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Minimum Wage Effects Across Heterogeneous Markets

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Abstract

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Keywords: minimum wage; monopsonistic labor market; production function estimation.
JEL Classification:J21; J23: J31.

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1 Introduction

The extent of market power in the labor market is an important topic in testing the employment effect of minimum wage. In a simple competitive labor market model, employers have little control over wages and reduce employment levels immediately when minimum wage rises. On the other hand, in a monopsonistic labor market model, employers have some power to control wages and workers are paid less than the value of the marginal product of labor. In the presence of such a surplus, the profit-seeking employers react to an increase in minimum wage differently from those in a competitive labor market model, sometimes resulting in a rise in employment level (Card and Krueger, 1994; Manning, 2003). However, despite the divergent consequences that the two models predict, studies have paid little attention to the detection of the extent of market power in testing the employment effect of minimum wage. In fact, there was a lack of convincing evidence to support the existence of monopsony labor market (Kuhn, 2004).

Only recently, a growing number of studies presented the evidences of market power (Staiger et al., 2010; Falch, 2010; Ransom and Sims, 2010; Dube et al., 2016; Benmelech et al., 2018; Azar et al., 2017, 2018). For instance, Benmelech et al. (2018) constructed the Herfindahl-Hirschman Index (HHI) from the Longitudinal Business Database to measure the labor market concentration, and found that the employer concentration is negatively associated with local wages. Interestingly, Azar et al. (2018) highlighted large geographical variations in the employer concentration. Analyzing a large-scale data set from Burning Glass Technologies—which collects job vacancy information from approximately 40,000 websites—they found that the less-populated commuting zones as well as the zones in the Great Plains tended to have lower employer concentrations. An important takeaway to the study of minimum wage is that the local labor markets are heterogeneous, in that employers can respond to an increase in minimum wage differently across local labor markets.

This paper directly estimates the labor market surplus by examining how far an employer is from its competitive optimal decisions, and tests whether the employment effect of minimum wage differs across regions depending on the extent of surplus. Specifically, we estimate the surplus or wage markdown that employers would face in labor markets with any frictions, which is defined as the discrepancy between the value of the marginal product of labor (VMPL) and the wage rate. The original idea comes from Petrin and Sivadasan (2013), who examined the correlation between plants surplus and the reform of firing restrictions in Chile. Taking a very similar approach, Dobbelaere et al. (2015) and Dobbelaere and Mairesse (2013) proposed a way to test market imperfections both in the labor and product markets. By applying the approach from the previous studies to Japanese manufacturing census data from 2001 to 2014, we first estimate the production functions and obtain estimates for the elasticities of factor inputs to calculate the surplus in the labor market. We then use the estimated extent of the surplus to examine whether the employment effect of minimum wage differs according to the extent of frictions faced by employers in the local labor market. In our main specification, we follow the framework of Meer and West (2016) and focus on employment growth rather than employment level, to account for the possibility that job destruction occurs gradually over time.

Our identification of the minimum wage effect relies on a quasi-natural experiment where a series of Japanese government policies substantially increased regional minimum wages over a decade. The first event took place in 2007, when the Minimum Wage Act was amended to provide a legal framework to increase regional minimum wages to or above the amount of welfare benefits defined in each region. Importantly, those regions exposed to this shock were those in urban areas or with cold weather, and not necessarily the regions that shared specific economic trends. Moreover, because a central policy such as this had much more influence on the determination of regional minimum wages than local authorities used to, it alleviates our concern that preexisting local employment trends may confound the results. The government's initiatives on minimum wage have continued in the following decade due to Prime Minister Abe's wage-boosting policy, which provides us with an opportunity to exploit minimum wage variations that are less likely to reflect local economic trends over a relatively long time period. We test the exogeneity of these events by adopting the suggestion of Meer and West (2016), and indeed found that preexisting local trends had no predictive power.

Consistent with a standard competitive labor market model, our main analysis revealed that plants significantly reduced employment growth in response to increases in minimum wage. However, the estimated negative impact masks the heterogeneity in plants' behavioral response: an increase in minimum wage affected plants in our sample in noticeably different ways, depending on the surplus that plants face. We found that in response to an increase in minimum wage, plants that initially experienced a large surplus did not significantly reduce their employment growth. While our main data does not contain wages and hours of work for individual employees, the prediction from another source of administrative wage records confirms that the effects of minimum wage are concentrated in plants with a larger proportion of minimum wage workers. Although the lack of individual hourly wage information prevents us from obtaining precise estimates, the results found in this paper largely support the view that the local labor markets are heterogeneous and plants respond to the minimum wage shock, depending on the extent of frictions they face in the labor market.

Our method differs from those employed in the previous literature in an important way. The size of the surplus or wage markdown allows us to infer whether a plant behaves as a monopsonist in the local labor market. Previous studies have mostly identified the market power of monopsonistic firms by estimating labor supply elasticity in the short run (Staiger et al., 2010; Falch, 2010; Dube et al., 2018), by estimating the elasticity of the separation rate with respect to wages in the long run (Ransom and Oaxaca, 2010; Ransom and Sims, 2010; Hirsch et al., 2010; Manning, 2003), and more recently by calculating HHI (Benmelech et al., 2018; Azar et al., 2017, 2018). We depart from the literature by directly estimating the extent of exploitation or surplus each plant faces. Importantly, our estimates measure an important aspect of labor market friction. Our estimates for the surplus are negatively associated with the number of rival plants in the same prefecture and industry.

This paper also contributes to the literature by adding another mechanism through which the mixed employment effects of minimum wage may be observed.[1] Previous studies have already analyzed how firms could otherwise respond to the minimum wage shock. Draca et al. (2011) examined the impact of minimum wage on firm profitability using a plant-level data set from the UK, and found no statistically significant behavioral response by firms. Instead, firms significantly reduced their profits to cover the increases in the total wage bill.[2] Horton (2017) ran field experiments in the online labor market to find that the implementation of a minimum wage reduced the hours worked, half of which was explained by increases in worker productivity, indicating labor-labor substitution. Aaronson et al. (2018) employed the contiguous-county comparison approach in Dube et al. (2010) to analyze the restaurant industry in the US and found evidence consistent with the model where an increased minimum wage induces the exit of labor-intensive restaurants and entry of capital-intensive

[1]Influential case studies by Card and Krueger (1994, 2000) in New Jersey and Pennsylvania found no disemployment effects, while Neumark and Wascher (1992) found significantly negative employment effects of an increase in minimum wage among teenagers in the state-level data set. Dube et al. (2010) constructed a data set containing all contiguous-border-county pairs in the US to generalize a case study by Card and Krueger (1994) and showed that an increase in minimum wage has a significantly positive earnings effect but no significant employment effect. Neumark et al. (2014) criticized Dube et al. (2010)'s approach by showing that they failed to include sufficient identification variations and test the need to control for local trends. Allegretto et al. (2018) argued against Neumark et al. (2014) by adopting a synthetic control approach.

[2]In a similar strand of literature, Bell and Machin (2015) found that an unexpected announcement to raise the minimum wage in the UK significantly reduced the stock market values of firms hiring low-wage workers.

restaurants. Harasztosi and Lindner (2017) exploited a sharp minimum wage hike in Hungary to report that firms did not reduce their profits but increased product prices and substituted labor with capital in response to the hike. Interestingly, they also found a heterogeneity in firms' responses that reductions in the level of employment are limited to firms in tradable sectors, where it is more difficult to raise product prices. Despite the numerous debates over the ambiguous evidence, there is little investigation on the potentially heterogeneous effect of minimum wage across local markets. This paper directly estimates the surplus that employers face in local labor markets and finds that the employment effect of minimum wage differs depending on the extent of frictions faced by employers in local labor markets. Thus, aggregating the employment effects across local labor markets can be misleading to the extent that each employer's market power differs across markets.

The remainder of the paper is organized as follows. Section 2 introduces the theoretical framework used to measure the extent of labor market surplus and summarizes the institutional background. Section 3 describes the data and identification strategies. Section 4 presents the results along with some robustness tests. Section 5 concludes.

2 Background

2.1 Measuring Surplus across Labor Markets

Although numerous studies have implied that the employment effects of minimum wage depend on a firm's ability to pass costs through to product prices (Harasztosi and Lindner, 2017), job-to-job turnover rates (Giuliano, 2013; Dube et al., 2016), and the degree of labor market monopsony (Card and Krueger, 1994), the majority of previous studies have treated labor markets as uniform within each nation. This paper measures the labor market competitiveness or frictions and examines whether this presumption is plausible.

To measure frictions in labor markets, we employ an approach proposed in previous studies (Petrin and Sivadasan, 2013; Dobbelaere and Mairesse, 2013; Dobbelaere et al., 2015; Lu et al., 2017), which calculates market competitiveness from production function estimates. The idea is to estimate how each plant deviates from its cost minimization behavior. In particular, A plant i at time period t has the following cost function:

$$TC\left(K_{it}, L_{it}, M_{it}\right) = C_K\left(K_{it}\right) + P_M M_{it} + W\left(L_{it}\right) L_{it}, \tag{1}$$

where K_{it}, L_{it}, and M_{it} denote capital, labor, and intermediate input, respectively. We assume perfect competition for intermediate input, and so the price of intermediate input, P_M, is constant within markets. For the labor markets, we assume the employer has monopsony power and faces an upward-sloping labor supply curve. The wage rate, $W\left(L_{it}\right)$, is therefore an increasing function of employment (inverse labor supply curve). $C_K\left(K_{it}\right)$ is the capital cost and the functional form is not imposed.

The plants choose the amounts of intermediate input and labor to minimize their production cost given a certain amount of production, $Q_{it}(K_{it}, L_{it}, M_{it}) = \bar{Q}$. The first-order condition for intermediate input is derived as follows:

$$P_M = \lambda_{it} \frac{\partial Q_{it}}{\partial M_{it}}, \tag{2}$$

where λ_{it} is the Lagrange multiplier and indicates marginal cost. Transforming the above condition, output elasticity with respect to the intermediate input, $\varepsilon_{M_{it}} \equiv \frac{\partial Q_{it}/Q_{it}}{\partial M_{it}/M_{it}}$, is derived as

$$\varepsilon_{M_{it}} = \frac{P_M M_{it}}{\lambda_{it} Q_{it}}. \tag{3}$$

We define markup as the ratio of the output price, P_{it}, to marginal cost. Using the above calculation, the markup can be expressed as the ratio of the output elasticity to the cost share of intermediate input, $\alpha_{M_{it}} \equiv \frac{P_M M_{it}}{P_{it} Q_{it}}$:

$$\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}} = \frac{\varepsilon_{M_{it}}}{\alpha_{M_{it}}}. \tag{4}$$

The condition of cost minimization for labor input is similarly derived as follows:

$$W_{it}\left(1 + \frac{1}{\varepsilon_{it}^L}\right) = \lambda_{it} \frac{\partial Q_{it}}{\partial L_{it}}, \tag{5}$$

where $\varepsilon_{it}^L \equiv \frac{\partial L_{it}/L_{it}}{\partial W_{it}/W_{it}}$ is the wage elasticity of the labor supply. To follow Lu et al. (2017), we measure the labor market competitiveness, or surplus, by $\eta_{it} \equiv \frac{W_{it}}{\lambda_i t \frac{\partial Q_{it}}{\partial L_{it}}} = \frac{\varepsilon_{it}^L}{\varepsilon_{it}^L + 1}$. Under a perfectly competitive market, $\eta_{it} = 1$. In this case, the wage rate is equalized to the marginal cost of labor. Under a monopsonistic market, on the other hand, the surplus term is strictly less than one ($\eta_{it} < 1$) and plants can lower the wage rate by reducing labor demand. Using the expression in equation (3), the surplus is written as follows:

$$\eta_{it} = \frac{\alpha_{L_{it}}}{\alpha_{M_{it}}} \frac{\varepsilon_{M_{it}}}{\varepsilon_{L_{it}}}, \tag{6}$$

where $\alpha_{L_{it}} \equiv \frac{W_{it}L_{it}}{P_{it}Q_{it}}$ is the cost share of labor input and $\varepsilon_{Lit} \equiv \frac{\partial Q_{it}/Q_{it}}{\partial L_{it}/L_{it}}$ is the output elasticity of labor input. We use η_{it} to measure the competitiveness of the local labor market that each plant faces. The calculation of η_{it} is straightforward, since we can directly calculate cost shares from our data and estimate output elasticities from production function estimations.

