature (Draca et al., 2011; Harasztosi and Lindner, 2019); the increase in the hourly wage of production workers increases the use of materials and reduces the profit margin. These estimates are again not statistically significant, but taking the estimates at their face value, the results mean that a one percent increase in the hourly wage increases the costs of materials by 0.44 percent (around \$73,500) and reduces the profit margin by 1.3 percentage points (around six percent). Finally, the estimate when the outcome variable is the TFP (Column 20) suggests that the increase in the hourly wage does not increase productivity.

Estimation of multiple outcomes may raise concerns that some statistically significant results are found by chance; Table B5 shows the results of multiple hypotheses testing using Benjamini and Hochberg False Discovery Rate. The only result become insignificant at 95-percent level is total capital expenditures.

## 4 Pre-trends, Falsification Test, and Sensitivity Analysis

After discussing the results, it is essential to test the robustness of the results. Validity of the identification strategy relies on the exogeneity of the changes in the minimum wage. If the changes are exogenous to the main sample, two conditions will be satisfied. First, establishments that are bound by the minimum wage at different intensities should follow parallel trends before the change in the minimum wage occurs. Second, the change in the minimum wage should not differentially affect the establishments whose average hourly wage is a lot higher than the minimum wage. These two conditions are checked in Section 4.1 and Section 4.2.

After discussing the validity of the instruments, I turn to test the sensitivity of the results to the threshold. In the analysis, I restrict the sample to the establishments whose distance measure,  $dminw_{est}$ , is below the 20th percentile of the national distribution of  $dminw_{est}$ . Section 4.3 discusses how the results change when the threshold varies.

### 4.1 Pre-trends

A crucial assumption for causal interpretation of the previous results is that establishments bound by the minimum wage at different levels would have followed parallel trends had the minimum wage not changed. This assumption can not be tested directly, but it is possible to test pre-trends. I use a distributed lag specification that interacts the treatment

variable with the leads and lags of the change in the log of the minimum wage. Formally, I estimate the following equation:

$$\Delta y_{est} = \theta_0 + \sum_{i=-5}^2 \theta_{i+6} \Delta \min w_{s(t-i)} \times T_{es(t-1)} + \theta_9 T_{es(t-1)} + \delta_{st} + \lambda_e + \varepsilon_{est}, \quad (4.1)$$

where  $\Delta \min w_{s(t-i)}$  is the change in the log of the minimum wage from year  $t-i-1$  to  $t-i$ . The state-by-year fixed effects,  $\delta_{st}$ , and the establishment fixed effects,  $\lambda_e$ , are included in the regressions. Conditional on state-by-year fixed effects and establishment fixed effects, if the outcome variables of establishments follow parallel pre-trends, estimates of  $\theta_1$ - $\theta_5$  will not display systematic trends.

Figures 6a and 6b plot the estimates for  $\theta_1$ - $\theta_8$  and the associated 95-percent confidence intervals. Event time on the  $x$ -axis corresponds to 5 lags of the change in the log of the minimum wage ( $x = -5$  to  $-1$ ), event time ( $x = 0$ ), and 2 periods after the increase of the minimum wage ( $x = 1$  and  $2$ ). The solid red vertical line divides each figure into two regions: pre-periods (the left-hand region of the solid line) and treated periods (the right-hand region of the solid line). The trends of the coefficients in the pre-periods are expected to be flat if the establishments follow parallel pre-trends. The coefficient at  $t = -1$  captures potential plants' anticipatory effect. Minimum wage hikes are usually announced several months (or even years) before the actual hike; manufacturing plants, therefore, may adjust their inputs before the actual implementation.

The outcome variable in Panel (a) of Figure 6a is total production worker hours. The estimates prior to the event year fluctuate, but do not present systematic trends, indicating that the establishments bound by the minimum wage at different levels follow parallel trends before the minimum wage increase. The estimate at  $x = -1$  is lower than the estimate one period ahead of it; the difference could suggest that establishments stop the increase in the use of labor prior to the change of the minimum wage. The estimate at  $x = 0$  shows that conditional on the leads and lags of the change in the minimum wage, an increase in the minimum wage has a statistically significant (at the 99 percent confidence level) negative impact on total hours worked by production workers. This result is consistent with the 2SLS result. The negative response does not persist into the following years: the point estimate at  $x = 1$  is less negative than in the previous period and turns positive in the following year.

Panel (b) of Figure 6a plots the pre-trends and the treatment effect when the outcome variable is capital expenditures on machines. Before the treatment, establishments follow parallel trends. The point estimate at  $x = 0$  is positive and statistically significant at the 95-percent confidence level, indicating that an increase in the minimum wage differentially increases capital expenditures on machines of establishments that are more bound by the minimum wage. The differential increase do not persist in the following two years. The pattern of the estimates when the outcome variable is the log(capital stock on machines/total

production worker hours) (Panel c) is similar—no systematic pre-trend or statistically significant treatment effect consistent with the 2SLS results. Finally, Panel (d) shows the results for the TVS: the revenue of the establishments do not evolve differently before the treatment. The point estimates in the treatment region indicate that the total value of the shipment increases and keeps increasing one year after the treatment, but neither estimate is statistically significant at any conventional level.

Figure 6b presents the pre-trends for other outcome variables, and no systematic pre-trends is observed on these variables. All of these figures provide supporting evidence that the establishments follow parallel trends before the treatment, and that the change in the minimum wage serves as a valid source of exogenous variation for the analysis.

## 4.2 Falsification Test

To show that the minimum wage does not differentially affect the high-wage establishments that are not supposed to be directly affected, I run a reduced-form regression, that is, regress the dependent variables on the interaction of the change in the log of the minimum wage and a hypothetical treatment variable  $HT_{es(t-1)}$ . The hypothetical treatment variable is defined to be  $HT_{es(t-1)} = 1 - (pct_{es(t-1)} - 60)/20$  or  $HT_{es(t-1)} = 1 - (pct_{es(t-1)} - 80)/20$  when the sample is restricted to the establishments whose distance measure in the lagged period,  $dminw_{es(t-1)}$ , is between the 80th and 100th percentiles or between the 60th and 79th percentiles. I use this specification, rather than the 2SLS, because the first stage will not be valid when the minimum wage does not differentially affect the wages across high-wage establishments. The regression equation is:

$$\Delta y_{est} = \phi_0 + \phi_1 \Delta minw_{st} \times HT_{es(t-1)} + \phi_2 HT_{es(t-1)} + \delta_{st} + \lambda_e + \varepsilon_{est}. \quad (4.2)$$

Table 6 reports the regression result of  $\phi_1$  with several key outcome variables. Panel A reports the results for establishment-year observations between the 60th and 79th percentiles, and Panel B corresponds to the 80th and 100th percentiles.

Columns 1–3 of both panels report the results when outcome variables are total production worker hours (Column 1), number of production workers (Column 2), and average hours worked per production workers (Column 3). The results show that, unlike the 2SLS results using the main sample, the change in the minimum wage does not predict a differential treatment effect on the establishments that are not supposed to be treated. Similarly, the change in the minimum wage does not have a large differential impact on the capital expenditures on machines (Column 4) and the capital-labor ratio (Column 5) of these establishments. The estimates of the capital-labor ratio in Panel B are marginally significant at the 90-percent confidence level, but the estimate is smaller than the corresponding estimate

when using the main sample (Column 5 of Table B3). Finally, the change in the minimum wage does not have statistically significant impact on the total value and shipment (Column 6) or employment (Column 7) of these establishments. These results suggest that the impact of the minimum wage is concentrated at the bottom of the wage distribution.

The results of the pre-trends and the falsification test support the credibility of the exclusion restriction of the 2SLS model. It is, therefore, reasonable to believe that the estimates from the 2SLS model show the causal impact of the change in the hourly wage on the outcome variables. In the next subsection, I check the sensitivity of the main results to the choice of the threshold.

### 4.3 Sensitivity to Thresholds

An establishment-year observation is included in the main analysis if its  $pct_{es(t-1)}$  is less than 20. To test if the results are driven by the choices of the sample, I run the 2SLS regression model in Equation 3.2, but with different cut-offs that are around the 20th percentile. Specifically, I restrict the analysis to the establishment-year observations whose  $dminw_{es(t-1)}$  is below the  $(10 + 2 \times i)$ th percentile, for  $i = 0-10$ . The treatment variables are defined to be  $T_{es(t-1)} = 1 - pct_{es(t-1)} / (10 + 2 \times i)$ . In these regressions, I use the quadratic instruments and include state-by-year and establishment fixed effects. The estimates and the associated 95-percent confidence intervals using those samples are reported in Figures 7a and 7b. The  $x$ -axis labels the cut-offs that restrict the sample.<sup>35</sup>

Panel (a) of Figure 7a plots the coefficients when the outcome variable is total production worker hours. The point estimates range from -0.89 ( $x = 10$ ) to -0.69 ( $x = 18$ ), but the smallest estimate is not statistically different from the largest estimate. All these estimates are statistically significant at the 99-percent confidence level. The coefficients when the outcome variable is capital expenditures on machines are plotted in Panel (b). The estimates when the sample is restricted to the bottom 10th or 12th percentiles are positive, but are not statistically significant at any conventional level. It is likely that establishments below the 12th percentile respond to the wage change in similar ways, so the estimates do not capture a differential response. The estimates beyond the 12th percentiles are similar to the main estimate.

Panel (c) plots the estimates for elasticity of substitution between capital and labor. The estimates range from 0.79 to 0.97. The confidence intervals of these estimates largely overlap. In all cases, one is included in the 95-percent confidence intervals, and most estimates below

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<sup>35</sup>For example, when  $x = 10$ , it indicates that the analysis is restricted to establishment-year observations whose  $dminw_{es(t-1)}$  is in the bottom decile of the national distribution. The estimates when  $x = 20$  are the same as the ones with the same specifications discussed in Section 3.2.

0.5 are not included. Finally, Panel (d) shows that changing the thresholds has almost no impact on the estimates when the outcome variable is the TVS and that in all cases, the point estimates are close to zero and statistically insignificant.

A sensitivity analysis of the other outcome variables is plotted in Figure 7b. It is worth mentioning that when the sample is restricted to the bottom 10th and 12th percentiles, the point estimates for the outcome variable on the number of production workers are statistically significant at the 95-percent confidence level (Panel a). This means that it is likely that the very low-wage manufacturing plants lay off workers, and cut average hours worked per worker (as shown in Panel b) at the same time.<sup>36</sup> It is also worth mentioning that the estimates for profit margin are more accurate when more observations are included (Panel f). When restricting the analysis to the bottom 24th and 26th percentiles, the t-values of the estimates are above 1.9. This observation suggests that the profit margin decreases when the hourly wage of production workers increases, though the results are not robust to the choices of the sample.<sup>37</sup> In summary, these figures show that the estimates are robust to the choice of the sample.

## 5 Possibility of Exit

The analysis has focused on the responses of manufacturing plants on the condition that they do not exit the market within their corresponding panel following a minimum wage hike. An establishment can, however, choose to exit the market when the hourly wage increases. Exiting the market and adjusting inputs are two related, but separate decisions; when the wage rate increases, a plant that chooses to stay can still choose to pay its workers accordingly without reducing labor demand or increasing capital expenditures.

In this section, I use data from the LBD to estimate establishments' exit responses. The LBD consists of data from a variety of sources, including the Economic Census and the IRS administrative tax records. Compiling the data from different sources, the LBD provides measures of the first year and the last year an establishment is in operation. As a result, for all establishments in the main sample, the year when a plant exits is observed.

I start by presenting evidence on plants' exit choices, and then I discuss the possible

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<sup>36</sup>The point estimates are -0.42 (with standard error 0.182) and -0.35 (with standard error 0.193) when the outcome variable is the number of production workers and when the sample is restricted to the bottom 10th and 12th percentiles. Using the mean of 129 production workers of the main sample, those two point estimates imply that a 10 percent increase in the hourly wage leads a very low-wage plant to lay off approximately five production workers. This means that for the plants that are largely affected by the minimum wage, a reduction in the number of workers remains an option.

<sup>37</sup>Using the most accurate point estimate at the 26th percentile, a 10 percent increase in the hourly wage of production workers reduces the profit margin by 8.2 percentage points. Because the average profit margin is 21 percent in the main sample, this estimate implies that the profit margin decreases by 39%.



impacts of the exit choices on the interpretation of the previous results. The choices of exit can muddle the interpretation of previous results through, for example, affecting the probability of filling out the questionnaires mailed out by the Census. Consider a situation in which the minimum wage increases from \$7 per hour in 2011 to \$8 per hour in 2012. If an establishment responds to the change by exiting the market in 2012, it is not likely to answer a questionnaire sent in 2012 asking for information from 2011. Then, this establishment will not show up in the main sample because the treatment variable is defined based on the hourly wage of this establishment in 2011.

The identification strategy for this analysis is the same as in the previous sections, but the sample used is slightly different. First, I keep an establishment-year observation as long as the first difference of the hourly wage of production workers is observed.<sup>38</sup> Second, I do not maintain the balanced three- or five-year panels as in the previous analysis; plants that exit the sample in the middle of each three- or five-year survey window are included in this analysis. I add these plants back because an increase in the hourly wage can cause a plant to exit the ASM and CM panel. These plants, however, are observed in the LBD; their exit choice is known even they do not show up in the ASM and CM panel. Third, I follow each establishment for five years after the treatment in the regressions, and because all establishments that do not exit before 2013 are assigned 2013 as their last year, it is hard to know which plants exited in and after 2013. To avoid confusion, I drop the observations that appear in the sample after 2007, so I know exactly if an establishment exited over the five-year window. After these steps, I follow the method described in Section 3.1 to further restrict the sample to establishments below the 20th percentile of the distribution of  $dminw_{est}$  and construct the treatment variable  $T_{es(t-1)}$ .

I estimate the following linear probability model:

$$Exit_{es(t+k)} = \alpha_0 + \alpha_1 \Delta w_{est} + \alpha_2 T_{es(t-1)}^2 + \alpha_3 T_{es(t-1)} + \delta_{st} + \lambda_e + \varepsilon_{est}, \quad (5.1)$$

where  $k = 1 - 5$ . The dependent variable  $Exit_{es(t+k)}$  is a dummy variable that equals one if establishment  $e$  in state  $s$  has exited the market in year  $t + k$ . Each  $k$  corresponds to one separate regression. The independent variable  $\Delta w_{est}$  remains to be the change in log of the hourly wage of production workers, and it is instrumented by the quadratic version of the instrument. The definitions of other variables are the same as in equation 4.1. The coefficient,  $\alpha_1$ , identifies the impact of changes in the hourly wage on probability of exit in year  $t + k$ .