2.2 Minimum Wage in Japan

Japanese minimum wage is determined mainly at the regional level. Japan consists of 47 prefectures, each of which sets its own regional minimum wage and considers a revision annually. It has a wide and almost complete coverage of workers, with only a limited number of exceptions.[3] In addition to the regional minimum wage, local labor bureaus also allow a small increment in some industries, although the number of workers covered by these industry minimums is usually small. We focus on the variations in regional minimum wages to identify the heterogeneous responses to the minimum wage increases.

Key to the analyses carried out in this paper is the fact that regional minimum wages have been raised substantially after 2007. One main reason for this rapid increase is an institutional change in wage policy. It was argued in the early 2000s that welfare recipients in some regions receive higher benefits than workers who earn minimum wage, leading to an amendment to the Minimum Wage Act in 2007. The new Minimum Wage Act stipulates that regional minimum wages are to be consistent with the amount of welfare benefits (Art. 9, Part 3), and legally validates a further increase in minimum wage in regions with relatively high initial benefits. The Japanese government also took the initiative to continuously raise the minimum wage due to their increasing interest in boosting

[3]Exceptions are granted for those workers with physical or mental disabilities and those on probation or basic training, where permitted by the local labor bureau.

wage standards.[4]

The continuous increases in minimum wage has substantially raised the proportion of workers affected by it. Figure 1 graphs the overall trend of regional minimum wages in the past decades. The blue line is the Kaitz index, which represents changes in the average regional minimum wage against the average market wage. The red line is the proportion of minimum wage workers for a plant with the median proportion of such workers in each year, such proportion being defined as the proportion of workers whose hourly wage is less than 120% of the regional minimum wage, which was to be revised in the following months. The data comes from administrative wage records: the Basic Survey on Wage Structure (BSWS). The two graphs suggest that regional minimum wages have risen continuously, while a median plant would have faced a spike in the proportion of minimum wage workers after the amendment to the Minimum Wage Act in 2007. The proportion has risen sharply from almost zero before 2007 to more than 6% in 2015; thus, an increasing number of plants have been exposed to the minimum wage shock in the last several years.

The sharp and continuous increases in minimum wage have raised the proportion of those who work at minimum wage disproportionately in specific groups of workers and plants. Appendix Figures 1 and 2 graph the proportions of minimum wage workers within certain groups, using data from the BSWS. minimum wage worker is defined here as a worker whose hourly wage rate is no more than the minimum wage rate that will be effective in the following autumn. To summarize the main points, the proportion of those who work for minimum wage has increased, especially among (1) female workers, (2) young and old workers ($age < 20$ or $age > 60$), and (3) workers in medium- or small-sized plants. The most pronounced change can be found in teenage workers: nearly 20% of them were working for minimum wage in 2015, which is four times the number in 2005. The proportion also more than doubled among small-sized plants.[5]

The series of policies after 2007 has two important features to our identification strategy. First, those regions that were exposed to the 2007 amendment shock are unlikely to share specific local economic trends. The 2007 amendment required regions with initially high welfare benefits to increase their regional minimum wage to or above the level of their regional benefits. Appendix Figure 3 presents the proportion of minimum wage workers by the extent of exposure to the amendment shock, where exposed prefectures are defined as those prefectures that initially had benefit levels

[4] Examples include annual requests made by Prime Minister Abe to the Council on Fiscal and Economic Policy.

[5] This is in sharp contrast with the modest increases observed among small-sized employers between 1982 and 2002 in an administrative household survey (Kawaguchi and Mori, 2009).

lower than minimum wage earnings and that therefore have been exposed to a relatively intense increase in minimum wage after the 2007 revision of the Minimum Wage Act. Importantly, these exposed regions are located in both urban (e.g., Tokyo and Osaka) and rural areas (e.g., Hokkaido and Akita). The welfare benefits were initially high in urban regions because of their relatively high living costs. Regions with cold weather have also had relatively high benefits because of their high heating costs. Thus, local economic conditions are unlikely to be the primary factor that explains this differential shock. These variations are part of the identification variation we use to estimate the impact of minimum wage in this paper.

Second, the central government has taken significant initiative in raising the target amount of regional minimum wages, attenuating our concern on local economic conditions which can potentially confound with our identification variation. Similar to other countries, local authorities take local market conditions into account when revising the regional minimum wages by examining local market statistics.[6] However, after the 2007 amendment, the government set a much higher target level of regional minimum wages before the local authorities made any adjustments, which limits the local authority's flexibility to control the absolute level of the minimum wage.

We consider that the 2007 amendment initiated sizable and exogenous increases in those affected by the minimum wage and exploit this variation to identify the employment effect of the minimum wage. However, one potential threat to this strategy is the possibility that the changes in minimum wage still reflects pre-existing local employment trends. Although the 2007 amendment and a subsequent wage-boosting policy had a significant influence on the increases in minimum wage (as seen in Figure 1), it is still possible for local authorities to make slight adjustments based on their review. Thus, in order to credibly identify the impact of minimum wage, we need to ensure that the minimum wage changes after 2007 did not arise from preexisting local employment trends. This paper follows the estimation framework suggested by Meer and West (2016) to directly test this point. In particular, we examine whether future minimum wages predict current employment changes by focusing on the post-amendment period during which the national policy was considered to have had a large and continuous influence in determining the increases in minimum wage.

[6] The revision process involves two steps. In the first step, the Central Minimum Wages Council proposes a target amount to which minimum wages are to be raised, after investigating overall market conditions such as prices and market wages. In the second step, the Regional Minimum Wages Council of each prefecture determines how much to raise the minimum wage by taking into account the target amount proposed by the Central Council as well as local labor market conditions and the standard of living in that region. The revisions take place in October or November every year.

3 Identification Strategy

3.1 Main Data

The main analyses draw on the plant-level administrative data set from the Census of Manufacture, which is conducted every year by the Japanese Ministry of Economy, Trade and Industry.[7] The Census of Manufacture covers nearly an entire population of plants in the manufacturing sector in Japan. It contains detailed information on factor inputs and produced outputs at each plant. Information on product prices and quantities is also available for some of the plants. We focus on annual files that cover all plants with 30 or more employees (*Kou Hyou*).[8] Panel A of Table 1 presents summary statistics of this data set. Appendix I provides the details on variable constructions necessary to estimate production functions. Production functions are estimated with observations from 2001 to 2014 (see section 3.2). The impacts of minimum wage are estimated with observations from 2008 to 2014, so as to avoid including endogenous variations of minimum wage prior to the 2007 amendment to the Minimum Wage Act (see section 3.4).

3.2 Estimating the Labor Market Surplus

We measure the labor market surplus using the method explained in section 2.1. To this end, we first estimate the production function to calculate the output elasticities of intermediate input and labor. We posit a translog production function defined as follows:[9]

$$\begin{aligned}\ln Q_{it} = {} & \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_M \ln M_{it} + \beta_{KK} (\ln K_{it})^2 + \beta_{LL} (\ln L_{it})^2 + \beta_{MM} (\ln M_{it})^2 \\ & + \beta_{KL} \ln K_{it} \ln L_{it} + \beta_{KM} \ln K_{it} \ln M_{it} + \beta_{LM} \ln L_{it} \ln M_{it} + u_{it}. \end{aligned} \tag{7}$$

OLS estimates are not consistent because the inputs are positively correlated with unobserved productivity, $E(u_{it} \ln X_{it}) \neq 0$, where $X_{it} \in \{K_{it}, L_{it}, M_{it}\}$. We therefore follow the method of Blundell and Bond (1998, 2000), which proposes using the system GMM to estimate the production

[7] The census information is available online in English through the ministrys web page: http://www.meti.go.jp/english/statistics/tyo/kougyo/index.html

[8] The survey also has other types of annual files that contain information on all plants with 29 or fewer employees (*Otsu Hyou*). Since some of these files lack information on fixed assets, which is necessary to estimate production functions, we decided not to use these files in this paper.

[9] We consider potential substitutions among input factors seriously and do not estimate Cobb-Douglas production functions here.

function.[10]. In this method, the unobserved productivity is decomposed into three terms:

$$u_{it} = \delta_i + \omega_{it} + m_{it}, \tag{8}$$

where δ_i denotes average productivity of plant i and is captured by plant fixed effects. ω_{it} denotes a productivity shock unobserved by the econometrician. The shock is observed by the managers before determining inputs. This term is therefore the main source of endogeneity. m_{it} denotes a measurement error or a productivity shock after the amounts of inputs are determined. The average productivity can be correlated with the levels of inputs but must be independent from the changes in the inputs, $E\left(\delta_i \mid \Delta \ln X_{it}\right) = 0$ for $t \geq 2$. The measurement error can be correlated with the contemporaneous levels of inputs, but must be independent from the inputs in the previous periods, $E\left(m_{it} \mid \ln X_{it-s}\right) = 0$ for $s \geq 1$.

The dynamic process of the productivity shock is specified as

$$\omega_{it} = \rho\omega_{it-1} + \xi_{it}, \tag{9}$$

where ρ is a parameter of the productivity process and ξ_{it} is an innovation term. ξ_{it} is the deviation from the expected productivity shock; it is therefore independent from all of the inputs in the previous periods, $E\left(\xi_{it} \mid \ln X_{it-s}\right) = 0$ for $s \geq 1$.

Substituting the process into the production function, the following expression is derived as

$$\begin{aligned} \ln Q_{it} \quad = \quad & \sum_X \left[\beta_X \ln X_{it} - \rho\beta_{Xsj} \ln X_{it-1} + \beta_{XX} \left(\ln X_{it}\right)^2 - \rho\beta_{XX} \left(\ln X_{it-1}\right)^2\right] \\ & + \sum_{X,X'} \left[\beta_{XX'} \ln X_{it} \ln X'_{it} - \rho\beta_{XX'} \ln X_{it-1} \ln X'_{it-1}\right] \\ & + \rho \ln Q_{it-1} + (1-\rho)\,\delta_i + \xi_{it} + m_{it} - \rho m_{it-1}. \end{aligned} \tag{10}$$

To obtain parameter estimates in this model, we first estimate a vector of parameters γ in the following estimating equation:

[10] The translog production function is estimated by the system GMM in Söderbom and Teal (2004) and Lee et al. (2013).

$$\begin{aligned}\ln Q_{it} &= \sum_{X}\left[\gamma_X \ln X_{it} + \gamma_X^{'} \ln X_{it-1} \gamma_{XX} \left(\ln X_{it}\right)^2 + \gamma_{XX}^{'} \left(\ln X_{it-1}\right)^2\right] \\ &+ \sum_{X,X'}\left[\gamma_{XX'} \ln X_{it} \ln X_{it}^{'} + \gamma_{XX'}^{'} \ln X_{it-1} \ln X_{it-1}^{'}\right] + \gamma_Q \ln Q_{it-1} + d_i + v_{it}. \qquad (11)\end{aligned}$$

The moment conditions for the first-differenced equations are written as

$$E\left[\begin{pmatrix} \ln Q_{it-s} \\ \ln X_{it-s} \\ \left(\ln X_{it-s}\right)^2 \\ \left(\ln X_{it-s} \ln X_{it-s}^{'}\right) \end{pmatrix} \Delta v_{it}\right] = \mathbf{0}, \text{ for } s \geq 3.$$

On the other hand, the moment conditions for the levels equations are written as

$$E\left[\begin{pmatrix} \Delta \ln Q_{it-2} \\ \Delta \ln X_{it-2} \\ \Delta \left(\ln X_{it-2}\right)^2 \\ \Delta \left(\ln X_{it-2} \ln X_{it-2}^{'}\right) \end{pmatrix} \left(d_i + v_{it}\right)\right] = \mathbf{0}.$$

Using consistent estimates of the unrestricted parameters and the variance-covariance matrix, we impose the restrictions $\gamma_X = -\gamma_X^{'}\gamma_Q$ by minimum distance to obtain the restricted parameter vector.[11] The production functions are estimated separately for each industry, on the assumption that plants in the same industry face the same technological parameters (β) across regions. Industry-level estimations allow us to estimate parameters efficiently. We choose industry-level estimation, not industry-prefecture-level estimation, as it allows us to avoid removing specific industries or prefectures from our sample when their sample size is too small at the industry-prefecture level.

Using estimated parameters, we calculate the output elasticities for each input. In our calculation,

[11] We use a Stata command, md_ar1, written by Mans Soderbom. See the following website: http://www.soderbom.net/Resources.htm. Hempell (2005) describes the procedure in detail.

we use the median values for the inputs in each industry-prefecture group:

$$\hat{\varepsilon}_K = \hat{\beta}_K + 2\hat{\beta}_{KK} \ln \bar{K} + \hat{\beta}_{KL} \ln \bar{L} + \hat{\beta}_{KM} \ln \bar{M} \tag{12}$$

$$\hat{\varepsilon}_L = \hat{\beta}_L + 2\hat{\beta}_{LL} \ln \bar{L} + \hat{\beta}_{KL} \ln \bar{K} + \hat{\beta}_{LM} \ln \bar{M} \tag{13}$$

$$\hat{\varepsilon}_M = \hat{\beta}_M + 2\hat{\beta}_{MM} \ln \bar{M} + \hat{\beta}_{KM} \ln \bar{K} + \hat{\beta}_{LM} \ln \bar{L}, \tag{14}$$

where $\bar{X}$ shows the median value for input X. The median values are taken across plant-year observations from 2001 to 2014; however, as a robustness check, we also use median values from 2000 to 2007 to exclude a potential endogeneity issue between the market scheme and the minimum wage in a later section. The median values are taken across industry-prefecture groups to account for the fact that plants in different prefectures face different production levels and therefore different output elasticities.[12] The cost shares are also aggregated into industry-prefecture groups by taking median values.[13] Finally, the markup and the labor market surplus are measured by taking the ratios of these elasticities and cost shares. We drop the observations in the markets where either labor or intermediate elasticity is negative. To deal with extreme values, the observations in markets with the top 5% of surplus, η, are also dropped.

Although studies have developed various ways to estimate production functions (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; De Loecker and Goldberg, 2013; Gandhi et al., 2013; Ackerberg et al., 2015), we adopt the system GMM approach over the other procedures for the following reasons. First, system GMM allows us to consistently estimate the parameters in the presence of plant fixed effects, which we consider a realistic specification. We aim to obtain consistent production function coefficients, rather than productivity estimates in this paper. Second, although we also estimate our production functions with Wooldridge (2009)'s widely adopted method in our robustness section, it yields negative or large estimates for output elasticities in a non-trivial proportion of industry-prefecture groups. Due to these implausible values, the number of industry-prefecture groups has to be reduced from 1,602 in system GMM to 799 in Wooldridge (2009)'s method. Although the results of the two methods point to similar implications, we adopt system

[12] Another reason is that it allows us to measure regional variations in labor market surpluses, which can arise from geographical proximity to rivals.

[13] The labor cost share is obtained by dividing the total wage bill by total revenue. The total wage bill includes salaries, bonuses, and severance payments. The labor cost share thus includes a part of the adjustment cost; however, adjustment costs can arise from expected costs of litigation and other non-pecuniary costs, which can be reflected in the estimated surplus.

GMM as a main framework so as not to disproportionately select specific industry-prefecture groups into our final minimum wage estimation.[14]

Table 2 presents summary statistics from production function estimations with this system GMM method. The estimates take plausible values. A sum of the three input elasticities ranges around unity, suggesting constant returns to scale. Summary statistics for $\hat{\eta}$ suggest that most of the industry-prefecture groups face some surplus in their local labor market.

Importantly, our estimates of plants' labor market surplus or wage markdown measure frictions in the labor market. To intuitively understand this point, Table 3 tabulates the median and average numbers of rival plants in the same prefecture-industry group by the estimated surplus. Similarly, Figure 2 draws kernel estimates for distributions of the number of rival plants by $\hat{\eta}$. Table 3 and Figure 2 imply that the estimated surplus $\hat{\eta}$ tends to correlate positively with the number of rival plants. In particular, plants with $\hat{\eta} < 0.4$ are likely to have smaller numbers of rivals. Appendix Tables 1 and 2 provide industry- or region-level summary statistics. Roughly speaking, urban regions such as Tokyo tend to have higher $\hat{\eta}$, while the same proportions are lower in rural regions such as Hokkaido. This is consistent with a monopsonistic labor market model where employers have control over wages and enjoy some surplus. Although surplus in the labor market could arise from other factors such as the heterogeneous preference of workers and adjustment costs (Petrin and Sivadasan, 2013) and we by no means argue that the number of rival plants have a high predictive power, our estimates suggest that geographical proximity is one source of friction workers face in local labor markets.

3.3 Identifying Minimum-Wage Plants

The Census of Manufacture provides a broad set of operational information including product prices at each plant, but unfortunately does not contain information on hours worked or wage rates for individual workers, which is necessary to measure the extent of minimum wage shock at each plant. To supplement our analysis, we use another administrative data source to compute the number of

[14] Potential biases in production function estimation includes omitted price bias. As is often the case in previous studies, we deflate the nominal revenues as well as input expenditures by the industry price index. If firms face a downward-sloping demand curve, a negative correlation might arise between firm-level price deviations and input price, thereby biasing the output elasticity estimates downward. On the other hand, other estimation issues arise if we adjust the revenues by the output price information. Estimation of a quantity-based production function without any quality adjustment again leads to downward-biased parameter estimates as the product price reflects the product quality (De Loecker and Goldberg, 2013). Although this is a significant issue to be addressed in future research, we consider this to be beyond the scope of our research, and follow a standard approach to adjust the revenue with industry price information as has been done in previous studies (Petrin and Sivadasan, 2013, for example).

minimum wage workers each plant employs, in keeping with the spirit of Draca et al. (2011) and Aaronson et al. (2012). In particular, we draw on worker files from the BSWS, which contains information on individual employees' hours of work, wages, and benefits, including overtime work hours and payment at each plant.[15] The BSWS is conducted annually by the Japanese Ministry of Health, Labour and Welfare.[16] This survey contains two types of questionnaire, plant-panel (*Jigyosho-hyo*), and employee-panel (*Kojin-hyo*). The survey samples plants with 10 or more regular employees and plants with five to nine employees in private sectors only. Employees are selected by a uniform sampling method from the plants that were selected for this survey.[17] We use pooled cross-sectional data from the BSWS to calculate the proportion of minimum wage workers, the total wage bill per regular employee, plant size, etc. Observations are limited to those plants/workers in manufacturing sectors.

To identify the extent of the minimum wage shock to each plant in the Census of Manufacture, we first calculate the proportion of minimum wage workers at each plant i at period t from the BSWS. A worker is defined as a minimum wage worker if his or her hourly wage rate was within 120% of the minimum wage that would be effective in the following October or November.[18] We then estimate the following simple linear model to identify the characteristics of manufacturing plants that hire relatively large proportions of minimum wage workers:

$$S_{it} = \delta_t + z_{it}\beta^0 + \epsilon_{it} \tag{15}$$

Covariates z_{it} include polynomials of the plant size and annual wage bill per regular employee, and the ratio of regular workers. We did not include prefecture and industry fixed effects and allowed individual plant traits to predict the proportion. In so doing, we can avoid the result where the predicted proportion mostly reflects prefecture or industry variations in minimum wage, leaving sufficient minimum wage variations even after we limit the sample by the predicted initial proportions

[15]Although it is possible to match worker-level information from the Wage Census with the Manufacturing Census to construct an employer-employee data set, we chose not to do so for the following reasons. First, the Wage Census oversamples large plants that are less likely to be affected by an increase in minimum wage. Second, the Wage Census is not a population survey, and matches only 9% of the original sample in the Manufacturing Census (Kawaguchi et al., 2007).

[16]The BSWS information is available in English through the ministry web page (accessed January 19, 2018): `http://www.mhlw.go.jp/english/database/db-slms/dl/slms-04.pdf`.

[17]In the most recent survey (BSWS2016), 78,095 establishments extracted from the population of 1,429,579 establishments based on prefecture, industry, and size . Responses were received from 57,657 establishments.

[18]We chose 120% so as to accommodate the fact that the industry minimum wage could take a value more than 10% higher than the regional minimum wage.

of minimum wage workers. The model is estimated with BSWS observations in manufacturing sectors from 2008 to 2014. Finally, we compute the predicted proportion of low-wage workers at each plant in the Census of Manufacture, using a common set of covariates z_{it} and the estimated parameters. Panels B and C of Table 1 present summary statistics for the BSWS and the Census of Manufacture in the corresponding period. A comparison of the two panels suggests that the Census of Manufacture is comparable to the BSWS in terms of the annual wage bill and ratio of regular workers, although the BSWS samples slightly larger plants than Census of Manufacture.

Appendix Table 3 provides the estimation results of this model. The estimated models have high explanatory powers. Adjusted R-squared values range above 0.6. A comparison of columns (1) and (2) suggests that the average annual wage bill per worker and its polynomials alone have sufficiently high explanatory power. This is consistent with an approach in Draca et al. (2011), where they defined a treatment status by establishing the average wage to measure the impact of introducing a national minimum wage in the UK. Figure 3 plots fitted values from column (1) of Appendix Table 3 using the BSWS. Predicted proportions of minimum wage workers become increasingly larger when the annual wage bill per worker at the plant is less than 4 million JPY ($\approx$ 36 thousand USD as of January 2018). Panel B in Table 1 presents the predicted proportions of minimum wage workers. The computed proportions take reasonable values (mean = 0.15, p25 = 0.02, p50 = 0.08, p75 = 0.23). These values are similar to those observed in the BSWS (mean = 0.17, p25 = 0, p50 = 0.04, p75 = 0.23; see Panel C in Table 1). In the main analysis with the Census of Manufacture, we use the computed proportions of minimum wage workers in 2008 to examine whether the impact of the minimum wage is intensified in plants with initially high proportions of minimum wage workers.