Figure 8 plots the coefficients  $\alpha_1$  for  $k = 1 - 5$ . The first estimate shows that if the hourly wage of production workers increases by 10 percent, the probability of exit increases

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<sup>38</sup>This is not an ideal setting, but keeping the first difference is necessary to maintain a valid first stage. As a result, the exit choices in the analysis are conditional on an establishment not exiting the market immediately.



by 3.2 percentage points one year following the hourly wage increase. Using the average exit rate of 10.7% among low-wage establishments, the 3.2 percentage points correspond to a 30 percent increase in the probability of exit.<sup>39</sup> The impact lasts in the following two years.<sup>40</sup>

Because of plant exits, the estimates discussed in the previous sections do not represent the overall responses of low-wage establishments. For example, if one is interested in the aggregate change in capital expenditures when the hourly wage increases, then my estimates will not provide an accurate answer. Depending on whether the exited establishments are more or less responsive to an increase in the wage rate than an average establishment that do not exit, the estimated responses can either overstate or understate the overall responses. If the exited establishments are above-average responders who are forced to leave the market because their budget constraint does not allow the adjustment, then the overall response can be larger if the budget constraint is removed. On the contrary, if the exited establishments have high costs for adjusting input ratios, and respond by entry and exit (in the Putty-Clay sense as in [Aaronson et al. \(2018\)](#)), then the estimated responses are larger than the overall responses when the exited establishments are assigned zero responses. When interpreting the previous results, therefore, it is important to keeping mind that those estimates represents stayers.

## 6 Single-unit versus Multi-unit Firms

The CM and ASM panel data are at the establishment level. Among all establishments in the main sample, approximately 42 percent are single-unit firms—the firms that have only one establishment. In this section, I separate the analysis for single- and multi-unit establishments. I first replicate the main analysis using single-unit firms in Section 6.1, then I discuss the responses of multi-unit firms in Section 6.2. The LBD allows researchers to link the establishments to their parent firm. The link makes it possible to investigate “spillover” effects within a firm when some of its establishments are affected by the minimum wage while others are not.

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<sup>39</sup>The average exit rate is calculated among all establishments in the industries that are listed in Table 2.

<sup>40</sup>Estimating the exit responses in period  $t$  is complex. While it is possible to do so using a reduced-form specification, the sample attrition can bias the estimate. I do not attempt to address the sample attrition problem in this paper, but to get a sense of what the estimate in year  $t$  will be, consider two establishments, one treated and the other untreated. If the treated plant is more likely than the untreated plant to exit immediately after the hourly wage increases because of the treatment, then the identified exit response at year  $t + 1$  is smaller than the actual response that happens in year  $t$ .

## 6.1 Single-unit Firms

The analysis uses the same strategy as described in 3.1, but includes only single-unit establishments. Results are reported in Table 7. I use the quadratic instruments in this analysis. In all regressions, state-by-year fixed effects and establishment fixed effects are included. The first-stage F-statistics are 9.6 in most regressions and 15.5 when the outcome variable is the TFP.

Several results stand out: First, the capital-labor substitution result still holds. A one percent increase in the hourly wage of production workers reduces total production worker hours by 0.56 percent (Column 1) and increases capital expenditure on machines by 2.32 percent (Column 4). The estimated  $\sigma$  is 0.9 (Column 5). The reduction in total production worker hours is also driven by the intensive-margin changes (Columns 2-3).

Second, a one percent increase in the hourly wage of production workers increases the employment of non-production workers by 0.74 percent (Column 7), and the estimate is statistically significant at 99-percent level. The decrease in total production workers and the increase in the employment of non-production workers indicate a labor-labor substitution (Clemens et al., 2018). Because an average single-unit establishment employs 10 non-production workers, a 14-percent increase in the hourly wage will drive the establishment to hire one non-production worker. The increase in both capital expenditures on machines and non-production worker is consistent with the complementarity between capital and workers who do not perform routine tasks. The 14-percent increase in the hourly wage will, however, drive the establishment to lay off 0.3 production workers (Column 3). The number is smaller than the increase in the employment of non-production workers, indicating a net increase in the employment.

Third, Columns 8 and 9 show that when the hourly wage of production workers increases by one percent, total revenue increases by 0.51 percent and real revenue increases by 0.44 percent. This could be a result of an increase in the price of output, an increase in the output, or an increase in the TFP. The output price is not observed, but the difference between the estimates in total revenue and the real value indicates that the price may play a role. The estimate in Column 13 shows that this is likely to be a result of the increased TFP. When restricting the analysis to single-unit establishments, increases in the hourly wage increase total factor productivity. Although the estimate is not statistically significant, it is roughly half of a standard deviation based on the summary statistics of the main sample.

Fourth, I find no statistically significant responses on other margins. Increases in the hourly wage of production workers lead to higher costs on electricity and fuel (Column 10), and on materials (Column 11). Profit margins are reduced (Column 12) as in the main

result.<sup>41</sup>

## 6.2 Multi-unit Firms

For this analysis, I aggregate the establishment-year panel data to the firm-year level and require a firm to have at least one affected and one unaffected establishment in a given year to enter the sample. This restriction reduces the sample size dramatically and leads to a weak first stage when using changes in the minimum wage as an instrument.<sup>42</sup> The weak first stage substantiates a reduced-form analysis.

Because the minimum wage has a large impact on low-wage establishments, I include establishments in the bottom 10 percentiles for this analysis as shown in Figure 4. Then I group affected and unaffected establishments separately for each firm in a given year and calculate the average change of the log of the outcome variables for each group-firm-year cell. Unaffected establishments are those in the state-year with no minimum wage increase. For this analysis, I use only state minimum wage changes because federal minimum wage changes can affect a firm's decision in a different way. In particular, it is not clear if a firm increases the wage of establishments in the non-binding states because of spillover effect, or simply because the minimum wage change is at the federal level. After the sample restriction, I estimate the responses of unaffected establishments using the following regression:

$$\Delta y_{uft} = \theta_0 + \sum_{i=-4}^1 \theta_{i+5} \Delta \min w_{af(t-i)} + \varepsilon_{aft}. \quad (6.1)$$

The dependent variable is the average one-year change in the log of outcome variables among unaffected establishments  $u$  in firm  $f$  from year  $t - 1$  to year  $t$ . The independent variables  $\Delta \min w_{af(t-i)}$  are the average one-year change in the log of minimum wage among the affected establishments  $a$  in firm  $f$ . I use the dynamic framework to check pre-trends and identify the spillover effect.

I also investigate the own-establishment responses, that is, using  $y_{aft}$  as the dependent variable. Figure 9 plots the estimates for  $\theta_1 - \theta_5$  when the outcome variable is hourly wage. Panel (a) is for establishments that are directly affected and Panel (b) for establishments not directly affected. In both cases, no meaningful pre-trends are detected. Estimates for  $\theta_5$  show that a one-percent increase in the minimum wage increases hourly wage of production workers among affected establishments by 1.20 percent, and among unaffected establishment by 0.75 percent. The finding suggests that multi-unit firms also increase the wage for unaffected establishments when some of their establishments are affected by the minimum wage. This spillover effect is probably for fairness across their establishments. Dube et al. (2019) find

<sup>41</sup>The main results and the results for single-unit establishments are robust to the inclusion of industry-by-year fixed effects (Table B6).

<sup>42</sup>This can be seen in Panel (a) of Figure 9.

a similar result when analyzing the impact of the minimum wage on a large U.S. retailer. Figure B2 shows the corresponding results for total production worker hours and capital expenditures on machines; I do not find spillover effect on these two margins.

## 7 Discussion and Conclusion

Using the minimum wage as a source of exogenous variation, this paper provides empirical evidence that manufacturing plants substitute capital for labor when wage rates increase. The estimation results imply that when the hourly wage of production workers increases by 10 percent (roughly \$0.90 in an average establishment), an average establishment reduces the total hours worked by production workers by 7.2 percent, and increases capital expenditures on machines and equipment by 24.3 percent.

The estimated elasticity of substitution between capital and labor is 0.85, with standard error of 0.177. The estimate is context-specific. First, this estimate is inferred from an analysis that uses only manufacturing industries. Second, the use of the minimum wage as an instrument picks up the substitution between machines and low-wage workers. In particular, Table 2 explicitly shows that the industries being affected are the low-skilled labor-intensive industries such as textile, apparel, shoe manufacturing, and food processing. Presumably, the workers in these industries are more likely to perform routine tasks, and thus, they are more susceptible to replacement by machines. My estimate, therefore, is expected to be higher than other estimates that involve the industries that hire a large number of high-skilled labor. Finally, I use capital expenditures on machines and production worker hours for the estimation because these two inputs are relevant counterparts in a production function. These two inputs are also close substitutes. For example, in a clothing manufacturing plant, we would expect that, machines are more likely to take the place of production workers, rather than designers or managers. Therefore, the estimated elasticity of substitution is expected to be higher than an estimate that includes all workers and all types of capital.

Different industries are not expected to respond to changes in wage rates in the same way. For instance, firms in service industries might be less likely to replace their workers with capital when wage rates increase because these jobs cannot easily be replaced by robots at this point in time. Understanding more about industry-specific responses is important for understanding aggregate responses. Estimating industry-specific responses is itself policy-relevant because the groups affected by different policies may be different. Therefore, it remains important to investigate the responses of other industries to exogenous changes in wage rates in future research.

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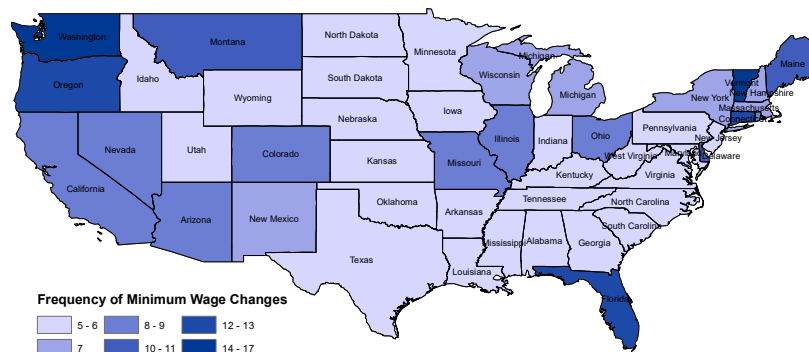
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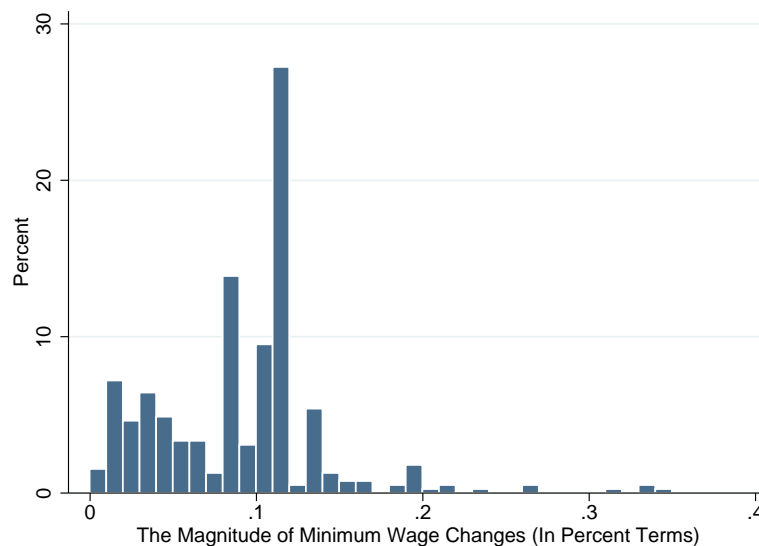
## Figures and Tables

Figure 1: Federal and State Minimum Wage Changes Between 1991 and 2013

(a) The Number of Changes

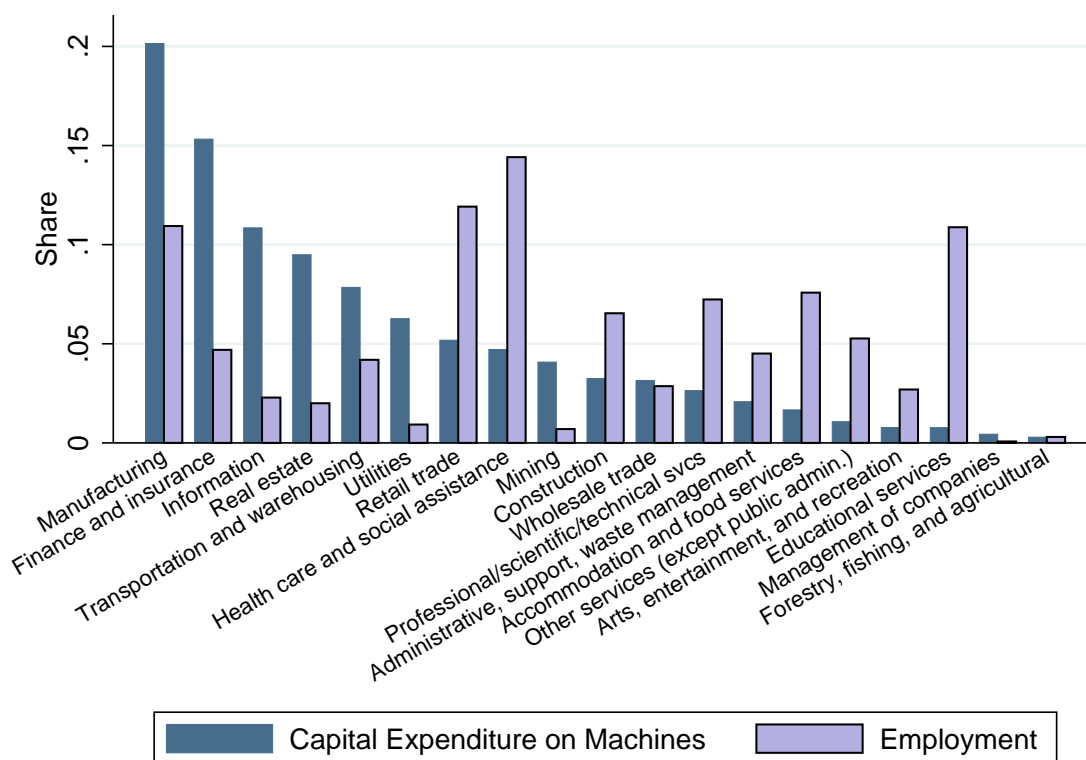


(b) Density of the Magnitude of Minimum Wage Changes



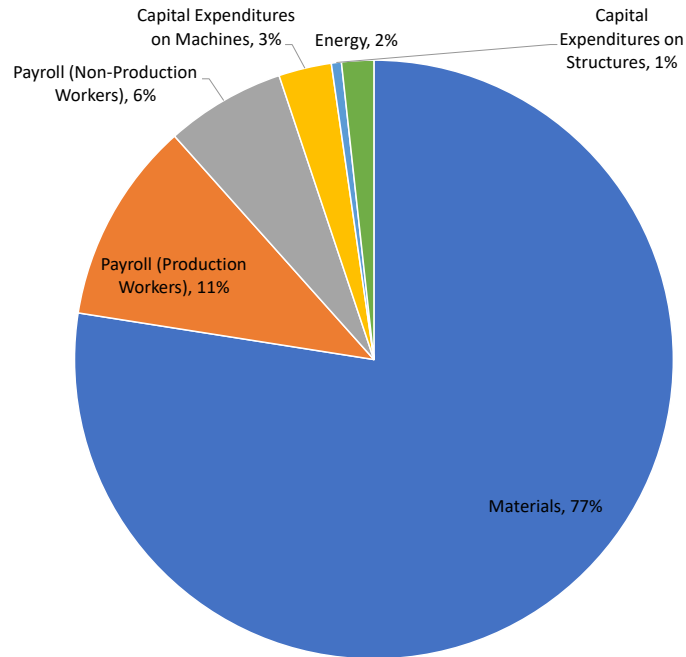
Note: This figure plots the frequency and the magnitude of minimum wage changes at state-year level between 1991 and 2013. The map in Panel (a) shows the number of minimum changes that took place in each state over the 23-year periods. A federal-level minimum wage change that affects multiple states is considered as one change for each of the affected states. Panel (b) plots the density of the magnitude of all minimum wage changes between 1991 and 2013. Data are collected and organized by David Neumark and are available at <https://www.socsci.uci.edu/~dneumark/datasets.html>