3.4 Testing the Impact of Minimum Wage

Similar to some previous studies, we exploit differential increases in the minimum wage across regions to test its impact; however, studies have raised potential identification issues in using such a difference-in-differences (DID) type of regional variation. First, the regional minimum wage could be confounded by any preexisting trend specific to the local area. Dube et al. (2010) proposes stacking county pairs across US state borders to control for common local trends among the pairs. A series of arguments clarified both the importance and difficulty of finding valid counterfactuals to control for the local preexisting trends (Neumark et al., 2014; Allegretto et al., 2013). Second, despite the first point, including region-specific time trends in a DID framework can be misleading if minimum wage affects the growth, not the level, of employment (Meer and West, 2016). When the minimum wage is increased, the adjustment to this new state may take some time and may not be smooth. For instance, job destruction may occur gradually due to adjustment costs and a slow substitution for other input factors such as capital (Baker et al., 1999). Estimating the employment effect in a level specification will then be misleading, because the staggered treatment effect follows a continuous trend-shaped pattern rather than a discontinuous jump. Controlling for region-specific linear trends in such a level specification masks the true dynamic treatment effect since it cannot be identified separately from the local linear trend (Meer and West, 2016).[19]

One way to avoid such a misspecification is to check whether we ever need to control for region-specific linear trends in the first place. The local linear trends have been controlled in previous studies since the preexisting employment trends may predict the current minimum wage Dube et al. (2010). We follow a suggestion in Meer and West (2016) and estimate the impact of minimum wage on employment growth and examine whether there are any preexisting local trends that could confound the changes in minimum wage. In particular, we estimate the following model of first-differenced employment levels with leads and lags of log differences in the prefectural minimum wage:

$$\Delta ln(E_{it}) = \sum_{s=-2}^{3} \gamma^s \Delta ln(mw_{p,t-s}) + \delta_t I_j + f_p + \Delta x_{pt}\beta + \Delta\nu_{it}, \tag{16}$$

where $ln(E_{it})$ is a logarithm of employment at plant i at year t. The employment here includes both regular and non-regular workers.[20] The model controls for industry-specific (j) year effects, prefecture-level (p) fixed effects, and some time-variant prefecture covariates. Prefecture control variables (x_{pt}) include log-population and the proportion of people aged 15–65. If the minimum wage change does not reflect any preexisting trends, the estimates for the lead terms of $\Delta ln(mw)$ should be insignificant and close to zero.

We argue that the above specification is appropriate especially for our case of Japan where we

[19] Figures 1 and 3 in Meer and West (2016) provide a graphical representation of this idea by comparing two hypothetical jurisdictions which experienced slowdowns in employment growth due to an increase in the minimum wage at different points in time. Wolfers (2006) first points out this weakness of analyzing the dynamic impact of policy shock in the level specification, for the case of unilateral divorce laws adoption in the US.

[20] We do not divide regular and non-regular employment, because we do not have separate total wage bills for each of the two groups; we therefore cannot estimate η separately. A main focus of this paper is to examine the labor market heterogeneity in terms of overall workers.

observed exogenous and continuous increases in regional minimum wages after 2007. As discussed in section 2.1, the regional minimum wage is determined based partially on the local authority's examinations of recent market statistics, and could thus reflect preexisting local market conditions. However, after 2007, minimum wage revisions have largely been based on the amendment to the Minimum Wage Act and the government's involvement in boosting the wage floor, rather than on the examination of the local authorities. Hara (2017) also uses a similar variation in minimum wages to estimate its impact on worker training in Japan. To test the exogeneity of the post-amendment variations in minimum wage, we estimate the above model with observations between 2008 to 2014 in the Census of Manufacture, during which the local authorities' influence is considered to be less.[21] Indeed, our results show no significant estimates for lead terms for $\Delta ln(mw)$, validating our approach.

To reflect the extent that each plant is differently bound by minimum wage, we estimate the above equation separately for plants with different exposures to the minimum wage shock ($\hat{S}_{i,t=\ 2008} > 0.1$, for instance). Similarly, we also examine the heterogeneity of the plants' response to the shock across different market regimes. In particular, we examine whether an increase in the minimum wage brings about the same consequences on employment growth as in the competitive labor market, even when $\hat{\eta}$ is low.

4 Results

4.1 Test of Preexisting Trends

Table 4 shows the results of our tests of whether there are any preexisting trends in the changes in minimum wage after 2008. Specifically, Table 4 presents the estimation results for equation (16) with various combinations of leads and lags for $\Delta ln(mw_{p,t})$. These specifications are similar to the first three columns of Table 4 in Meer and West (2016), although we use plant-level observations from a Japanese manufacturing census, instead of state-level observations from the Business Dynamics Statistics in the US. The results in Table 4 suggest that the elasticity of employment with respect to minimum wage is about -0.497. The impact of the first lagged change in minimum wage remains quite stable across specifications. The elasticity remains around -0.5 across specifications, implying that the negative impact found on the first lagged term is not driven by any preexisting employment

[21] We limit our observations to those in and after 2008, not 2007, so that we can avoid including information from 2006, given that lagged minimum wage has a high explanatory power in our preferred specification, as will be shown later.

trend. In fact, the estimates of lead terms for minimum wage in columns (3) and (4) take insignificant and small values. Thus, the current employment growth is not statistically associated with the future growth of minimum wage. The changes in minimum wage are unlikely to reflect preexisting local trends.

Although regional minimum wages have been raised substantially in the past decades, the results in Table 4 blur the plants that are actually exposed to the minimum wage shock. To confirm that increases in minimum wage are indeed concentrated in plants with a higher proportion of low-wage workers, we estimate the same models in Table 4, separated by the initial extent of the exposure. In particular, we divide the sample by the predicted proportions of minimum wage workers as of 2008, $\hat{S}_{i,t=2008}$, computed from administrative wage records, as was explained in section 3.3.

Table 5 shows the results. Columns (1) and (5) replicate the results from columns (4) and (5) in Table 4. Comparisons across columns confirm that increases in minimum wage indeed have stronger negative impacts on those plants with higher proportions of minimum wage workers. The employment elasticity is -0.64 in plants with more than 5% of low-wage workers, -0.65 in plants with more than 10% of low-wage workers, and -1.06 in plants with more than 20% of low-wage workers. The monotonically increasing pattern is consistent with Figure 3 where the predicted proportions of minimum wage workers become increasingly higher when plants average annual wage bills are less than 4 million JPY. Similar to the findings in Table 4, these results are robust against controls for leads and lags of the minimum wage changes. A comparison between the first and last four columns indicates that the estimates for elasticity are mostly stable with or without the lead and lag terms for minimum wage. Although the prediction of proportions of minimum wage workers prevents us from obtaining precise estimates for the impact of minimum wage, the results in this table suggest the plausibility of our predicted proportions in reflecting the extent of exposure to the shock. Since the first lagged term, $\Delta ln(mw_{p,t-1})$, has the largest impact in terms of magnitude, we will focus on the impact of this term in the remainder of this paper.

The estimated elasticities in Tables 4 and 5 are notably large, compared to those reported in previous state-level studies in the US. Our results so far suggest that a 10% increase in minimum wage leads to about a 6% decrease in plant employment if the share of minimum wage workers, $\hat{S}_{i,t=2008}$, is *higher* than 10%. Unfortunately, the predicted proportion of minimum wage workers is not a perfect measurement of the exposed shock. We also condition our estimates on the predicted share as of 2008 to allow sufficient within-plant variations in our estimations. Thus, it is possible that the plant's actual proportion of minimum wage worker is much higher than the predicted proportions indicate. As Figure 1 suggests, an increasing fraction of plants were affected by the minimum wage after the 2007 amendment. It is also important to note that, since price levels have been relatively stagnant in Japan, *real* minimum wage has increased, thereby restricting firms labor-demand decisions quite severely. Kambayashi et al. (2013) exploited the similar significant bite of minimum wage in a deflationary period to study its impact on the wage inequality. A sharp and rapid increase in minimum wage at face value can have a severe effect in a long and continuous deflationary economy.

4.2 Minimum Wage Effects across Heterogeneous Markets

Production function estimation in section 3.2 revealed that the estimated extent of surplus or wage markdown, $\hat{\eta}$, measures important frictions in the labor market such as the one driven by geographical proximity with rival plants. This section tests a prediction of a monopsonistic labor market model, where plants do not reduce their employment level in response to increases in minimum wage.

Panel A of Table 6 estimates the impact of growth in minimum wage on employment growth, separately by the level of the estimated surplus. The sample is limited to the plants located in the market for which the surplus is estimated. Recall that $\hat{\eta}$ represents the extent of wage markdown. Plants face no surplus in a competitive labor market, thus, $\hat{\eta} = 1$. Column (1) replicates column (5) in Table 4. We do not add and lead and lagged terms for changes in minimum wage, because we have obtained quite robust results in controlling for the leads and lags in previous tables, and also because we prefer to maintain the powers of the test by keeping as many observations as possible since sample sizes are reduced substantially in some specifications below.[22]

The results in this panel are consistent with the presence of surplus. As we limit the sample to those plants with smaller $\hat{\eta}$, the estimates become insignificant and smaller in magnitude, and even take positive values; increases in minimum wage do not significantly reduce employment growth when plants face a large extent of surplus or wage markdowns. This is in contrast to the significant and negative impact of minimum wage in the baseline case in column (1). As standard competitive labor market model suggests, plants in a perfectly competitive labor market do not have sufficient wedges before they immediately decrease the employment level in response to an increase in minimum

[22] Although not shown in the paper, we also estimated the same sets of specifications with leads and lags of $\Delta\, ln(mw_{p,t})$. None of the lead terms were significant, and we thus did not observe any preexisting employment trend.

wage. Importantly, a plant deviates from the competitive model if it has some control over market wages due to some frictions in the local labor market (Manning, 2003). The initial surplus between the value of the marginal product of labor and the wage rate imposes less pressure on the plant to reduce its employment level. A plant can even increase its profit by increasing its employment level to expand the surplus. This is consistent with our results here since we observe that the magnitude of the estimate monotonically increases as we restrict our sample to smaller $\hat{\eta}$, although they are not statistically significant.

On the other hand, plants can also deviate from the standard case if they face adjustment costs of labor. In their dynamic model, Bentolia and Bertola (1990) formalized the idea that, even in a competitive setting, the value of the marginal product of labor deviates from the equilibrium wage rate when firms face firing or hiring costs. In fact, Petrin and Sivadasan (2013) measures the extent of firing costs for manufacturers in Chile by estimating the wedge between the value of the marginal product of labor and the wage rate from production function estimations. Our estimates seem consistent with the existence of firing costs: the negative estimates disappear only when $\hat{\eta}$ is smaller than 0.4, but not when it is smaller than 1.

However, the results here are likely to reflect market frictions, rather than the adjustment costs of labor, for following reasons. First, when we construct $\hat{\eta}$, we use the total wage bill which includes severance payments. Thus, the surplus measured by $\hat{\eta}$ excludes an important part of the adjustment costs. Second, although the adjustment costs may still arise from expected cost of litigation and other non-pecuniary costs, the regional pattern of $\hat{\eta}$ does not match with the potential differences in such unobserved firing cost at each region.[23] Given that the extent of surplus is negatively associated with the number of rival plants in the local labor market (Figure 2 and Table 3), our results suggest that the heterogeneous estimates have mostly arisen from heterogeneity in labor market frictions.

A key to valid identification in Table 6 is to have sufficient variations in minimum wage changes by the extent of surplus. If variations in minimum wage are significantly smaller in regions or industries with smaller $\hat{\eta}$, the insignificant estimates obtained in Table 6 may reflect small identification variations, rather than large frictions in the labor market. We consider that this is not the case in our estimates for the following two reasons. First, despite the fact that the standard error becomes

[23]Firing costs can vary across regions in Japan due to differences in local court discretion (Okudaira, 2018). However, the observed regional difference in firing costs look different from the estimated surplus by prefecture in Appendix Table 2. In particular, the Osaka District and High Courts are known to have a more stringent interpretation of the firing regulations than the courts in Tokyo (Okudaira, 2018), a pattern that does not coincide with the regional pattern of $\hat{\eta}$ in Appendix Table 2.

larger as we limit the sample from columns (6) to (2), the estimates also get smaller in magnitude or even positive, suggesting that our insignificant results are not driven merely by small sample size. Second, despite a relatively small sample size, we do have sufficient *actual* variations in minimum wages even for cases with smaller $\hat{\eta}$. Figure 4, which shows histograms for the differences in the logarithm of regional minimum wages, confirms this point. Beige bars indicate the distribution when the estimated wage markdown is smaller: $\hat{\eta} < 0.4$. Similarly, red-lined bars indicate the distribution $\hat{\eta}$. While plants with $\hat{\eta} \leq 0.4$ have slightly larger changes in minimum wage, the two histograms mostly overlap. At the bottom of each panel in Table 6, we also show the % of minimum wage variation in terms of the baseline case in column (1). The % of minimum wage variation is calculated by dividing the standard deviation in $\Delta ln(mw_{p,t-1})$ in that sample by the same standard deviation in column (1). Although the standard deviation becomes slightly smaller as $\hat{\eta}$ decreases, the minimum wage variations have not been significantly reduced. This tendency is more prominent in specifications which will be shown below. Thus, the insignificant estimates observed in Table 6 are unlikely to only be driven by small identification variations. Rather, they suggest the fact that plants with small $\hat{\eta}$ did not have to immediately reduce the growth rate of employment due to the surplus they face.

Panel B of Table 6 conducts the same estimations by limiting the observations with at least 10% of minimum wage workers, $\hat{S}_{i,t=2008} > 0.1$. We observe more intensified effects when plants had an initially larger proportion of minimum wage workers. Again, the negative impact is observed only when plants have little surplus or larger $\hat{\eta}$. Plants facing some frictions in the labor market do not significantly reduce their employment growth. Similar to the results in Table 6, the estimates become substantially smaller in magnitude, suggesting that the insignificant results are not only driven by the smaller sample size. Although not shown here, similar patterns are observed when we limit observations with different values of $\hat{S}_{i,t=2008}$. The previous empirical studies have focused on the aggregate employment effect of minimum wage and ignored the potential heterogeneity in local labor markets faced by plants. The overall impact of the minimum wage often observed in the literature masks the heterogeneous response of plants operating in diverse labor markets.

Finally, Panel C of Table 6 conducts a placebo test to examine whether the results in Panels A and B represent the actual impact of minimum wage. In particular, we limit our observations to those plants with an initial computed proportion of minimum wage workers less than or equal to zero: $\hat{S}_{i,t=2008} \leq 0$. Since these plants did not have minimum wage workers in 2008, they were much less likely to be exposed to the minimum wage shock after 2007. Indeed, none of our estimates are significant in Panel C. Importantly, our estimates become smaller in all specifications except in column (2). Thus, Panel C reinforces the causal interpretation of the results in Panels A and B that the increases in minimum wage slow down the employment growth only in plants facing less surplus.

4.3 Robustness Tests

One important concern on the results in the previous section is the potential endogeneity in labor market surplus. For instance, if the local labor market becomes competitive and $\hat{\eta}$ becomes closer to 1, the harsh competitive environment may induce firms to invest more in technologies that can substitute labor inputs away from production, and at the same time improve the efficiency in the production process in the long run. A reduction in production costs can expand the firm's production. If this is the case, it may invite further increases in minimum wage, since economic expansion often accelerates upward revisions of the minimum wage. Because we construct our labor market parameter, $\hat{\eta}$, from production function estimates based on observations in 2001–2014, it is possible that our estimates using the level of $\hat{\eta}$ in Table 6 disproportionately selects plants in specific prefecture-industry groups. Furthermore, $\hat{\eta}$ also includes the contemporaneous changes in labor input, L_{it}, since we use industry-prefecture-level median values of input factors and cost shares to calculate the output elasticities for each input (see section 3.2).

In order to address this endogeneity concern, Panels A and B in Table 7 conduct robustness estimations using the information prior to our main sample period. In particular, panel A constructs $\hat{\eta}$ from the same production function estimates in Table 6 (i.e., system GMM estimations separately for each industry, 2001–2014), but with median input values and median cost shares from the pre-sample period (2001–2007) only. In Panel B, $\hat{\eta}$ is constructed from production function estimates from the pre-sample period only (i.e., system GMM estimations separately for each industry, 2001–2007), and median input values and median cost shares are taken from observations in pre-sample period, 2001–2007. Observations in the main minimum wage analyses are limited to those plants with $\hat{S}_{i,t=2008} > 0.1$.

The results in Panels A and B show that the negative impacts of minimum wage are again concentrated among those plants with $\hat{\eta}$ closer to one. In both panels, the elasticities of employment with respect to minimum wage take significant and negative values between -0.5 and -0.6 in columns

(5) and (6). On the other hand, the estimates for the smaller $\hat{\eta}$ are smaller in magnitude and not significant, except for cases in column (3) where the magnitude of the estimates are slightly larger in both panels.

It should be noted that a non-trivial proportion of plants are dropped from these specifications due to the lack of a parameter estimate for η. For instance, in Panel A, we drop plants in those industry-prefecture groups where the output elasticities of input factors take unrealistic values such as negative. In Panel B, those industry-prefecture groups with a relatively fewer plants are dropped from the sample due to the insufficient sample size in production function estimations. Moreover, while these estimations can mitigate the endogeneity concerns on the surplus, the production function estimations ignore technological advancements after the Lehman shock since they only use information from prior to the event. If the market structure has been substantially changed over time, limiting the production function estimations prior to the 2007 amendment can be misleading. Because of these limitations, we consider our preferred estimates as those presented in Table 6. However, the estimation results shown in Panels A and B in Table 7 still point to a similar direction as our previous estimations.

So far, we estimated $\hat{\eta}$ using system GMM suggested by Blundell and Bond (2000). As explained in section 3.2, we adopt system GMM since it provides consistent coefficient estimates in the presence of plant fixed effects. However, in order to examine the flexibility of our framework over different estimation procedures, we also estimate production functions by following Wooldridge (2009) to construct $\hat{\eta}$. Wooldridge (2009) extends the two-step estimation framework in Levinsohn and Petrin (2003) to a two-equation system which provides more efficient estimators by allowing the error component to be correlated with current labor input but not the labor input at the previous period. Similar to the previous case, we estimate production functions separately for each industry with observations between 2001 to 2014. The median values are obtained from observations between 2001 to 2007. Panel C in Table 7 presents the estimation results. Although a pattern in the magnitude of the estimate is not as clear as previous cases, we again obtained significant and negative estimates for a case with little surplus. Unfortunately, in many industry-prefecture groups, this procedure also provides us with negative output elasticity values and we dropped these industry-prefecture groups from our sample. Since our final sample size in Table 7 is disproportionately reduced, we consider that our preferred estimates are those based on system GMM estimations, although the results with Wooldridge (2009)'s method also point to similar implications.

5 Conclusion

The overall evaluation of minimum wage depends on the extent to which firms bear its burden. This paper sheds light on direct aspects of firms internal responses to increases in minimum wage, so as to examine whether the local labor markets are heterogeneous, and whether the employment effect of minimum wage differs across markets, depending on employers' market power or frictions in the labor market. Specifically, we estimate the surplus between the value of the marginal product of labor and the wage rate from standard production function estimations. We then tested the minimum wage impact on employment growth across the extent of surplus that plants enjoy in the local labor markets.

By applying the estimation framework to a Japanese manufacturing census, we first observed that plants significantly reduced their employment growth in response to increases in minimum wage. However, the estimated negative impact masks the heterogeneity in plants' behavioral response: an increase in minimum wage affected plants in our sample in rather different ways, depending on the surplus that plants face. We found that in response to an increase in minimum wage, plants that initially experienced a large surplus did not significantly reduce their employment growth. Interestingly, albeit insignificant, the estimates become larger and even positive when plants have larger surplus. While our main data does not contain the wages and hours of work for individual employees, computation from another source of administrative wage records confirms that the minimum wage effects are concentrated in plants with larger proportions of minimum wage workers. Although a lack of individual hourly wage information prevents us from obtaining precise estimates, the results found in this paper largely support the view that the local labor market is diverse and plants respond to the minimum wage shock depending on the extent of frictions they face in the labor market.

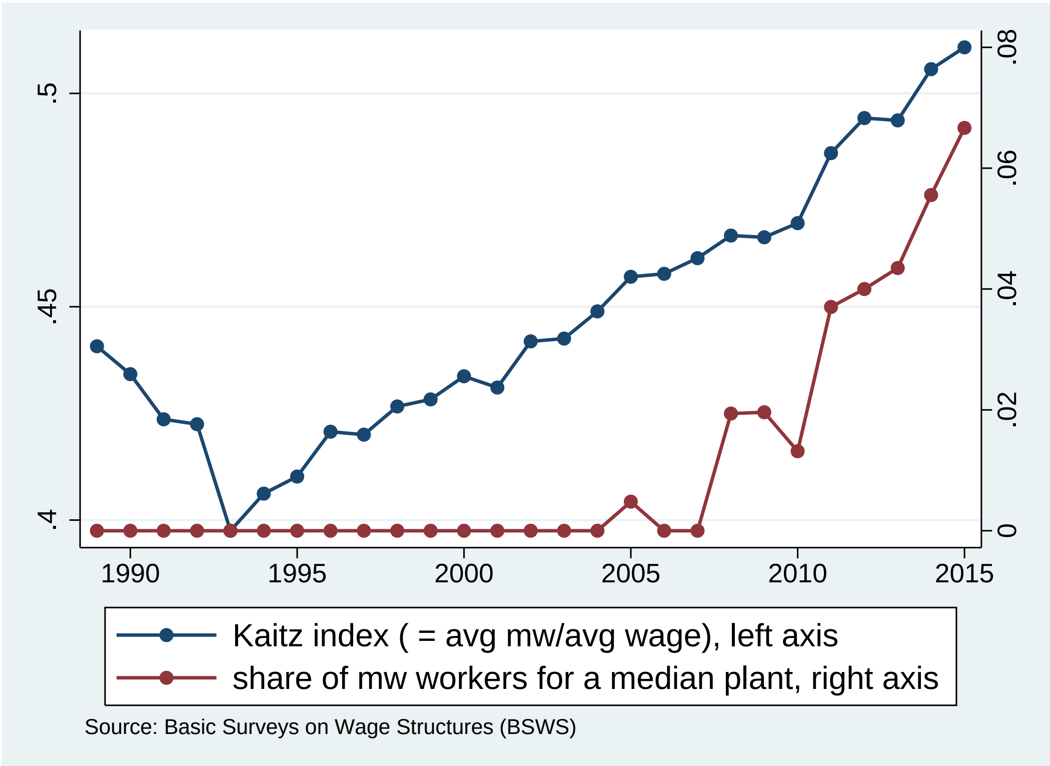


Figure 1: Kaitz Index and Proportion of Minimum Wage Workers for a Median Plant.