Figure 2: Employment and Capital Expenditures on New Machines or Equipment in Manufacturing and Other Industries (2016)



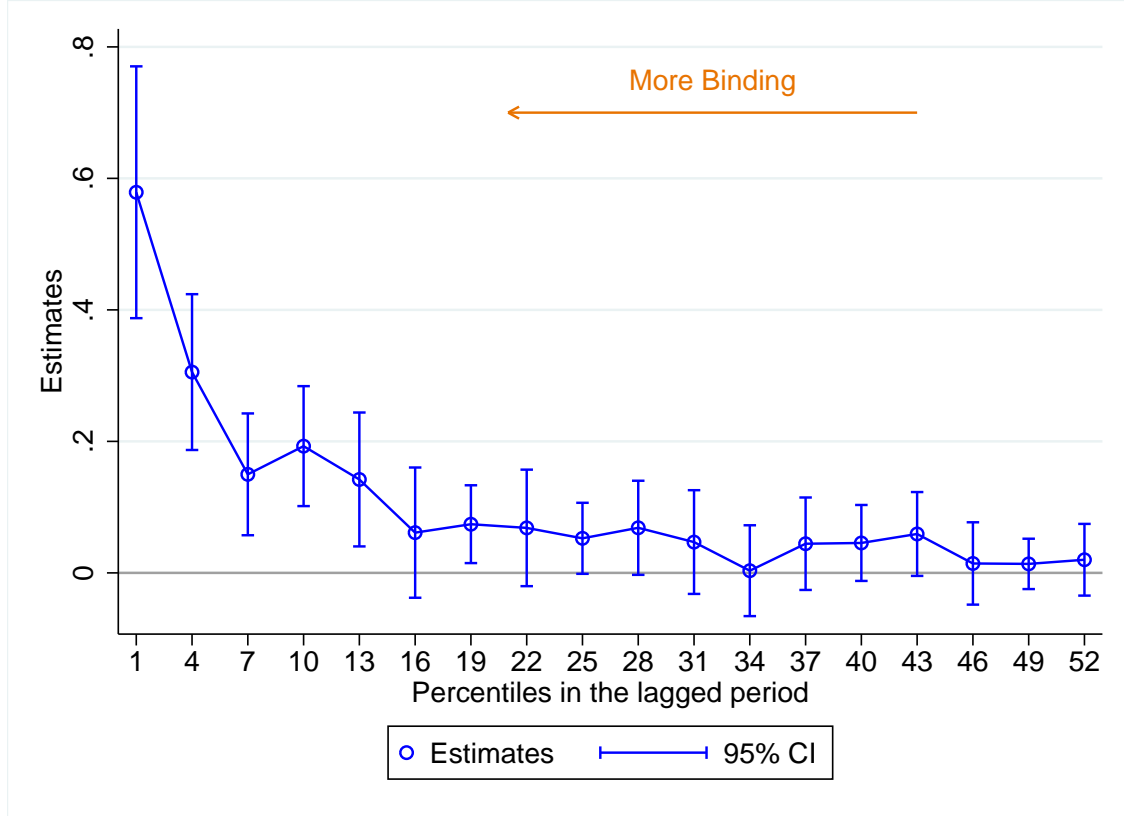
Note: This bar chart presents the share of the employment and the capital expenditures on machinery and equipment, out of national total, of each industry group in 2016. The y-axis represents shares. Farm and public service industries are excluded when calculating these numbers. Industry groups in the figure are ordered by their annual capital expenditures on machinery and equipment in 2016. Data source: the Annual Capital Expenditure Survey (ACES) by the Census Bureau (Table 4a of <https://www.census.gov/data/tables/2016/econ/aces/2016-aces-summary.html> and the American Community Survey (ACS) from the IPUMS-USA. )

Figure 3: Cost Shares of the Inputs (the Main Sample)



Note: This figure plots the cost shares of the inputs using the main sample. See footnotes of Figure 4 and Figure 5 for the construction of the main sample. Capital expenditures on machines and on structures are reported separately. Total payroll is reported separately for production workers and non-production workers. Energy includes costs of electricity and fuels. Material includes the costs of materials and parts, costs of resales and costs of contract worker. Data Source: the ASM and the CM from 1991 to 2013.

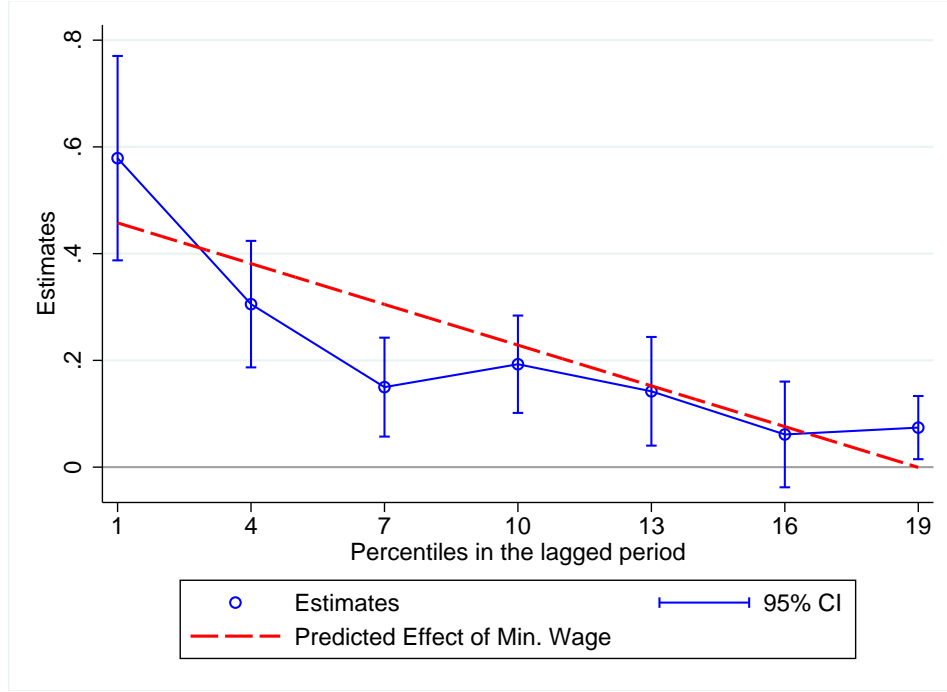
Figure 4: The Impact of the Minimum Wage on the Hourly Wage of Production Workers by How Binding the Minimum Wage is to Each Establishment in the Lagged Period



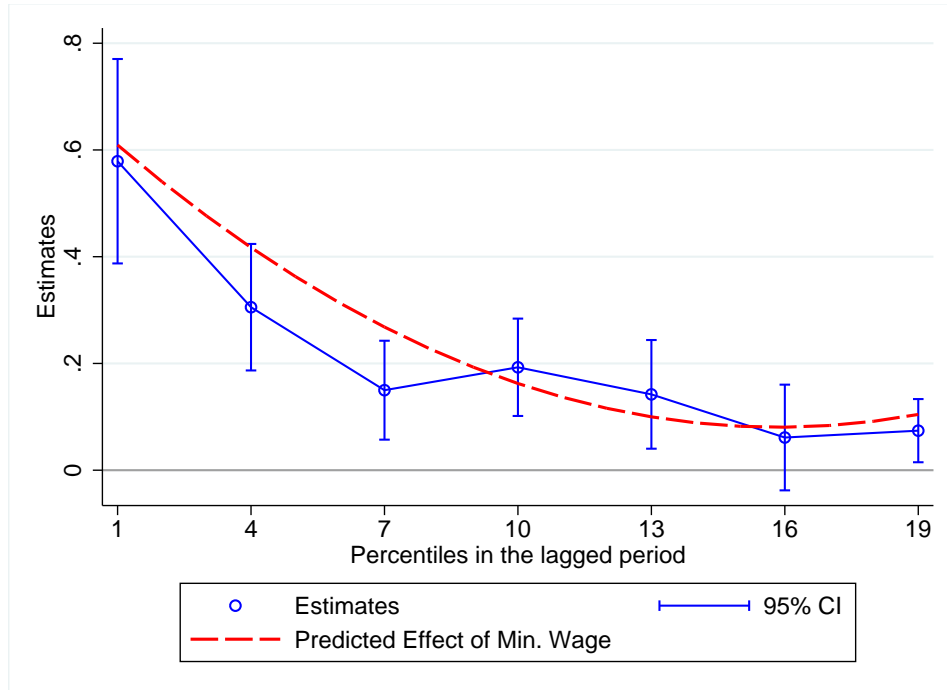
Note: This figure shows the impact of the minimum wage on the hourly wage of production workers by how binding the minimum wage is to each establishment in the lagged period. It plots the coefficients of 18 bivariate regressions. The dependent variable of the regressions is the change in the log of hourly wage of production workers, and the independent variable is the change in the log of the minimum wage. Each bin corresponds to one regression. The  $x$ -axis shows the sample used in each regression: when  $x = i$ , the sample used is the establishment-year observations whose  $pct_{es(t-1)}$  is between  $i$  and  $i + 2$ , for  $i = 1, 4, \dots, 52$ . To construct  $pct_{es(t-1)}$ , I first calculate the distance between the average hourly wage of production workers in each plant-year and the minimum wage of that state-year, denoted as  $dminw_{est}$ . Then, for each year, I rank establishments using  $dminw_{est}$  to construct a national distribution, and  $pct_{est}$  is an establishment's position in the national distribution. The line segments show the 95-percent confidence intervals. Standard errors are clustered by states. Data sources: the ASM and the CM from 1991 to 2013.

Figure 5: The Fit of the Predicted Impact of the Minimum Wage on the Hourly Wage of Production Workers Using the Instruments (Main Sample:  $pct_{es(t-1)} < 20$ )

(a) Linear Instrument:  $\Delta minw_{st} \times T_{es(t-1)}$ , where  $T_{es(t-1)} = 1 - pct_{es(t-1)}/20$

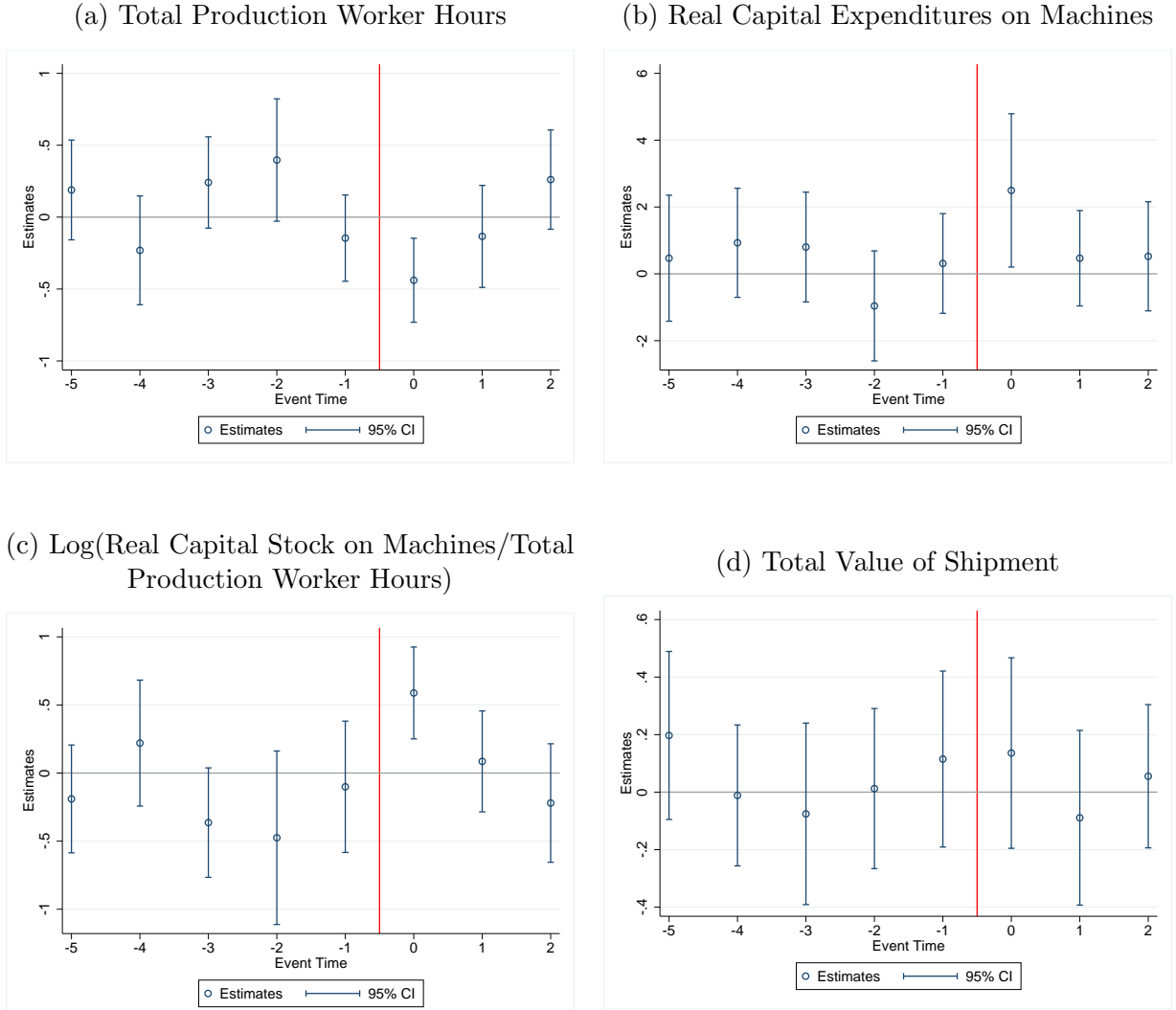


(b) Quadratic Instruments:  $\Delta minw_{st} \times T_{es(t-1)}$  and  $\Delta minw_{st} \times T_{es(t-1)}^2$



Note: These two figures and the solid lines are based on Figure 4 with the establishment-year observations whose  $pct_{es(t-1)}$  is above 22 are dropped. Each figure has an additional dashed line plotting the predicted marginal effect of the minimum wage, for each  $pct_{es(t-1)}$  between 1 and 19, using estimated coefficients from the first stage. The estimated coefficients are from models without state-by-year FEs or establishment FEs. Data sources: the ASM and the CM from 1991 to 2013.