Note: Blue line indicates Kaitz index (left axis). Red line indicates a proportion of minimum wage workers for a plant with median value of the proportion in each year. The data comes from administrative wage records, Basic Survey on Wage Structures (BSWS).

Table 1: Summary Statistics

	N	Mean	Std. Dev.	P25	P50	P75
Panel A. Census of Manufactures (2001-14)						
lnY	635234	16.52	1.37	15.61	16.35	17.27
lnL	635234	4.35	.8	3.74	4.14	4.75
lnK	605489	17.11	1.78	16.05	17.04	18.12
lnM	617111	10.78	1.89	9.76	10.8	11.91
cost share (labor)	630120	.24	.16	.13	.2	.3
cost share (material)	631158	.38	.23	.21	.38	.55
Panel B. Census of Manufactures (2008-14)						
prefecture share of those aged 15-64	301372	.62	.02	.61	.62	.64
log(prefecture population)	301372	14.97	.79	14.42	14.86	15.79
computed proportion of MW workers ($\hat{S}_{it}$)	301372	.15	.18	.02	.08	.23
annual wage bill per employee ($10^4 JPY$)	301372	376.84	156.87	265.58	359.87	464.31
plant size	301372	127.56	283.34	42	63	117
ratio of regular workers	301372	.34	.24	.14	.27	.5
Panel C. BSWS (2008-14, manufactures)						
proportion of MW workers (S_{it})	82509	.17	.25	0	.04	.23
annual wage bill per employee ($10^4 JPY$)	82509	361.18	151.92	253.65	340.98	447.41
plant size	82509	173.69	495.13	13	38	126
ratio of regular workers	82509	.33	.26	.13	.25	.48

Table 2: Production Function Estimates

	N	Mean	Std. Dev.	P25	P50	P75
$\hat{\varepsilon}_L$	1602	.45	.23	.26	.4	.59
$\hat{\varepsilon}_M$	1602	.48	.14	.4	.48	.57
$\hat{\varepsilon}_K$	1602	.11	.13	.06	.12	.19
$\hat{\varepsilon}_L + \hat{\varepsilon}_M + \hat{\varepsilon}_K$	1602	1.03	.25	.87	.96	1.18
$\hat{\eta}$	1602	.67	.35	.43	.6	.84
$\hat{\mu}$	1602	1.3	.52	.97	1.22	1.54

Note: Translog production functions are estimated separately for each industry group. The estimation procedure follows System GMM. The estimated production function estimates are then used to calculate the parameters in this table by using median values for other input variables within each prefecture-industry group (see section 3.2). The data comes from Census of Manufactures (METI).

Table 3: Number of Rival Plants

$\hat{\eta_{pj}}$	< 0.1	< 0.2	< 0.3	< 0.4	< 0.5	< 0.6	< 0.7	< 0.8	< 0.9	< 1	all
median	0	7	6	7	9	10	11	11	11	11	9
mean	6.8	20.6	13.9	16.8	23.5	24.14	24.3	24.4	24.1	23.9	20.9

Note: Figures present median or mean of number of rival plants within the same prefecture-industry group by the extent of wage markdown or surplus or $\hat{\eta}_{pj}$. The data comes from Census of Manufactures (METI).

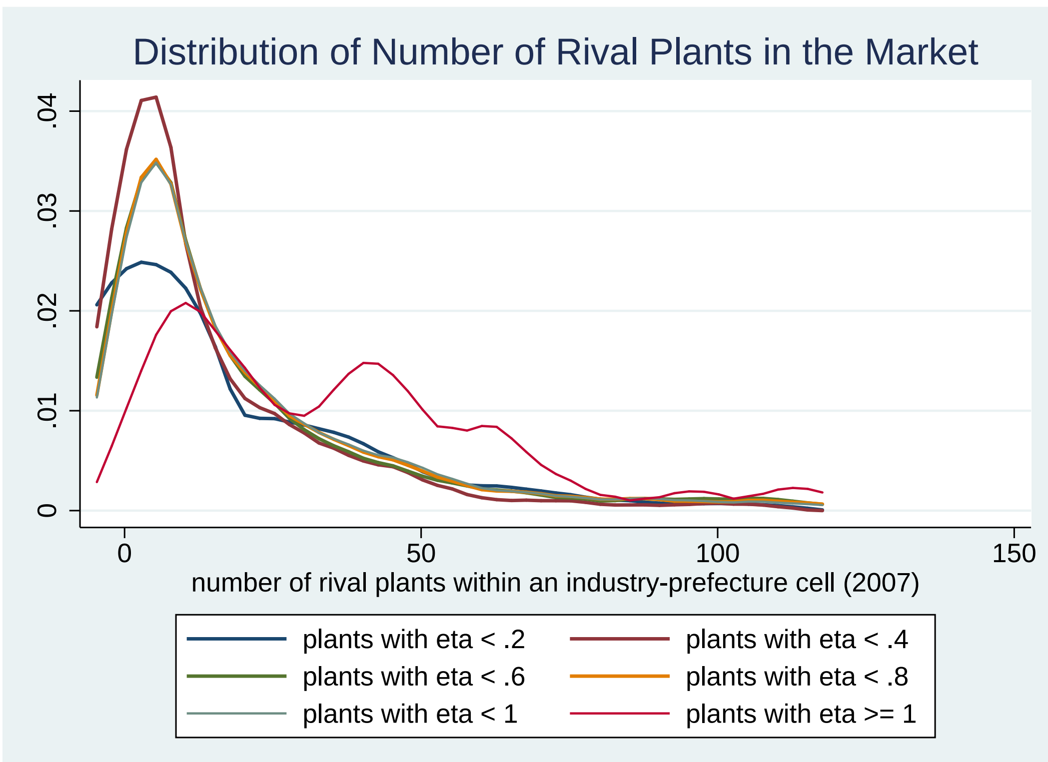


Figure 2: Number of Rival Plants within the Same Prefecture-Industry Group by $\hat{\eta_{pj}}$.

Note: The figures show kernel estimates for the number of rival plants in the same prefecture-industry group. The data comes from Census of Manufactures (METI).

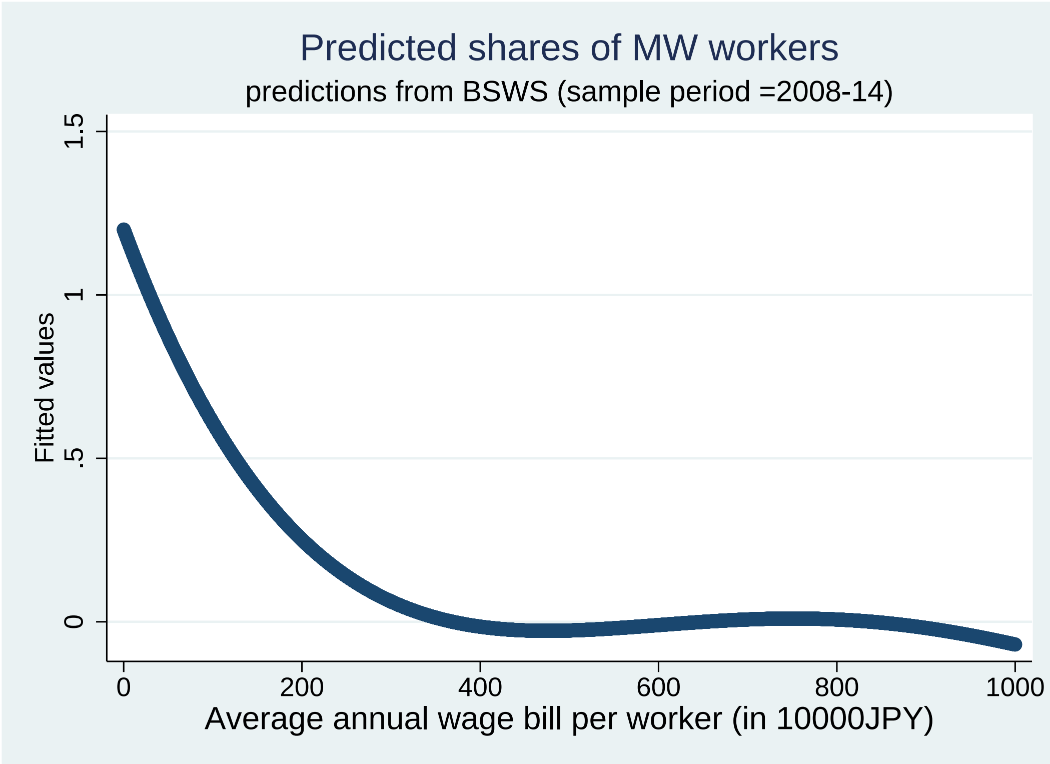


Figure 3: Predicted Proportion of Minimum Wage Workers at Each Plant

Note: The figures show the fitted values from a simple regression model to predict a proportion of minimum wage workers at each plant. The covariates include; polynomials of plant size and annual wage bill per regular employee, and ratio of regular workers (column (1) in Appendix Table 1). See section 3.3 for details. The data comes from administrative wage records, Basic Survey on Wage Structures (BSWS).

Table 4: Test of Pre-existing Local Trends

	(1)	(2)	(3)	(4)	(5)
$\Delta ln(mw_{p,t-3})$		0.0400	0.0295	0.0481	
		(0.129)	(0.155)	(0.138)	
$\Delta ln(mw_{p,t-2})$		-0.125	-0.121	-0.119	
		(0.172)	(0.184)	(0.171)	
$\Delta ln(mw_{p,t-1})$	-0.538***	-0.499***	-0.512***	-0.497**	-0.518***
	(0.132)	(0.185)	(0.186)	(0.191)	(0.135)
$\Delta ln(mw_{p,t})$	0.107	0.0987	0.106	0.113	
	(0.123)	(0.166)	(0.163)	(0.160)	
$\Delta ln(mw_{p,t+1})$			-0.0254	-0.0364	
			(0.201)	(0.200)	
$\Delta ln(mw_{p,t+2})$				0.0398	
				(0.131)	
N	281,388	281,388	281,014	280,112	281,388

Note: Robust standard errors clustered at the prefecture level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column controls for industry-specific linear trends and prefecture control variables. Prefecture control variables (x_{pt}) include log-population and the share of those aged 15-65. The data comes from Census of Manufactures (METI).

Table 5: Minimum Wage Effects by Predicted Shares of Minimum Wage Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	all	$\hat{S} > 0.05$	$\hat{S} > 0.1$	$\hat{S} > 0.2$	all	$\hat{S} > 0.05$	$\hat{S} > 0.1$	$\hat{S} > 0.2$
$\Delta ln(mw_{p,t-3})$	0.0481	-0.136	-0.293	-0.323				
	(0.138)	(0.153)	(0.199)	(0.259)				
$\Delta ln(mw_{p,t-2})$	-0.119	-0.0514	0.000622	0.136				
	(0.171)	(0.184)	(0.182)	(0.251)				
$\Delta ln(mw_{p,t-1})$	-0.497**	-0.640**	-0.646**	-1.057***	-0.518***	-0.596***	-0.633***	-0.891***
	(0.191)	(0.239)	(0.272)	(0.339)	(0.135)	(0.178)	(0.225)	(0.278)
$\Delta ln(mw_{pt})$	0.113	0.131	0.0885	0.226				
	(0.160)	(0.200)	(0.229)	(0.312)				
$\Delta ln(mw_{p,t+1})$	-0.0364	-0.260	-0.226	-0.277				
	(0.200)	(0.253)	(0.299)	(0.319)				
$\Delta ln(mw_{p,t+2})$	0.0398	-0.0304	0.0353	-0.208				
	(0.131)	(0.193)	(0.267)	(0.315)				
N	280,112	151,091	110,844	67,403	281,388	151,830	111,398	67,785

Note: Robust standard errors clustered at the prefecture level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column controls for industry-specific linear trends and prefecture control variables. Prefecture control variables (x_{pt})include log-population and the share aged 15-65. $\hat{S}$ stands for $\hat{S}_{i,t=2008} > 0.1$, or a predicted share of minimum wage workers at the plant in 2008. The data comes from Census of Manufactures (METI).

Table 6: Minimum Wage Effects across Heterogeneous Labor Markets

Panel A. all plants

	(1) all	(2) $\hat{\eta} < 0.2$	(3) $\hat{\eta} < 0.4$	(4) $\hat{\eta} < 0.6$	(5) $\hat{\eta} < 0.8$	(6) $\hat{\eta} < 1$
$\Delta ln(mw_{p,t-1})$	-0.518***	0.667	-0.126	-0.256**	-0.372***	-0.414***
	(0.135)	(0.723)	(0.409)	(0.118)	(0.130)	(0.127)
N	281,388	6,966	34,491	120,173	173,345	199,693
% of MW variation	100 (base)	87.6	92.9	94.0	98.5	99.0

Panel B. plants with $\hat{S}_{i,t=2008} > 0.1$

	(1) all	(2) $\hat{\eta} < 0.2$	(3) $\hat{\eta} < 0.4$	(4) $\hat{\eta} < 0.6$	(5) $\hat{\eta} < 0.8$	(6) $\hat{\eta} < 1$
$\Delta ln(mw_{p,t-1})$	-0.633***	0.0115	-0.0823	-0.497**	-0.571**	-0.556**
	(0.225)	(0.937)	(0.566)	(0.243)	(0.231)	(0.248)
N	111,398	5,504	17,423	44,936	61,272	70,272
% of MW variation	100 (base)	88.7	95.3	94.4	98.2	98.5

Panel C. Plants with $\hat{S}_{i,t=2008} \leq 0$ (placebo test)

	(1) all	(2) $\hat{\eta} < 0.2$	(3) $\hat{\eta} < 0.4$	(4) $\hat{\eta} < 0.6$	(5) $\hat{\eta} < 0.8$	(6) $\hat{\eta} < 1$
$\Delta ln(mw_{p,t-1})$	-0.529	2.173	-0.0209	0.0576	-0.0731	-0.128
	(0.321)	(2.240)	(1.046)	(0.417)	(0.417)	(0.390)
N	25,526	49	2,662	12,241	17,473	19,896
% of MW variation	100 (base)	147.4	87.3	94.8	98.5	99.0

Note: Robust standard errors clustered at the prefecture level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column controls for industry-specific linear trends and prefecture control variables. Prefecture control variables (x_{pt})include log-population and the share aged 15-65. The data comes from Census of Manufactures (METI). % of MW variation is calculated by dividing standard deviation in $\Delta ln(mw_{p,t-1})$ in that sample by the same standard deviation in column (1) or all observations.

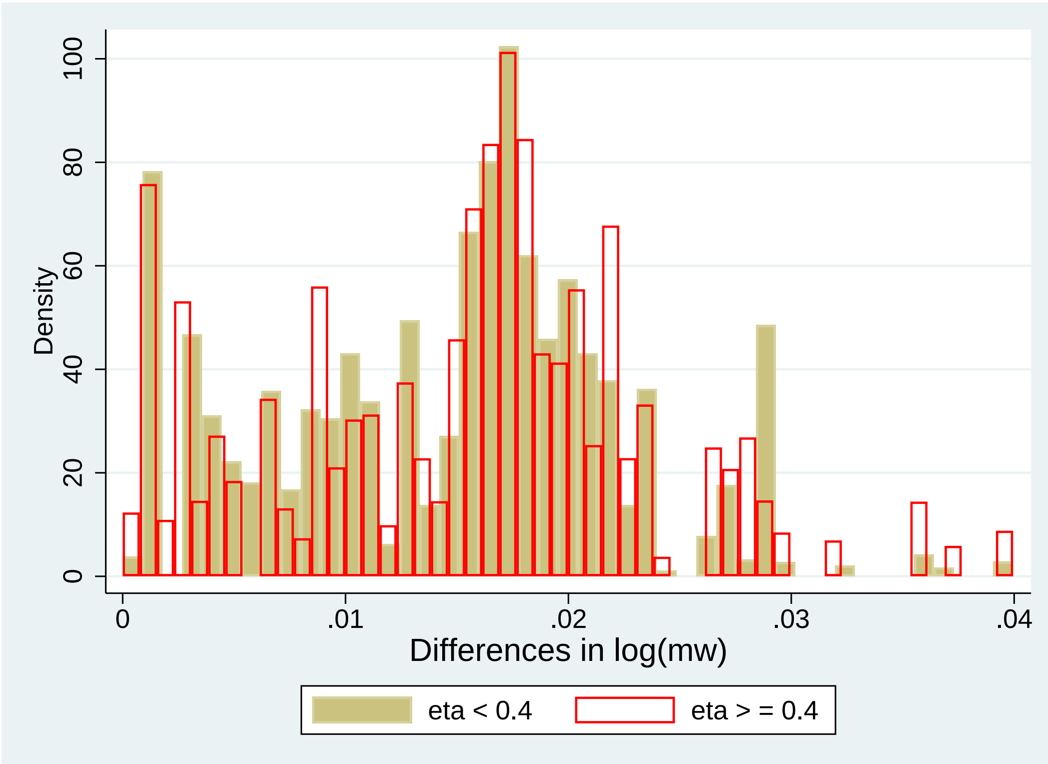


Figure 4: Are There Sufficient Variations within Group?

Note: The histograms represent variations in $\Delta ln(mw)$ by $\hat{\eta}$.

Table 7: Robustness Against Alternative Parameter Constructions
(plants with $\hat{S}_{i,t=2008} > 0.1$).

Panel A. Parameters constructed with median values in pre-sample period (2001-2007)

	(1) all	(2) $\hat{\eta} < 0.2$	(3) $\hat{\eta} < 0.4$	(4) $\hat{\eta} < 0.6$	(5) $\hat{\eta} < 0.8$	(6) $\hat{\eta} < 1$
$\Delta ln(mw_{p,t-1})$	-0.657**	-0.136	-0.409	-0.298	-0.569**	-0.560**
	(0.260)	(0.802)	(0.608)	(0.282)	(0.232)	(0.247)
N	77,563	4,979	14,248	42,623	60,610	69,127
% of MW variation	100 (base)	87.3	96.5	95.5	98.5	100.7

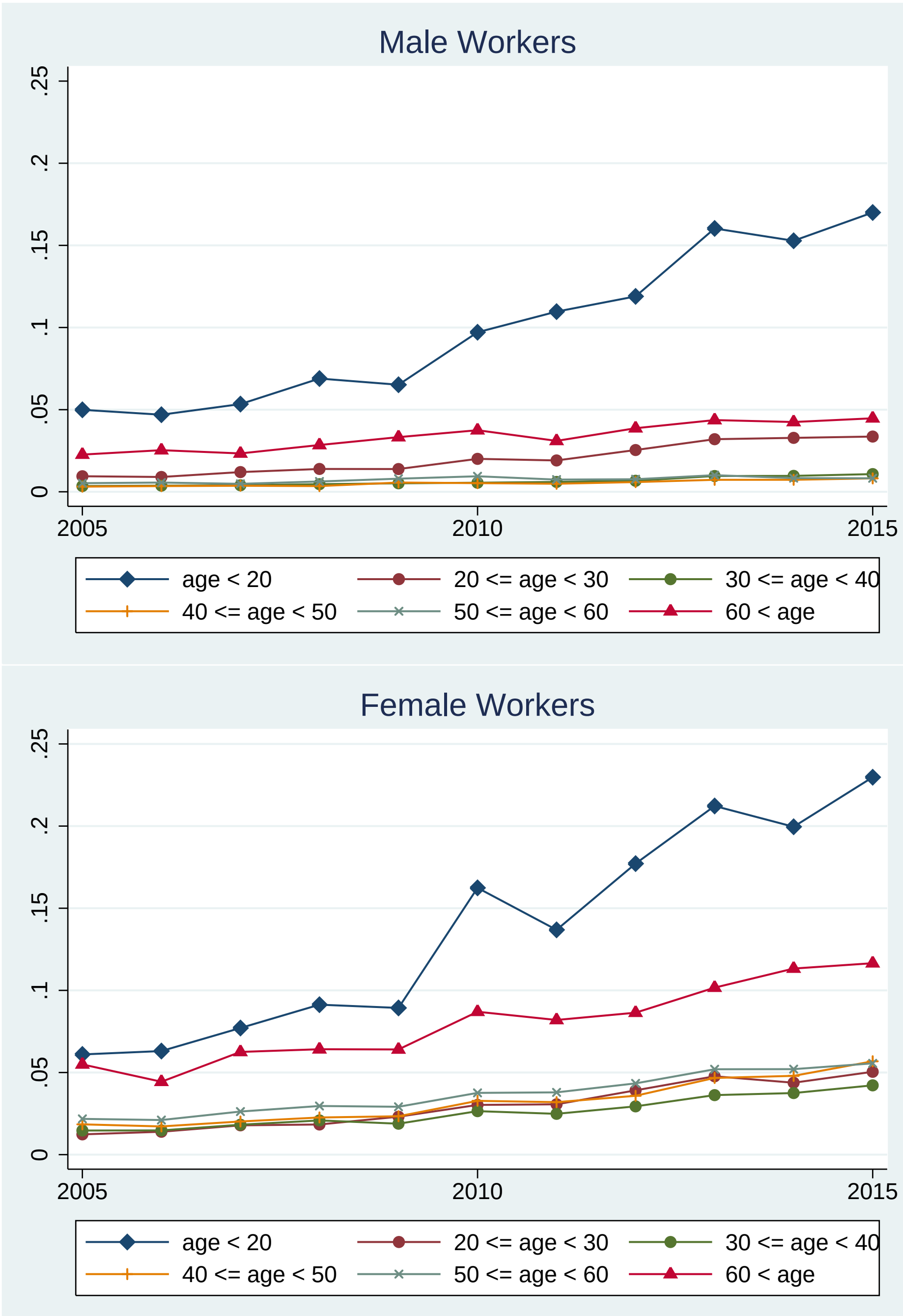
Panel B. Production functions estimated with pre-sample observations only (2001-2007)