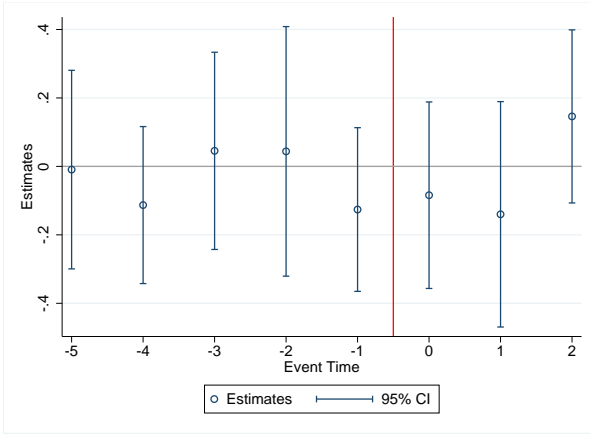
Figure 6a: Pre-treatment Trends



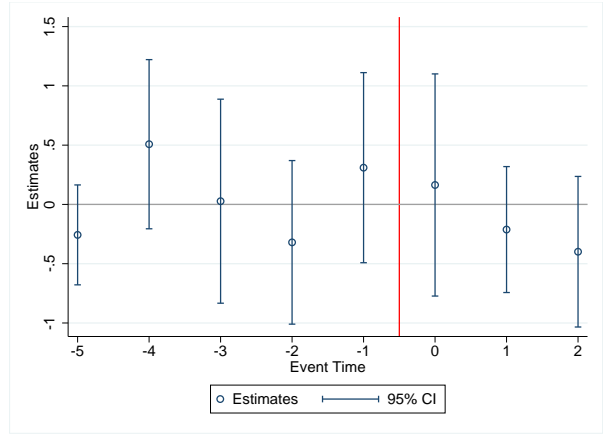
Note: This figure plots the coefficients  $\theta_1$ – $\theta_8$  in Equation 4.1 and the associated 95-percent confidence intervals. The “Event Time” on the  $x$ -axis corresponds to 5 lags of the change in the minimum wage ( $x = -5$  to  $-1$ ), event time or the year when the minimum wage changes ( $x = 0$ ) and 2 years after the change of the minimum wage ( $x = 1$  and  $2$ ). The solid red vertical lines label the beginning of the minimum wage change. Each panel is corresponding to one outcome variable. Data sources: the ASM and the CM from 1991 to 2013.

Figure 6b: Pre-treatment Trends (Other Outcomes)

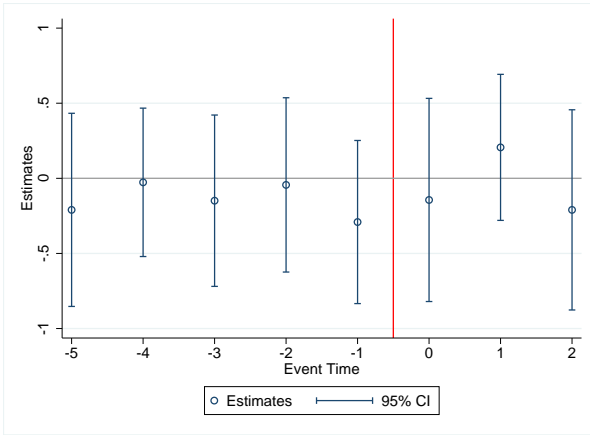
(a) Total Employment



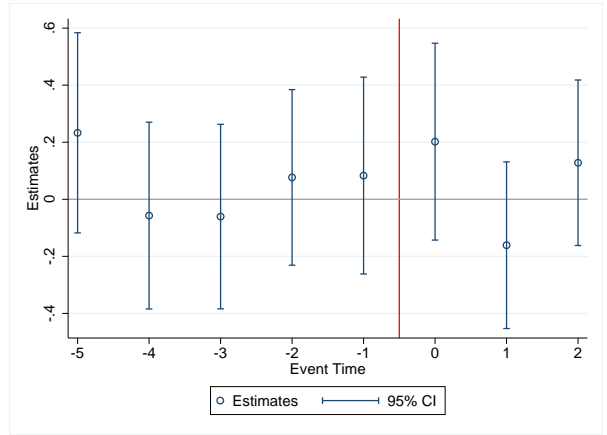
(b) Real Costs of Materials



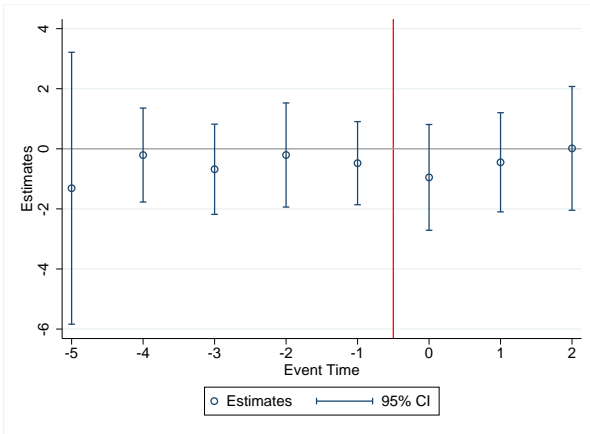
(c) Real Costs of Electricity and Fuel



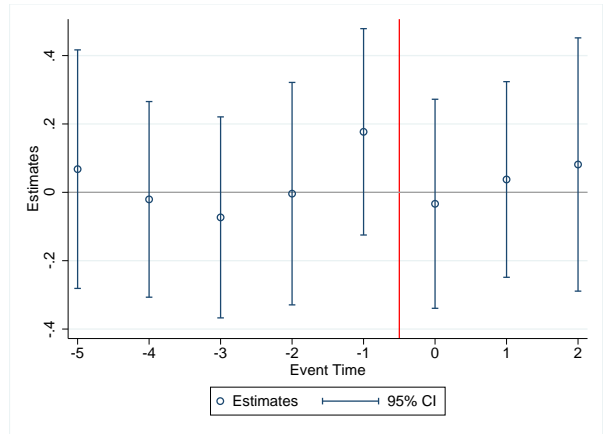
(d) Real Revenue



(e) Profit Margin



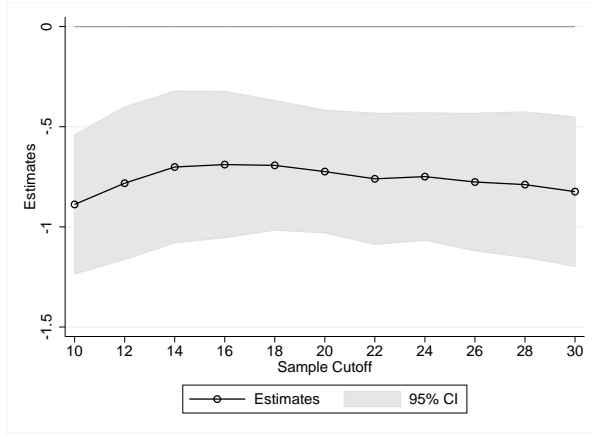
(f) Total Factor Productivity



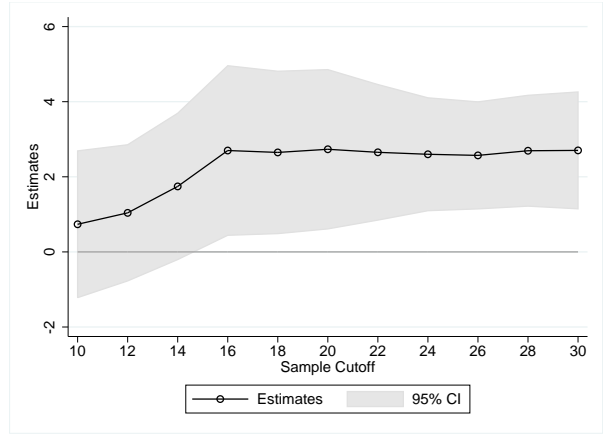
Note: This figure plots the coefficients  $\theta_1 - \theta_8$  in Equation 4.1 and the associated 95-percent confidence intervals. See text and the footnote of Figure 6a for more details. Data sources: the ASM and the CM from 1991 to 2013.

Figure 7a: Sensitivity of the Results to Cutoffs that Restrict the Main Sample

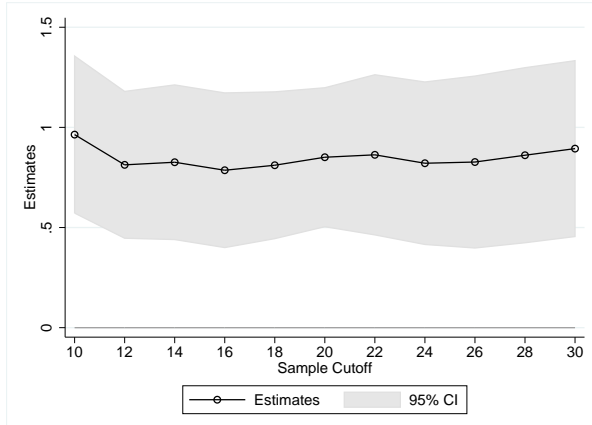
(a) Total Production Worker Hours



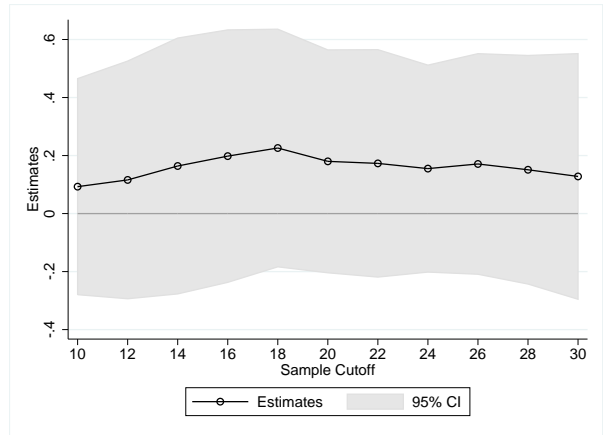
(b) Real Capital Expenditures on Machines



(c) Elasticity of Substitution Between Capital and Labor



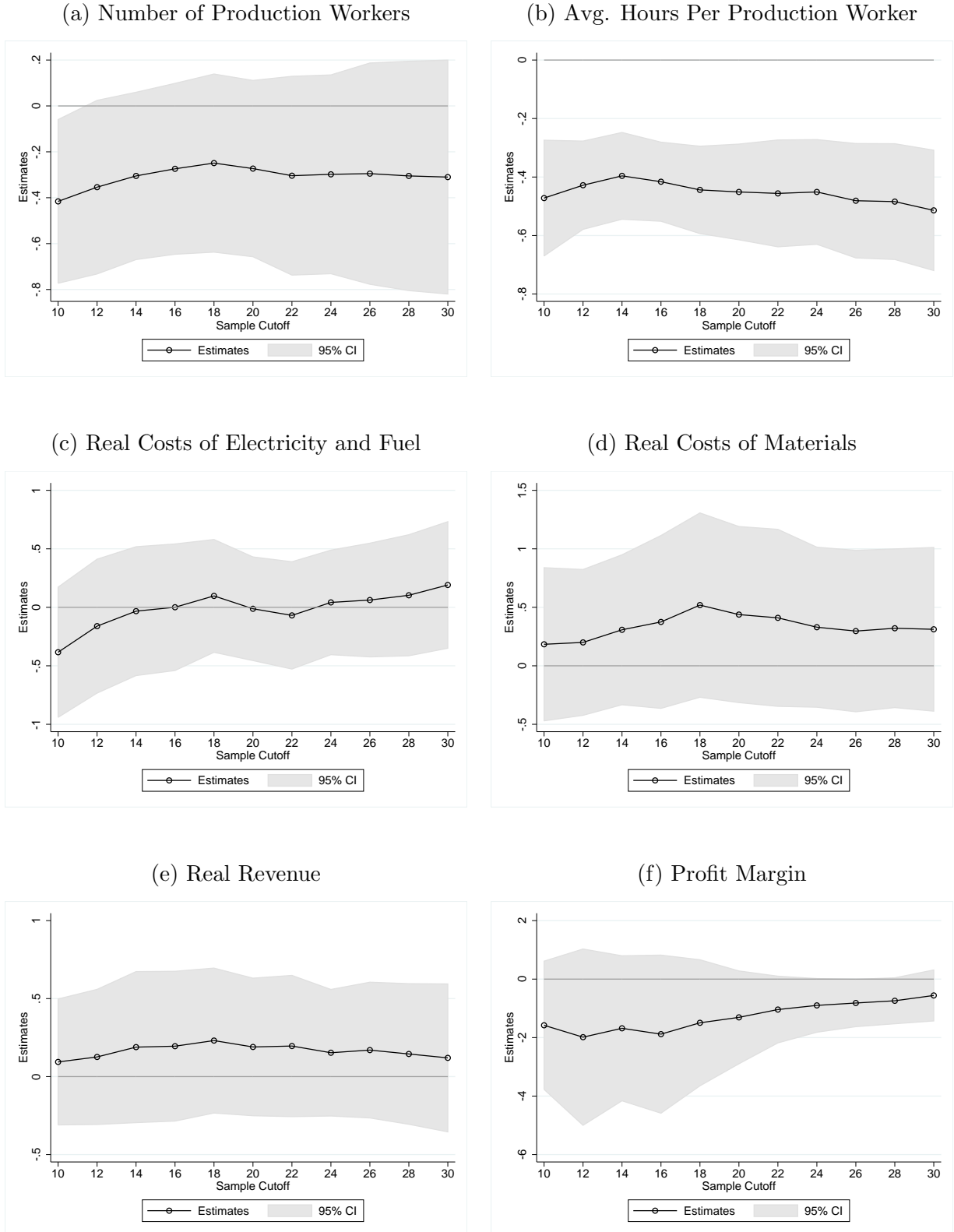
(d) Total Value of Shipment



Note: These figures plot the coefficient  $\beta_1$  of the 2SLS regression equation 3.2, together with 95-percent confidence intervals, with different samples that are discussed in the text. State-by-year fixed effects and establishment fixed effects are included in all regressions. The  $x$ -axis indicate the cut-off of the choice of the sample. For example, when  $x = 10$ , it indicates that the analysis is restricted to establishment-year observations whose distance measure,  $dminw_{est}$ , is in the bottom 10th percentile of the national distribution. Each sub-figure corresponds to one outcome variable. Data sources: the ASM and the CM from 1991 to 2013.

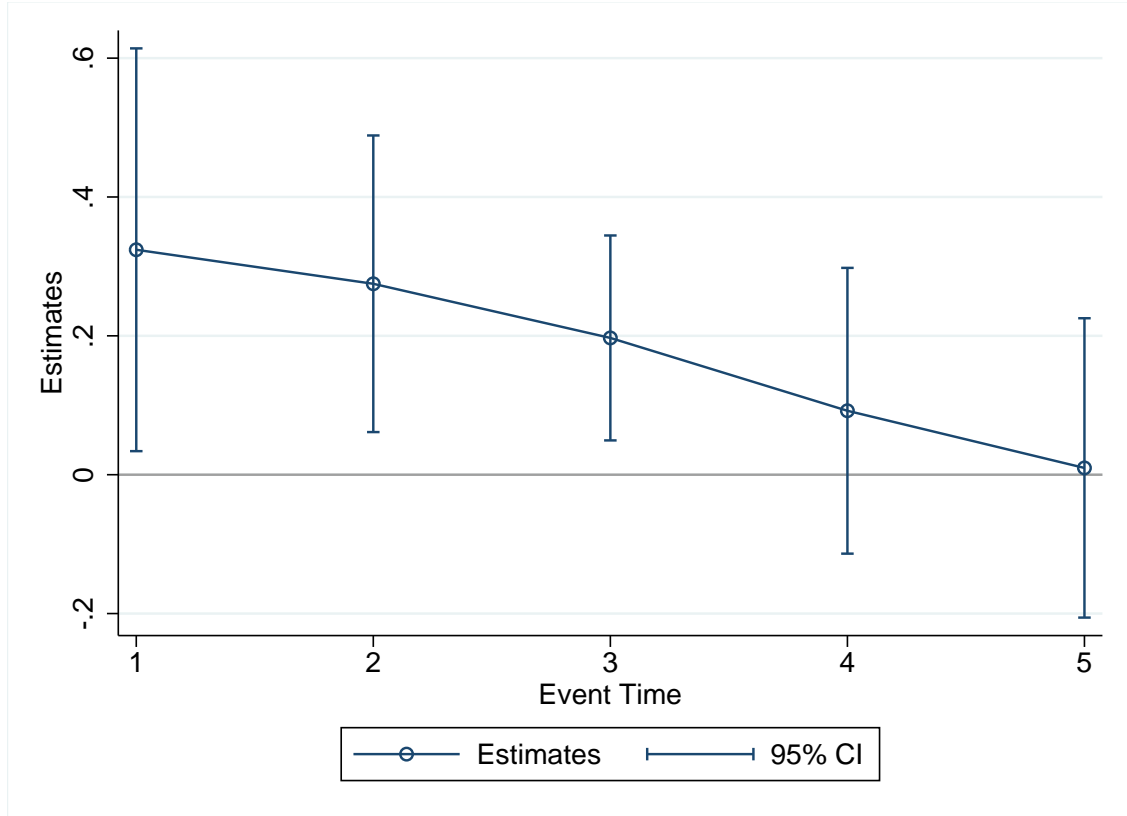


Figure 7b: Sensitivity of the Results to Cutoffs that Restrict the Main Sample (Other Outcomes)



Note: These figures plot the coefficients  $\beta_1$  of the 2SLS regression equation 3.2, together with 95-percent confidence intervals, with different samples. State-by-year fixed effects and establishment fixed effects are included in all regressions. Each sub-figure corresponds to one outcome variable. More details are given in the footnote of Figure 7a. Data sources: the ASM and the CM from 1991 to 2013.

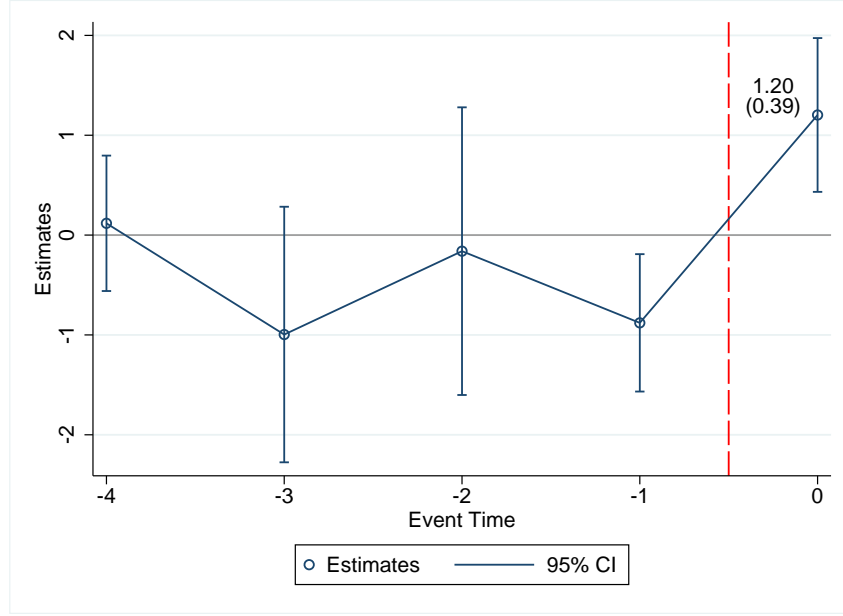
Figure 8: Establishment Exit



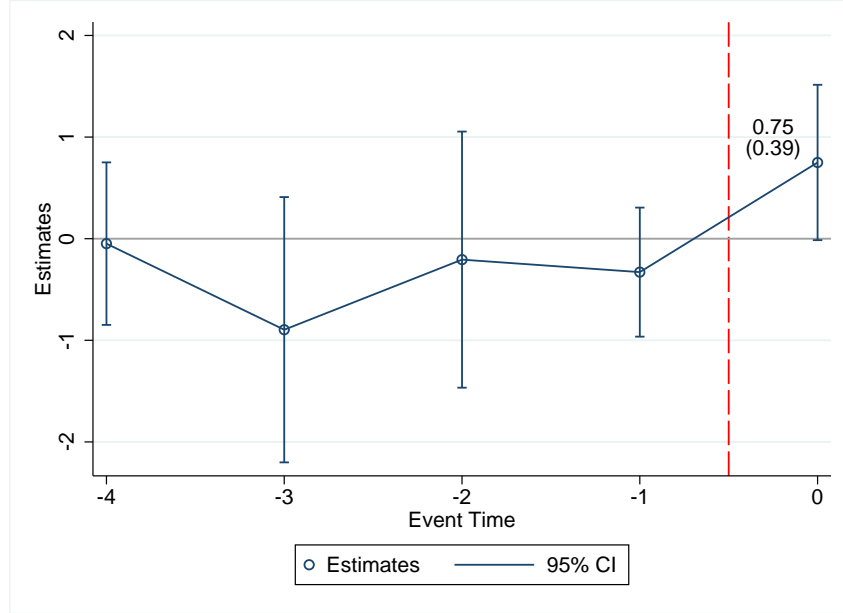
Note: This figure plots the coefficients  $\alpha_{1s}$  of equation 5.1 and the associated 95-percent confidence intervals. It shows the impact of the increases in the hourly wage of the production workers from year  $t - 1$  to year  $t$  on probability of exit in year  $t + 1$  to year  $t + 5$ . The “Event Time” on the  $x$ -axis corresponds to years  $t + k$  for  $k = 1 - 5$ . The quadratic version of the instrument is used in these estimations. Data source: the ASM, the CM and the LBD.

Figure 9: Responses of Multi-unit Firms to the Minimum Wage  
(Hourly Wage of Production Workers)

(a) Establishments that are Directly Affected



(b) Establishments that are Not Directly Affected



Note: This figure shows the responses of multi-unit firms. It plots the estimated coefficients  $\theta_{i+5}$  in equation 6.1, for  $i$ s between -4 and 1. The dependent variables are the average change in the log of hourly wage of production workers among establishments, in firm  $f$ , that are directly affected (Panel a) and not directly affected (Panel b) by the minimum wage. The independent variable is the average change in the log of the minimum wage among affected establishments in firm  $f$ . The unit of observation is firm-year. The  $x$ -axis shows the value of  $i$ , or event time. The red dashed line labels the time of the event. For this analysis, I use data between 1991 and 2013, but I dropped the observations in the years when the federal minimum wage changed: 1996, 1997, 2007, 2008, and 2009. Number of observations is 600. See text for more details regarding the sample used in the analysis. Standard errors are clustered by firms. Data sources: the ASM, the CM and the LBD.

Table 1: Summary Statistics

	Panel A – Full Sample			Panel B – Main Sample		
	Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations
Hourly Wage (1997\$)	13.48	8.41	983000	8.86	3.46	128000
Employment	93.45	304.2	983000	165	300.4	128000
Number of Production Workers	66.36	191	983000	128.5	219	128000
Total Hours Worked by Production Workers (in Thousand)	135.7	395.8	983000	267.2	472.5	128000
Avg. Hours Worked Per Production Worker (in Thousand)	2.04	1.757	983000	2.07	1.553	128000
Payroll of Production Workers (in Thousand, 1997\$)	1969	8284	983000	2278	4198	128000
Payroll of Production Workers/Payroll of All Workers	0.63	0.2072	983000	0.628	0.217	128000
Real Capital Expenditures on Machines (in Thousand, 1997\$)	762.5	16120	983000	618.3	3927	128000
Real Capital Expenditures on Structures (in Thousand, 1997\$)	126.3	4230	983000	117.6	1126	128000
Real Capital Stock on Machines (in Thousand, 1997\$)	6819	54740	983000	5314	21200	128000
Real Capital Stock on Structure (in Thousand, 1997\$)	4303	35980	983000	3731	15820	128000
Log of Real Capital Stock on Machines/Production Worker Hours	2.97	1.255	983000	2.58	1.249	128000
Real Revenue (in Thousand, 1997\$)	29280	481700	983000	34430	506200	128000
Real Costs of Materials (in Thousand, 1997\$)	14120	120000	983000	16790	72910	128000
Real Costs of Electricity and Fuel (in Thousand, 1997\$)	487.5	4176	983000	375.6	1562	128000
Profit Margin (Profit/Total Value of Shipment)	0.17	44.09	983000	0.21	8.425	128000
How Many Times an Establishment is Observed	6.24	4.096	983000	2.94	2.6	128000
Total Factor Productivity (TFP)				1.76	0.579	122000

Note: This table gives the summary statistics of a full sample (Panel A) in the 5-year ASM/CM panel, weighted to be national representative, and the main sample (Panel B) used in the analysis. In the full sample, observations with missing values in any of the listed variables, except TFP, are dropped. See text for definitions of each variable and sample selection of the main sample. Fewer observations of the TFP is a result of the construction choices made by [Foster et al. \(2016\)](#); when constructing the TFP, only establishment-year observations with strictly positive values of real revenue, capital stock on machines and structures, cost of energy and wage bill are included, while observations with zero values for these variables are included in the main sample. Throughout the paper, number of observations are rounded to meet the disclosure requirement. Data sources: the ASM and the CM from 1991 to 2013.

Table 2: Industries With the Largest Share of Establishments that are Bound by the Minimum Wage

NAICS 2002	Industry Name	Percent of Low-Wage Establishments ( $pct_{est} < 10$ )
3152	Cut and Sew Apparel Manufacturing	>40%
3169	Other Leather and Allied Product Manufacturing	30-40%
3159	Apparel Accessories and Other Apparel Manufacturing	30-40%
3162	Footwear Manufacturing	20-30%
3151	Apparel Knitting Mills	20-30%
3117	Seafood Product Preparation and Packaging	20-30%
3141	Textile Furnishings Mills	20-30%
3149	Other Textile Product Mills	10-20%
3118	Bakeries and Tortilla Manufacturing	10-20%
3379	Other Furniture-Related Product Manufacturing	10-20%
3219	Other Wood Product Manufacturing	10-20%
3116	Animal Slaughtering and Processing	10-20%
3351	Electric Lighting Equipment Manufacturing	10-20%
3113	Sugar and Confectionery Product Manufacturing	10-20%
3212	Veneer, Plywood, and Engineered Wood Product Manufacturing	10-20%

Note: This table lists the 10 industries with the largest fraction of establishments, in each industry, whose  $pct_{est}$  is below 10. The fraction for each industry is calculated every year (weighted using the sample weight) and then averaged across years. All establishments are assigned an 2002 NAICS using methods developed in [Fort and Klimek \(2016\)](#) until 2010. I assigned 2002 NAICS to post-2010 data using the Census NAICS Concordance. Data sources: the ASM and the CM from 1991 to 2013 and the LBD NAICS files.

Table 3: Correlations Between the Hourly Wage of Production Workers and the Outcome Variables  
(OLS Regressions; Variables in the Analysis are Log- or IHS-Transformed and are in Changes Unless Otherwise Stated)

	(1) Total Production Worker Hours	(2) Real Capital Expenditures on Machines	(3) Elasticity of Substitution Between Capital and Labor	(4) Total Employment	(5) Total Value of Shipment (Measures Total Revenue)	(6) Real Revenue	(7) Real Costs of Electricity and Fuel	(8) Real Costs of Materials	(9) Profit Margin	(10) Total Factor Productivity
Panel A: Baseline Regressions										
Hourly Wage of Production Workers	-0.491*** (0.00948)	-0.00364 (0.0287)	0.499*** (0.0106)	-0.161*** (0.00660)	0.0327*** (0.00531)	0.0339*** (0.00631)	0.0193* (0.0108)	0.0303*** (0.00954)	-0.121 (0.111)	0.212*** (0.00775)
Observations	128000	128000	128000	128000	128000	128000	128000	128000	128000	122000
Panel B: With State-by-year FEs										
Hourly Wage of Production Workers	-0.487*** (0.00914)	-0.00458 (0.0287)	0.496*** (0.00997)	-0.157*** (0.00617)	0.0381*** (0.00495)	0.0373*** (0.00590)	0.0156 (0.0103)	0.0327*** (0.00936)	-0.101 (0.0801)	0.210*** (0.00768)
Observations	128000	128000	128000	128000	128000	128000	128000	128000	128000	122000
Panel C: With State-by-year FEs & Establishment FEs										
Hourly Wage of Production Workers	-0.522*** (0.0139)	0.0115 (0.0392)	0.526*** (0.0150)	-0.169*** (0.0109)	0.0159* (0.00880)	0.0156 (0.0100)	-0.00284 (0.0144)	0.00874 (0.0171)	-0.116 (0.106)	0.213*** (0.00824)
Observations	113000	113000	113000	113000	113000	113000	113000	113000	113000	107000

Note: Panel A of this table reports the coefficient  $\beta_1$  of equation 3.1. Panel B reports the estimates for  $\beta_1$ , but the regression includes state-by-year FEs, and Panel C shows the results with both state-by-year and establishment FEs. The independent variable is the one-year change of the log of the hourly wage of production workers. The dependent variables are the change of log (or inverse hyperbolic sine transformed when a variable contains zero) of each outcome variable. The profit margin and the total factor productivity are not log-transformed; they enter the regressions in first difference. Statistic significance levels are labeled as the following: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are in parentheses and are clustered by states. Data sources: the ASM and the CM from 1991 to 2013.

Table 4: First-stage Regressions — The Instruments Exploiting Variations in State and Federal Minimum Wage Changes and a Measure of How Binding the Minimum Wage is to Each Establishment

	(1)	(2)	(3)	(4)
	$\Delta \text{Log}(\text{Hourly Wage of Production Workers})$			
$\Delta \text{Log}(\text{Min. Wage}) \times T_{es(t-1)}$	0.509*** (0.0864)	0.493*** (0.0984)	0.747*** (0.115)	-0.821** (0.396)
$\Delta \text{Log}(\text{Min. Wage})$	-0.0259 (0.0373)			
$\Delta \text{Log}(\text{Min. Wage}) \times T_{es(t-1)}^2$				1.719*** (0.452)
$T_{es(t-1)}$	0.242*** (0.00759)	0.251*** (0.00725)	0.478*** (0.00700)	-0.158*** (0.0231)
$T_{es(t-1)}^2$				0.665*** (0.0237)
First-Stage F-Stat	35.23	25.57	46.38	34.9
State-by-Year FEs		X	X	X
Establishment FEs			X	X
Quadratic Instrument				X
Observations	128000	128000	113000	113000
R-squared	0.051	0.084	0.394	0.409

Note: This table reports the results for the first-stage regressions. Column 1 shows the estimates for  $\delta_1 - \delta_3$  in equation 3.3. In Column 2, I augment the regression by including state-by-year FEs, and in Column 3, I further include the establishment FEs. In Column 4, I use the quadratic version of the instrument; that is, interact both the treatment variable and its square with the change in the log minimum wage as instruments. See Figure 4 and Figure 5 or text for how the treatment variable  $T_{es(t-1)}$  is constructed. Data sources: the ASM and the CM from 1991 to 2013.

Table 5a: 2SLS Results — Production Workers and Capital Expenditures on Machines

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Production Workers												
	Total Production Worker Hours				Average Hours Per Production Worker				Number of Production Workers			
Hourly Wage of Production Workers	-0.977*** (0.183)	-1.030*** (0.188)	-0.820*** (0.166)	-0.724*** (0.156)	-0.626*** (0.150)	-0.637*** (0.154)	-0.522*** (0.135)	-0.451*** (0.0835)	-0.351 (0.246)	-0.393 (0.242)	-0.297 (0.233)	-0.273 (0.196)
Panel B: Capital Expenditures on Machines and Elasticity of Substitution Between Capital and Labor												
	Real Capital Expenditure on Machines				Positive Capital Expenditures on Machines (Dummy Variable)				Elasticity of Substitution Between Capital and Labor			
Hourly Wage of Production Workers	4.101*** (1.090)	3.039*** (1.034)	2.710* (1.359)	2.733** (1.082)			0.406* (0.208)	0.458*** (0.163)	1.330*** (0.351)	1.109*** (0.283)	0.967*** (0.211)	0.851*** (0.177)
First-Stage F-Stat	35.23	25.57	46.38	34.9	35.23	25.57	46.38	34.9	35.23	25.57	46.38	34.9
State-Year FEs		X	X	X		X	X	X		X	X	X
Establishment FEs			X	X			X	X			X	X
Quadratic Instruments				X				X				X
Observations	128000	128000	113000	113000	128000	128000	113000	113000	128000	128000	113000	113000

Note: This table reports the coefficient  $\beta_1$  of the 2SLS model described in Equation 3.2. The independent variable is one-year change in the log of the hourly wage of production workers; it is instrumented by the interaction term of the change in the log of the state minimum wage and the treatment variable. In Columns 4, 8, 12, I use the quadratic version of the instrument described in the text. The dependent variables are the change in the log of the outcome variables: total production worker hours, average hours worked per production worker, number of production workers. I use IHS transformation for real capital expenditures on machines to incorporate zeros. The dummy variable for positive capital expenditures on machines is not log- or IHS-transformed; it enters the regression in the first difference. The dependent variable for estimating the elasticity of substitution between capital and labor is the change in  $\log(\text{capital stock on machines}/\text{total production worker hours})$ . Statistical significance levels are labeled as the following: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are in parentheses and are clustered by states. Data sources: the ASM and CM from 1991 to 2013.



Table 5b: 2SLS Results – Other Outcome Variables

	Total Employment		Employment of Non-Production Workers		Real Capital Expenditures on Structures		Real Total Capital Expenditures		Total Value of Shipment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Hourly Wage of Production Workers	-0.189 (0.210)	-0.155 (0.190)	0.206 (0.247)	0.164 (0.216)	1.624 (1.271)	1.165 (0.970)	2.595* (1.322)	2.431** (1.097)	0.150 (0.225)	0.180 (0.196)
First Stage F-Stats Observations	46.38 113000	34.9 113000	46.38 113000	34.9 113000	46.38 113000	34.9 113000	46.38 113000	34.9 113000	46.38 113000	34.9 113000
	Real Revenue		Real Costs of Electricity and Fuel		Real Costs of Materials		Profit Margin		Total Factor Productivity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Hourly Wage of Production Workers	0.174 (0.258)	0.190 (0.225)	-0.0973 (0.299)	-0.0123 (0.226)	0.339 (0.480)	0.438 (0.384)	-0.903* (0.459)	-1.308 (0.810)	0.00646 (0.176)	-0.0249 (0.156)
First Stage F-Stats Observations	46.38 113000	34.9 113000	46.38 113000	34.9 113000	46.38 113000	34.9 113000	46.38 113000	34.9 113000	34.09 107000	27.56 107000
State-Year FEs	X	X	X	X	X	X	X	X	X	X
Establishment FEs	X	X	X	X	X	X	X	X	X	X
Quadratic Instruments		X		X		X		X		X

Note: This table reports the coefficient  $\beta_1$  of the 2SLS model described in Equation 3.2. The independent variable is one-year change in the log of the hourly wage of production workers, and it is instrumented by two different instruments. The dependent variables are the change of log (or inverse hyperbolic sine transformation when a variable contains zero) of each outcome variable. The profit margin and total factor productivity are not log-transformed. Statistic significance levels are labeled as the following: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are in parentheses and are clustered by states. Data sources: the ASM and CM from 1991 to 2013.

Table 6: Falsification Test for Main Results

	Total Production Worker Hours	Employment of Production Workers	Average Hours Per Production Worker	Capital Expenditures on Machines	Log(Real Capital Stock on Machines/Total Production Worker Hours)	Total Value of Shipment	Total Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: 60-79 Percentiles							
$\Delta \text{Log}(\text{Min. Wage})$ $\times$ Hypothetical Treatment Variable	-0.0779 (0.0648)	-0.0488 (0.0747)	-0.0291 (0.0543)	-0.473 (0.529)	0.0380 (0.0697)	0.116 (0.0753)	-0.683 (0.533)
N	147000	147000	147000	147000	147000	147000	147000
Panel B: 80-100 Percentiles							
$\Delta \text{Log}(\text{Min. Wage})$ $\times$ Hypothetical Treatment Variable	-0.113 (0.100)	-0.131 (0.103)	0.0177 (0.0384)	-0.0537 (0.528)	0.151* (0.0867)	-0.0458 (0.0754)	-0.270 (0.424)
N	180000	180000	180000	180000	180000	180000	180000
State-Year FEs	X	X	X	X	X	X	X
Establishment FEs	X	X	X	X	X	X	X

Note: This table reports the coefficient  $\phi_1$  of estimation Equation 4.2. The dependent variables are the change in the log (or inverse hyperbolic sine transformation when a variable contains zero) of each outcome variable. The independent variable is the one-year change of the log of the minimum wage interacted with a hypothetical treatment variable. The hypothetical treatment variable is defined to be  $HT_{es(t-1)} = 1 - (pct_{es(t-1)} - 60)/20$  for the estimation in Panel A and  $HT_{es(t-1)} = 1 - (pct_{es(t-1)} - 80)/20$  for Panel B. Panel A restricts the sample to the establishment-year observations whose  $pct_{es(t-1)}$  is between 60 and 79, and Panel B restricts to the establishment-year observations between 80 and 100. State-by-year fixed effects and establishment fixed effects are included in all the regressions. Statistic significance levels are labeled as the following: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are in parentheses and are clustered by states. Data sources: the ASM and the CM from 1991 to 2013.

Table 7: 2SLS Results — Restricting the Sample to the Firms that Have Only One Establishment (Single-unit Firms)

	Total Production Worker Hours	Average Hours Per Production Worker	Employment of Production Workers	Capital Expenditure on Machines	Elasticity of Substitution Between Capital and Labor	Total Employment	Employment of Non-Production Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hourly Wage of Production Workers	-0.564** (0.252)	-0.496*** (0.147)	-0.0678 (0.292)	2.317* (1.255)	0.898** (0.354)	0.0845 (0.273)	0.743*** (0.267)
First Stage F-Stats	9.56	9.56	9.56	9.56	9.56	9.56	9.56
Observations	47500	47500	47500	47500	47500	47500	47500
Mean of Outcome Variables			35.71	\$104.50 (in thousands)		45.51	9.8
	Total Value of Shipment	Real Revenue	Electricity and Fuel	Materials	Profit Margin	Total Factor Productivity	
	(8)	(9)	(10)	(11)	(12)	(13)	
Hourly Wage of Production Workers	0.512** (0.201)	0.443* (0.239)	0.0657 (0.366)	0.5 (0.550)	-1.432 (1.749)	0.283 (0.209)	
First Stage F-Stats	9.56	9.56	9.56	9.56	9.56	15.45	
Observations	47500	47500	47500	47500	47500	43500	
Mean of Outcome Variables	\$5,025 (in thousands)	\$4,697 (in thousands)					
State-Year FEs	X	X	X	X	X	X	X
Establishment FEs	X	X	X	X	X	X	X
Quadratic Instrument	X	X	X	X	X	X	X

Note: This table reports the coefficient  $\beta_1$  of the 2SLS model described in Equation 3.2. Only single-unit firms are included in the analysis. The independent variable is one-year change of the log of the hourly wage of production workers, which is instrumented by the quadratic version of the instrument. Headings show the outcome variable. In all these regressions, state-by-year FEs and establishment FEs are included. Dollar values are in 1997 dollars. Statistic significance levels are labeled as the following: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are in parentheses and are clustered by states. Data sources: the ASM and CM from 1991 to 2013.

## Appendix:

### A Model Appendix

#### A.1 Cost Minimization

Plants' cost minimization problem implies that optimal choice of capital, production worker hours and other inputs can be written as

$$K = K(p_K, p_L, p_M, X),$$

$$L = L(p_K, p_L, p_M, X),$$

$$M = M(p_K, p_L, p_M, X).$$

Total differentiation of these functions yields:

$$\hat{K} = a_{KK} \hat{p}_K + a_{KL} \hat{p}_L + a_{KM} \hat{p}_M + \delta_K \hat{X}, \quad (\text{A1})$$

$$\hat{L} = a_{LK} \hat{p}_K + a_{LL} \hat{p}_L + a_{LM} \hat{p}_M + \delta_L \hat{X}, \quad (\text{A2})$$

$$\hat{M} = a_{MK} \hat{p}_K + a_{ML} \hat{p}_L + a_{MM} \hat{p}_M + \delta_M \hat{X}. \quad (\text{A3})$$

where  $\delta$ 's are elasticity of inputs with respect to a change in the output. For example,  $\delta_K = \partial \ln K / \partial \ln X$ . By subtracting equation A2 from A1 and A3, one can derive equations 1.1 and 1.2.

#### A.2 Morishima Elasticity of Substitution

A Morishima elasticity of substitution is defined to be

$$m_{ij} = \frac{\partial \ln(x_i/x_j)}{\partial \ln(p_j/p_i)}. \quad (\text{A4})$$

The definition of Morishima elasticity is usually used when estimating the elasticity of substitution between capital and labor. For example, [Raval \(2019\)](#) assumes constant elasticity of substitution (CES) production function and estimates the Morishima elasticity.<sup>43</sup> [Black-orby and Russell \(1989\)](#) show that Allen elasticity and Morishima elasticity of substitution are related through the following identity:

$$m_{ij} = \theta_i(e_{ji} - e_{ii}). \quad (\text{A5})$$

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<sup>43</sup>Note that while Allen elasticities are symmetric, Morishima elasticities are not. Assuming CES production function, however, implicitly imposes symmetric Morishima elasticities.

Following Karney (2016), I can rewrite equations 1.1 and 1.2 using Morishima elasticities:

$$\begin{bmatrix} \hat{K} - \hat{L} \\ \hat{M} - \hat{L} \end{bmatrix} = \begin{bmatrix} -m_{KL} & m_{KL} - m_{LK} & m_{LK} \\ m_{ML} - m_{LM} & -m_{ML} & m_{LM} \end{bmatrix} \begin{bmatrix} \hat{p}_K \\ \hat{p}_M \\ \hat{p}_L \end{bmatrix} + \begin{bmatrix} \delta_{KL} \\ \delta_{ML} \end{bmatrix} \hat{X} \quad (\text{A6})$$

In this paper, however, I only provide the estimate of  $m_{LK} = \partial \ln(L/K) / \partial \ln(p_K/p_L)$ . In order to identify  $m_{LK}$ , exogenous changes in  $p_L$  is needed. In the empirical analysis, I use state-by-year variation in the minimum wage to generate exogenous changes of wage. Theoretically, estimation of  $m_{LK}$  requires that input prices  $p_K$  and  $p_M$  and the output  $X$  is held constant. However, because plant-level input prices and output are not observed, I estimate a “gross” Morishima elasticity of substitution in which plants are allowed to adjust output optimally. I make the assumption that input prices and the output price do not adjust immediately or the adjustment is small.

### A.3 Separate Hours and Employment

The baseline model assumes that establishments adjust total labor hours they use without specifying if they adjust the number of workers or average hours of work per worker. However, recent empirical evidence, Horton (2017) for instance, indicates that firms are more likely to adjust the average hours per worker. This difference implies that the adjustment cost on these two margins may be different for different establishments. I extend the model to allow firms to adjust employment and hours separately. Consider a production function in the form of:

$$X = X(K, L(E, H), M),$$

where total labor hour  $L$  is a function of employment ( $E$ ) and average hours of work by each worker ( $H$ ). Note that without assumptions on the functional form, I allow the change in employment and hours to contribute differently to the overall change in total hours.<sup>44</sup> Firms need to pay a fixed adjustment cost of  $c_E$  to change one percent of employment, and they pay a fixed cost of  $c_H$  if they adjust average hours per worker by one percent. The total adjustment cost is then  $c_E \hat{E} + c_H \hat{H}$ . Thus, establishments solve two problems. First, they solve the profit-maximization problem laid out in the previous section. Then, they minimize adjustment costs by choosing the changes in employment and hours:

$$\min c_E \hat{E} + c_H \hat{H},$$

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<sup>44</sup>This assumption is mostly made to avoid corner solutions. In a straightforward case where  $\hat{L} = \hat{E} + \hat{H}$ , firms will simply adjust the factor with lower cost while keep the other unchanged. This general form is reasonable because the same worker may be less productive if he is asked to work more hours.

subject to  $\hat{L} = \hat{L}(\hat{E}, \hat{H})$ . The FOCs of the cost-minimization problem imply that the ratio of the adjustment of the employment and the hours is a function of cost ratios:

$$\hat{E}/\hat{H} = \alpha(c_H/c_E) \equiv \alpha, \quad (\text{A7})$$

such that  $\partial\alpha/\partial c_H > 0$  and  $\partial\alpha/\partial c_E < 0$ . That is, the higher the cost to adjust employment, the lower is the adjustment on employment relative to hours. In other words, if empirical evidence shows that firms are more likely to adjust hours relative to employment, this would imply that the perceived cost to adjust employment is higher than the cost of adjusting hours.

## B Data Appendix

This appendix introduces definitions of the variables used in the paper.

Production worker (number, hours of work, hourly wage): according to the Census’s definition, production workers include “workers (up through the line-supervisor level) engaged in fabricating, processing, assembling, inspecting, receiving, storing, handling, packing, warehousing, shipping (but not delivering), maintenance, repair, janitorial and guard services, product development, auxiliary production for plant’s own use (e.g., power plant), record-keeping, and other services closely associated with these production operations at the establishment covered by the report. Employees above the working-supervisor level are excluded from this item.” Total payroll of production workers, number of production workers, and total hours worked by these workers are reported. The hourly wage of production workers can be calculated by dividing the total payroll by the total hours worked.

Total employment: number of all workers employed in a plant.

Total value of shipments (TVS): the TVS includes all received or receivable net selling values in a year. This is a measure of total revenue of a manufacturing plant.

Real Revenue: constructed in Foster et al. (2016). It is defined as the TVS plus end-of-year inventories (finished goods inventories and work-in-process inventories) minus beginning-of-year inventories. The nominal value is then adjusted by the industry-level shipments deflator from the NBER-CES Manufacturing Industry Database.<sup>45</sup> Compared to the TVS, this measure is more likely, than the TVS, to capture the actual production takes place in a plant year because it adjusts for possible changes in prices of the output in order to capture actual quantity changes separately from price changes.

Materials: real costs of materials constructed in Foster et al. (2016). Costs of Materials include the costs of materials and parts, costs of resales, and costs of contract work (payment to others for the work done by them on the materials owned by the establishment). The value is then adjusted by the industry-level material deflator from the NBER-CES Manufacturing Industry Database.

Electricity and Fuels: real costs of energy constructed in Foster et al. (2016). The sum of costs of purchased electricity and costs of fuels. The sum is then deflated by the industry-level energy deflator from the NBER-CES Manufacturing Industry Database.

Capital: two sets of capital variables are used in the analysis: capital expenditures and the capital stock. Capital expenditures are reported directly by the establishments. I use

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<sup>45</sup>The deflators are constructed from a variety of data sources. See Bartelsman and Gray (1996) for details regarding the sources and construction of the deflators and the technical notes at [http://www.nber.org/nberces/nberces5811/nberces\\_5811\\_technical\\_notes.pdf](http://www.nber.org/nberces/nberces5811/nberces_5811_technical_notes.pdf) for updates.

the updated version of the capital stock constructed in Foster et al. (2016). Both capital expenditures and the capital stock are deflated using industry-level investment price deflator. The deflator for total capital stock is derived from the Federal Reserve Board data, and is available in the NBER-CES Manufacturing Industry Database. The BLS provides the industry-level investment price deflator for machines and structure separately.

The Census gives establishments detailed instructions regarding what to include or not to include when reporting the capital expenditures. In particular, the value of expensed tools (which do not add to an establishment's assets), the value of land, and leased vehicles or vehicles that are exclusively used to transport materials are not included in the capital expenditures.<sup>46</sup>

Profit Margin: nominal values of profit is constructed by subtracting costs of materials, costs of electricity and fuel, total capital expenditures and total payroll (to all workers) from the inventory-adjusted TVS. Then the profit margin equals the nominal values of profits divided by the TVS.

Total Factor Productivity (TFP): a measure of establishment-level productivity constructed in Foster et al. (2016) as

$$TFP_{est} = \log(RealRevenue_{est}) - S_{it}^{KM} \log(KM_{est}) - S_{it}^{KS} \log(KS_{est}) - S_{it}^M \log(M_{est}) - S_{it}^E \log(E_{est}) - S_{it}^{TH} \log(TH_{est}), \quad (B1)$$

where  $S_{it}^{KM}, S_{it}^{KS}, S_{it}^{KS}, S_{it}^M, S_{it}^E$  and  $S_{it}^{TH}$  are cost share of capital stock on machines ( $KM$ ), capital stock on structures ( $KS$ ), materials ( $M$ ), energy ( $E$ ) and labor ( $TH$ ) in industry  $i$  and year  $t$ , calculated using data from the BLS and the NBER-CES Manufacturing Industry Database. The labor measure,  $TH_{est}$ , is imputed total hours worked by all workers in a plant, and it is constructed in the following way:

$$TH = PH * \frac{\text{Total payroll of all workers}}{\text{Total payroll of PW}},$$

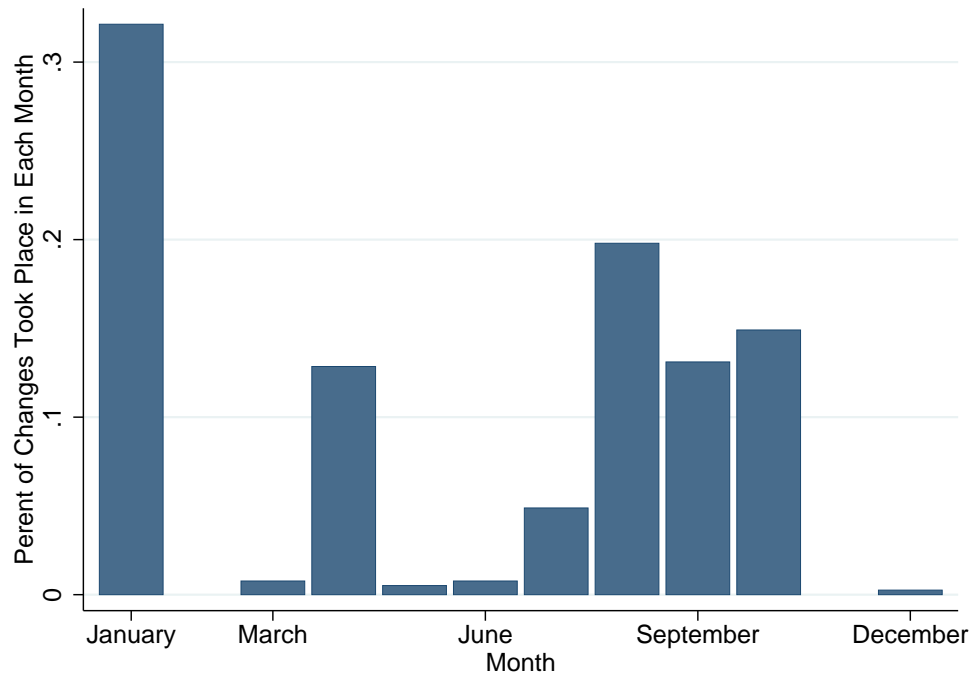
where the  $PH$  is total hours worked by production workers. Other variables in Equation B1 are real values of revenue ( $RealRevenue_{est}$ ), capital stock on machines ( $KM_{est}$ ) and structures ( $KS_{est}$ ), materials ( $M_{est}$ ) and energy ( $E_{est}$ ) discussed above.

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<sup>46</sup>Interested readers can refer to [https://www2.census.gov/programs-surveys/asm/technical-documentation/questionnaire/2016/instructions/MA-10000\(S\)%20Instruction%20Sheet.pdf](https://www2.census.gov/programs-surveys/asm/technical-documentation/questionnaire/2016/instructions/MA-10000(S)%20Instruction%20Sheet.pdf) for more details.

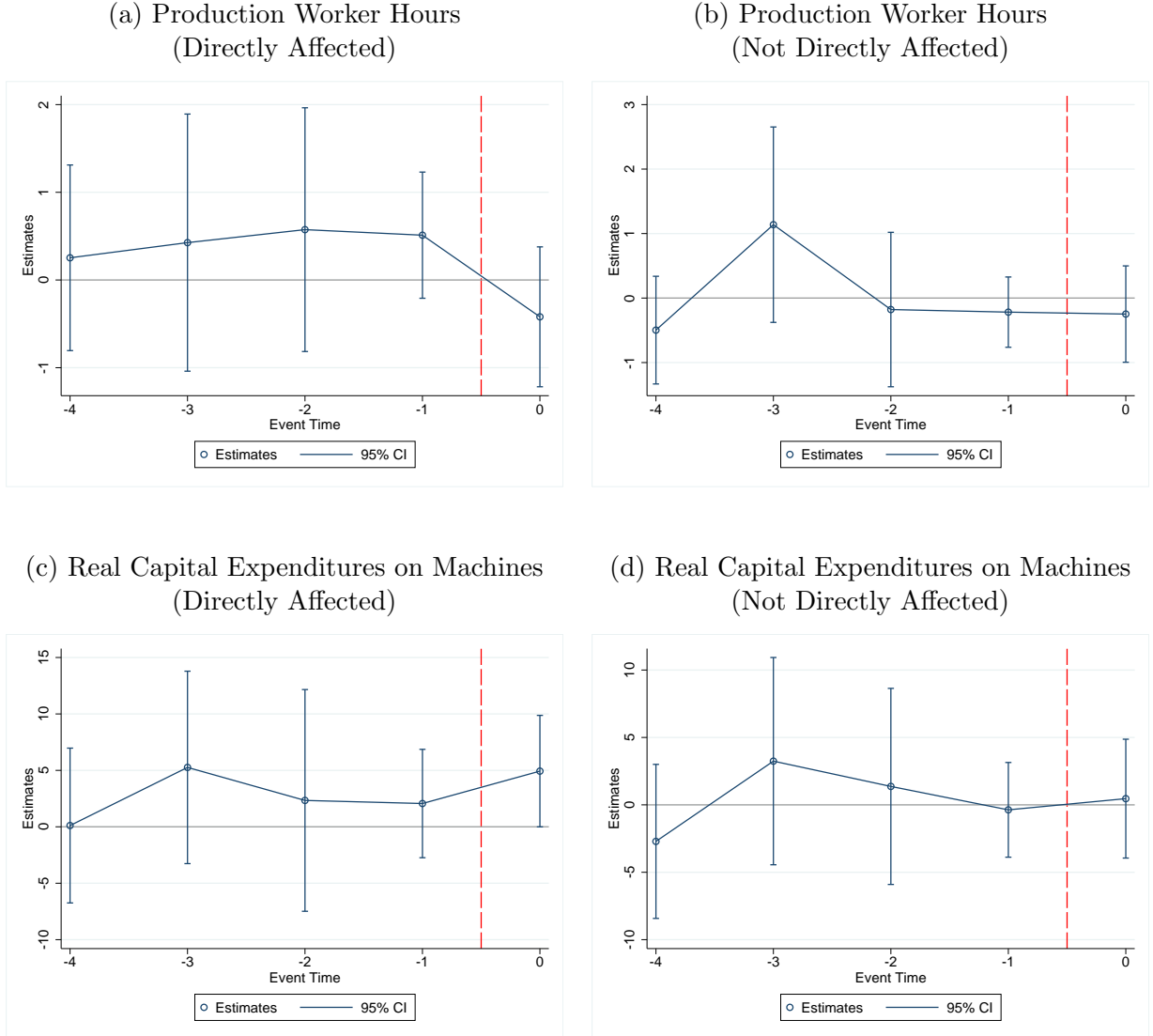


Figure B1: Months in Which Minimum Wage Changes Take Place (1991-2013)



Note: This figure plots the share of minimum wage changes that took place in each month out of all changes. Data are collected and organized by David Neumark and are available at <https://www.socsci.uci.edu/~dneumark/datasets.html>

Figure B2: Responses of Multi-unit Firms to the Minimum Wage



Note: This figure shows the responses of multi-unit firms. It plots the estimated coefficients  $\theta_{i+5}$  in equation 6.1, for  $i$ s between -4 and 1. The dependent variables are the average change in the total production worker hours and the capital expenditures on machines of establishments, in firm  $f$ , that are affected and not affected by the minimum wage. The independent variable is the average change in the log of minimum wage among affected establishments in firm  $f$ . The unit of observation is firm-year. The  $x$ -axis shows the value of  $i$ , or event time. The red dashed line labels the time of the event. For this analysis, I use data between 1991 and 2013, but I dropped the observations in the years when the federal minimum wage changed: 1996, 1997, 2007, 2008, and 2009. Number of observations for each regression is 600. See text in Section 6.2 for more details regarding the sample used in the analysis. Data sources: the ASM and the CM.

Table B1: Recent Empirical Evidence on Possible Channels of Adjustment (Literature Review)

Paper	Data	Labor (Ext.)	Labor (Int.)	Output Price	Capital	Material	Revenue	Profit	Prod- ctivity	Exit
This paper	U.S. (firm)	✓	—		+	✓	✓	✓(-)	✓	+
Dube et al. (2010)	U.S. (county)	✓								
Allegretto et al. (2011)	U.S. (individual)	✓								
Neumark et al. (2014)	U.S. (state)	—								
Meer and West (2016)	U.S. (state)	—								
Dube and Zipperer (2015)	U.S. (state)	✓								
Jardim et al. (2017)	U.S. (county/city)	—	—							
Horton (2017)	U.S. (RCT, firm-individual)	—	—							
Doppelt (2018)	U.S. (state)		+							
Aaronson (2001)	U.S. (product)			+						
Ganapati and Weaver (2017)	U.S. (product)			✓						
Harasztosi and Lindner (2019)	Hungarian (firm-individual)	—		+	+	+	+	—		✓
Hau et al. (2017)	Chinese (firm)	—			+		+	+	+	
Gustafson and Kotter (2018)	U.S. (Compustat)				—					
Draca et al. (2011)	British (firm)							—		
Riley and Bondibene (2017)	British (firm)								+	
Aaronson et al. (2018)	U.S. (firm)									+
Luca and Luca (2018)	U.S. (Eat24)									+

Note: This table summarizes the findings of the minimum wage literature by outcome variables and signs of the estimated results. Each row corresponds to a study, and each column gives an outcome variable. The data column gives sources of data and unit of observation used in estimation. Plus (+) and minus (-) signs indicate the sign of the findings. A check mark (✓) is given to statistically insignificant estimates.

Table B2: Possible Confounders of Minimum Wages

	(1)	(2)	(3)	(4)	(5)
	Log of Minimum Wages				
Investment Tax Credit (%)	-0.118 (0.189)				-0.112 (0.189)
State Corporate Tax Rate (%)		-1.286 (0.920)			-1.295 (0.915)
R&D Tax Credit (%)			-0.051 (0.045)		-0.056 (0.047)
Log of Government Expenditures				-0.011 (0.037)	
N	1020	1020	1020	1000	1020

Note: This table shows the correlation between changes in the minimum wage and changes in several state policies that can affect capital investment between 1991 and 2011. I use the data compiled by [Moretti and Wilson \(2017\)](#), and their data are available at <https://www.aeaweb.org/articles?id=10.1257/aer.20150508>. Log of Government Expenditures have fewer observations because District of Columbia is not included.

Table B3: Reduced-form Regressions

	Total Production Worker Hours	Average Hours Per Production Worker	Employment of Production Workers	Real Capital Expenditures on Machines	Real Capital Stock on Machines/Total Production Worker Hour	Total Employment	Employment of Non-Production Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta \text{Log}(\text{Min. Wage}) \times T_{cs(t-1)}$	-0.601*** (0.185)	-0.403*** (0.0982)	-0.198 (0.202)	2.146** (0.938)	0.724*** (0.219)	-0.119 (0.177)	0.15 (0.198)
$T_{cs(t-1)}$	(0.0102)	-0.105*** (0.00687)	-0.100*** (0.00986)	-0.00611 (0.0721)	0.209*** (0.0135)	-0.0820*** (0.00849)	-0.0501** (0.0203)
Observations	113000	113000	113000	113000	113000	113000	113000
$R^2$	0.312	0.23	0.298	0.175	0.297	0.303	0.211
	Total Value of Shipment (8)	Real Revenue (9)	Real Costs of Electricity and Fuel (10)	Real Costs of Materials (11)	Profit Margin (12)	Total Factor Productivity (13)	
$\Delta \text{Log}(\text{Min. Wage}) \times T_{cs(t-1)}$	0.157 (0.178)	0.181 (0.204)	-0.0258 (0.242)	0.269 (0.367)	-0.493 (0.408)	0.0223 (0.136)	
$T_{cs(t-1)}$	0.0308*** (0.00945)	0.0341*** (0.0114)	0.0411** (0.0179)	0.0292 (0.0194)	0.0539 (0.0543)	0.101*** (0.0106)	
Observations	113000	113000	113000	113000	113000	107000	
$R^2$	0.289	0.275	0.224	0.228	0.484	0.214	
State-Year FEs	X	X	X	X	X	X	X
Establishment FEs	X	X	X	X	X	X	X

Note: This table reports the reduced-form results in which I regress the dependent variables of interest on the line instrument. In all these regression, I control for state by year FEs and establishment FEs. Statistic significance levels are labeled as the following: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are in parentheses and are clustered by states. Data sources: the ASM and CM from 1991 to 2013.

Table B4a: Production Workers and Capital Expenditures — 2SLS Results (Alternative Measures for the Change in the Minimum Wage)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Production Workers									
	Total Production Worker Hours			Average Hours Per Production Worker			Number of Production Workers		
Hourly Wage of Production Workers	-0.931*** (0.176)	-0.973*** (0.180)	-0.828*** (0.159)	-0.602*** (0.155)	-0.614*** (0.161)	-0.559*** (0.144)	-0.330 (0.234)	-0.358 (0.230)	-0.268 (0.226)
Panel B: Capital Expenditures on Machines and Elasticity of Substitution Between Capital and Labor									
	Real Capital Expenditures on Machines			Positive Capital Expenditures on Machines (Dummy Variable)			Elasticity of Substitution Between Capital and Labor		
Hourly Wage of Production Workers	4.862*** (1.236)	3.728*** (1.155)	3.041** (1.398)			0.462** (0.221)	1.384*** (0.362)	1.130*** (0.298)	1.025*** (0.210)
First-Stage F-Stat	37.05	25.13	35.19	37.05	25.13	35.19	37.05	25.13	35.19
State-Year FE		X	X		X	X		X	X
Establishment FE			X			X			X
Observations	128000	128000	113000	128000	128000	113000	128000	128000	113000

Note: This table reports the coefficient  $\beta_1$  of the 2SLS model described in Equation 3.2. The independent variable is one-year change of the log of the hourly wage of production workers, and it is instrumented by the interaction term of the change in the log of the state minimum wage and the treatment variable. The state minimum wage used in this table is the minimum wage that is in place for the longest periods during a year. See text for the construction of the treatment variable. The dependent variables in Panel A are in change of the log of each outcome variables: total hours of worked by production workers (Columns 1–3), average hours per production worker (Columns 4–6) and the number of production workers (Columns 7–9). In Panel B, the dependent variables are the change in the IHS-transformed real capital expenditures on machines (Columns 1–3), the change in the probability of positive expenditures on machines (Column 6), and the change in log of (real capital stock on machines/total production worker hours) (Columns 7–9). In Columns 2, 5, 8, state-by-year fixed effects are included, and in Columns 3, 6, 8, both state-by-year fixed effects and establishment fixed effects are included. Statistic significance levels are labeled as the following: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are in parentheses and are clustered by states. Data sources: the ASM and CM from 1991 to 2013.

Table B4b: Other Outcome Variables — 2SLS Results (Alternative Measures for the Change in the Minimum Wage)

	Employment	Employment of Non-production Workers	Real Capital Expenditures on Structures	Real total Capital Expenditures	Total Value of Shipment
	(1)	(2)	(3)	(4)	(5)
Hourly Wage of Production Workers	-0.168 (0.209)	0.273 -0.282	2.502* (1.327)	3.053** (1.355)	0.109 (0.209)
First Stage F-Statistics Observations	35.19 113000	35.19 113000	35.19 113000	35.19 113000	35.19 113000
	Real Revenue	Real Costs of Electricity and Fuel	Real Costs of Materials	Profit Margin	Total Factor Productivity
	(6)	(7)	(8)	(9)	(10)
Hourly Wage of Production Workers	0.138 (0.254)	0.108 (0.360)	0.272 (0.508)	-1.121** (0.519)	-0.0655 (0.214)
First Stage F-Statistics Observations	35.19 113000	35.19 113000	35.19 113000	35.19 113000	25.07 107000
State-Year FEs	X	X	X	X	X
Establishment FEs	X	X	X	X	X

Note: This table reports the coefficient  $\beta_1$  of the 2SLS model described in Equation 3.2. The independent variable is one-year change of the log of the hourly wage of production workers, and it is instrumented by the interaction term of the change in the log of the state minimum wage and the treatment variable. The state minimum wage used in this table is the minimum wage that is in place for the longest period during a year. See text for the construction of the treatment variable. The dependent variables are in the changes of the log (or inverse hyperbolic sine transformation when a variable contains zero) of each outcome variable, except for profit margin and TFP, which enter the regression in the first change directly. Statistic significance levels are labeled as the following: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are in parentheses and are clustered by states. Data sources: the ASM and CM from 1991 to 2013.

Table B5: Multiple Hypotheses Testing (Benjamini and Hochberg False Discovery Rate)

Outcomes	Estimates	S.E.s	t (absolute value)	p	P-value Thresholds Under B&H FDR	Significant Under B&H FDR?
Hours Worked per Production Worker	-0.4510	0.0835	5.4012	<0.0001	0.0031	Yes
Elasticity of Substitution between Capital and Labor	0.8510	0.1770	4.8079	<0.0001	0.0063	Yes
Total Production Worker Hour	-0.7240	0.1560	4.6410	<0.0001	0.0094	Yes
Positive Capital Expenditures on Machines	0.4580	0.1630	2.8098	0.0070	0.0125	Yes
Real Capital Expenditures on Machines	2.7330	1.0820	2.5259	0.0148	0.0156	Yes
Real Total Capital Expenditures	2.4310	1.0970	2.2160	0.0313	0.0188	No
Profit Margin	-1.3080	0.8100	1.6148	0.1126	0.0219	No
Number of Production Workers	-0.2730	0.1960	1.3929	0.1698	0.0250	No
Real Capital Expenditures on Structures	1.1650	0.9700	1.2010	0.2354	0.0281	No
Real Costs of Materials	0.4390	0.3840	1.1432	0.2584	0.0313	No
Total Value of Shipment	0.1800	0.1960	0.9184	0.3629	0.0344	No
Real Revenue	0.1900	0.2250	0.8444	0.4025	0.0375	No
Employment	-0.1550	0.1900	0.8158	0.4185	0.0406	No
Employment of Non-production Workers	0.1640	0.2160	0.7593	0.2256	0.0438	No
Total Factor Productivity	-0.0249	0.1560	0.1596	0.8738	0.0469	No
Real Costs of Energy and Fuel	-0.0123	0.2260	0.0544	0.9568	0.0500	No

Note: This table shows the results for multiple hypotheses testing. I test the significance of 16 estimates in Table 5a and Table 5b using Benjamini and Hochberg False Discovery Rate (B&H FDR). I compute the t-values and p-values based on the estimates, standard errors and degrees of freedom of 50. The p-value thresholds under B&H FDR are computed by the formula  $j/16*0.05$ , where  $j = 1 - 16$  is the rank of the corresponding estimate. Data sources: the ASM and CM from 1991 to 2013.



Table B6: Estimation Results with Industry-by-year FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Total Production Worker Hours	Average Hours Per Production Worker	Employment of Production Workers	Real Capital Expendi- ture on Machines	Real Capital Stock on Ma- chines/Total Production Worker Hours	Total Em- ployment	Employment of Non- Production Workers	Total Value of Shipment	Real Revenue	Real Costs of Electricity and Fuel	Real Costs of Materials	Profit Margin	Total Factor Pro- ductivity
Panel A – Reduced-form Regressions													
$\Delta \text{Log}(\text{Min. Wage}) \times T_{es(t-1)}$	-0.588*** (0.174)	-0.409*** (0.0996)	-0.179 (0.185)	2.082** (0.932)	0.716*** (0.204)	-0.105 (0.155)	0.12 (0.203)	0.147 (0.157)	0.175 (0.182)	-0.0869 (0.261)	0.125 (0.361)	-0.551 (0.492)	0.119 (0.136)
$T_{es(t-1)}$	-0.206*** (0.0108)	-0.104*** (0.00683)	-0.102*** (0.0104)	-0.00777 (0.0730)	0.209*** (0.0139)	-0.0833*** (0.00907)	-0.0501** (0.0204)	0.0304*** (0.00934)	0.0336*** (0.0114)	0.0425** (0.0179)	0.0345* (0.0198)	0.0685 (0.0656)	0.0970*** (0.0111)
Observations	113000	113000	113000	113000	113000	113000	113000	113000	113000	113000	113000	113000	107000
Panel B – Linear Instrument													
Hourly Wage of Production Workers	-0.786*** (0.173)	-0.547*** (0.140)	-0.24 (0.230)	2.786* (1.439)	0.958*** (0.208)	-0.14 (0.199)	0.16 (0.269)	0.197 (0.215)	0.235 (0.255)	-0.116 (0.349)	0.167 (0.484)	-0.738 (0.641)	0.156 (0.171)
First-stage F Observations	39.71 113000	39.71 113000	39.71 113000	39.71 113000	39.71 113000	39.71 113000	39.71 113000	39.71 113000	39.71 113000	39.71 113000	39.71 113000	39.71 113000	29.98 107000
Panel C – Quadratic Instruments													
Hourly Wage of Production Workers	-0.666*** (0.155)	-0.478*** (0.0871)	-0.188 (0.194)	2.749** (1.109)	0.806*** (0.172)	-0.0848 (0.180)	0.132 (0.221)	0.232 (0.188)	0.253 (0.221)	-0.0024 (0.257)	0.315 (0.398)	-1.312 (0.837)	0.1 (0.138)
First-stage F Observations	32.38 113000	32.38 113000	32.38 113000	32.38 113000	32.38 113000	32.38 113000	32.38 113000	32.38 113000	32.38 113000	32.38 113000	32.38 113000	32.38 113000	25.87 107000
Panel D – Single-unit Firms and Quadratic Instruments													
Hourly Wage of Production Workers	-0.516** (0.218)	-0.480*** (0.135)	-0.0353 (0.227)	2.115* (1.150)	0.851*** (0.301)	0.108 (0.205)	0.688** (0.260)	0.493*** (0.177)	0.470** (0.211)	0.0169 (0.343)	0.206 (0.499)	-0.623 (0.871)	0.432* (0.225)
First Stage F-Statistics Observations	10.42 47500	10.42 47500	10.42 47500	10.42 47500	10.42 47500	10.42 47500	10.42 47500	10.42 47500	10.42 47500	10.42 47500	10.42 47500	10.42 47500	15.55 43500
State-by-Year FEs	X	X	X	X	X	X	X	X	X	X	X	X	X
Establishment FEs	X	X	X	X	X	X	X	X	X	X	X	X	X
Industry-by-Year FEs	X	X	X	X	X	X	X	X	X	X	X	X	X

Note: This table replicates the main results in the paper but with additional control with industry-by-year FEs. I use three-digit NAICS code for industries. Statistic significance levels are labeled as the following: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are in parentheses and are clustered by states. Data sources: the ASM and CM from 1991 to 2013.