	(1) all	(2) $\hat{\eta} < 0.2$	(3) $\hat{\eta} < 0.4$	(4) $\hat{\eta} < 0.6$	(5) $\hat{\eta} < 0.8$	(6) $\hat{\eta} < 1$
$\Delta ln(mw_{p,t-1})$	-0.523**	-0.263	-0.429	-0.397	-0.536*	-0.608**
	(0.250)	(0.498)	(0.387)	(0.319)	(0.287)	(0.271)
N	93,244	15,028	32,414	42,504	52,474	55,294
% of MW variation	100 (base)	96.4	94.0	95.5	96.0	96.7

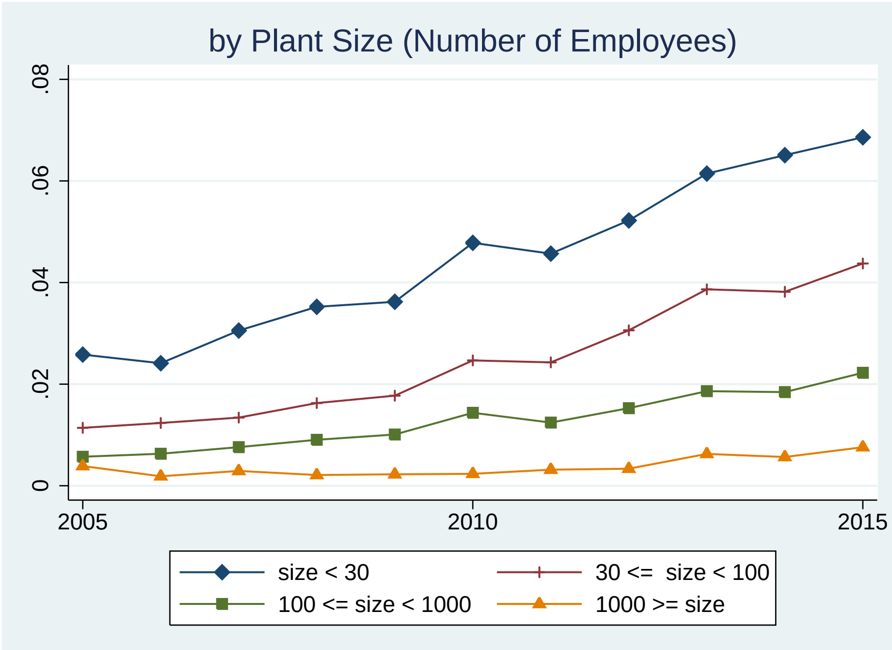
Panel C. Production functions estimated by (Wooldridge, 2009)'s method

	(1) all	(2) $\hat{\eta} < 0.2$	(3) $\hat{\eta} < 0.4$	(4) $\hat{\eta} < 0.6$	(5) $\hat{\eta} < 0.8$	(6) $\hat{\eta} < 1$
$\Delta ln(mw_{p,t-1})$	-0.451*	1.598	-1.076	-0.777	-0.415	-0.810**
	(0.227)	(1.393)	(0.720)	(0.653)	(0.449)	(0.397)
N	60,641	2,265	8,670	12,293	20,277	33,922
% of MW variation	100 (base)	94.0	95.8	99.3	92.7	103.3

Note: Robust standard errors clustered at the prefecture level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In panel A, $\hat{\eta}$ is constructed from the same production function estimates (System GMM, industry-level, 2001-2014) in Table 6, but with median input values & median cost shares from pre-sample period (2001-2007) only. See section 3.2 for the exact procedure to construct the market parameter using these median values. In panel B, $\hat{\eta}$ is constructed from production function estimates with pre-sample period only (System GMM, industry-level, 2001-2007). Median input values and median cost shares are taken from those from the pre-sample period, 2001-2007. In panel C, $\hat{\eta}$ is constructed from production function estimates with Wooldridge (2009)'s method (industry-level, 2001-2014). Median input values and median cost shares are taken from observations from 2001-2007. Each column controls for industry-specific linear trends and prefecture control variables. Prefecture control variables (x_{pt})include log-population and the share aged 15-65. The data comes from Census of Manufactures (METI). % of MW variation is calculated by dividing standard deviation in $\Delta ln(mw_{p,t-1})$ in that sample by the same standard deviation in column (1) or all observations.

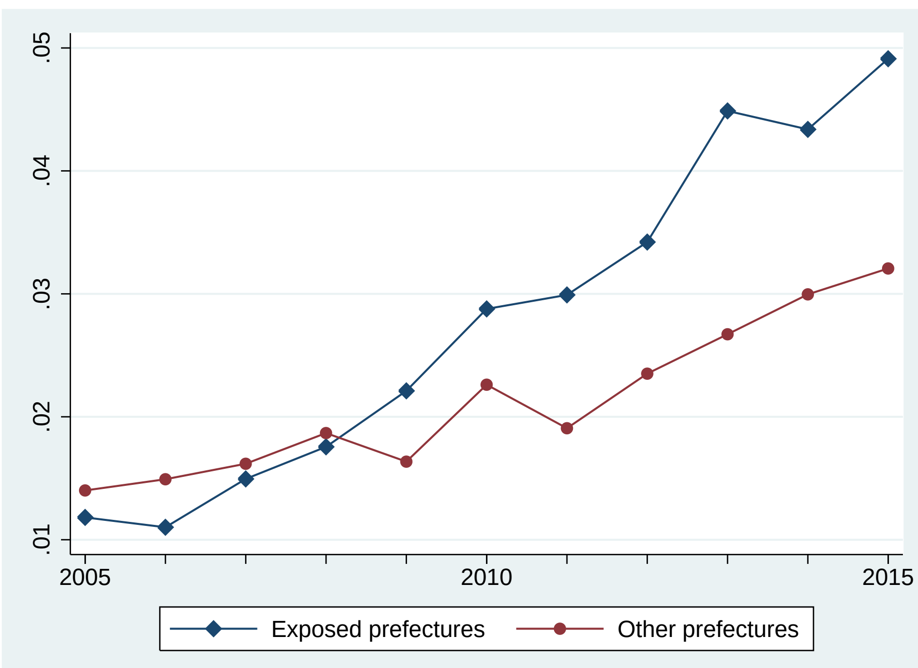


Appendix Figure 1: Shares of MW Workers ($wage_t \leq mw_{t+1}$) by Gender and Age Group
Note: Based on authors' calculation from Basic Survey of Wage Structures (Japanese Ministry of Health, Labour and Welfare).



Appendix Figure 2: Shares of MW Workers ($wage_t \leq mw_{t+1}$) by Plant Size

Note: Based on authors' calculation from Basic Survey of Wage Structures (Japanese Ministry of Health, Labour and Welfare).



Appendix Figure 3: Shares of MW Workers ($wage_t \leq mw_{t+1}$) by Extent of Exposed Shock

Note: Based on authors' calculation from Basic Survey of Wage Structures (Japanese Ministry of Health, Labour and Welfare). Exposed prefectures are defined as those prefectures initially had relatively lower benefit level compared to minimum wage earnings, therefore, were exposed to intense increases in minimum wage after the revision of Minimum Wage Act, which was approved in 2007. Specifically, exposed prefectures are those prefectures requested by Ministry of Health, Wealth, and Labour to increase minimum wage due to the relatively low benefit level in May 2007: Hokkaido, Miyagi, Akita, Saitama, Chiba, Tokyo, Kanagawa, Kyoto, Osaka, Hyogo, and Hiroshima.

Appendix Table 1: Estimated η by Industry

	mean	p25	p50	p75
livestock products	0.35	0.3	0.36	.4
food and fisheries	0.17	0.14	0.16	.19
fine grain milling	1.03	0.66	1.05	1.35
organic fertilizers feed	0.36	0.21	0.28	.51
beverage	0.69	0.53	0.65	.84
tobacco	0.04	0.03	0.03	.07
textile goods	0.64	0.57	0.64	.74
sawing lumbering wooden products	0.43	0.37	0.43	.48
furniture equipment	0.62	0.58	0.62	.64
coated paper pulp,paper and paperboard	0.77	0.66	0.75	.78
pre press binging	0.67	0.59	0.69	.75
furs leather and leather products	0.39	0.32	0.37	.38
rubber products	1.34	1.22	1.42	1.55
chemical fertilizer	0.89	0.53	0.8	1.16
basic inorganic chemical products	0.46	0.38	0.42	.52
basic organic chemical products	0.01	0	0	.02
organic chemical products	0.74	0.5	0.67	.9
final chemical products	0.64	0.56	0.66	.7
medical and pharmaceutical products	0.69	0.53	0.66	.71
glass and glass products	0.44	0.37	0.4	.47
cement and cement products	1.48	1.46	1.51	1.63
ceramics and porcelain	0.86	0.67	0.8	.97
other ceramic and clay products	1.45	1.32	1.56	1.59
pi giron crude steel	0.55	0.31	0.59	.66
other iron and steel	0.59	0.54	0.59	.63
refining non-ferrous metal smelting	1.45	1.45	1.45	1.45
non-ferrous metal products	1.42	1.4	1.47	1.51
metal products for building and construction	0.97	0.81	0.91	1.01
other metal products	0.52	0.48	0.5	.52
general industrial machinery	0.83	0.75	0.82	.88
special industrial machinery	0.58	0.53	0.58	.61
other general machinery	0.5	0.45	0.5	.54
equipment for office and service	0.76	0.7	0.71	.81
heavy electrical machinery	0.26	0.23	0.25	.28
electronics-applied equipment,electronic measuring instrument	0.65	0.57	0.61	.77
semiconductor element, integrated circuit device	1.12	0.75	1.18	1.36
electronic components	0.94	0.84	0.89	1.07
other electrical equipment	0.9	0.81	0.88	.95
motorcar	1.24	1.24	1.31	1.38
automotive parts automobile accessories	0.44	0.39	0.44	.49
other transportation equipment	1.13	0.86	1.06	1.4
precision machine	0.65	0.6	0.68	.69
plastic products	0.44	0.41	0.43	.46
other manufactured products	1.3	1.26	1.3	1.45
Total 0.64	0.45	0.58	.76	

Note: This table summarises statistics from plant-level observations. Estimates are obtained from translog production function estimations. The translog production functions are estimated separately for each industry group. The estimation procedure follows System GMM. The estimated production function estimates are then used to calculate η_i by using median values for other input variables within each prefecture-industry group (see section 3.2). The data comes from Census of Manufactures (METI).

Appendix Table 2: Estimated η by Region

	mean	p25	p50	p75
Hokkaido	.46	.14	.48	.64
Aomori	.51	.15	.38	.86
Iwate	.63	.41	.54	.78
Miyagi	.62	.36	.52	.88
Akita	.7	.52	.6	.89
Yamagata	.63	.52	.57	.75
Fukushima	.66	.45	.56	.83
Ibaragi	.61	.41	.47	.81
Tochigi	.62	.44	.51	.79
Gunma	.55	.4	.49	.72
Saitama	.68	.46	.59	.75
Chiba	.6	.4	.51	.71
Tokyo	.75	.68	.79	.79
Kanagawa	.67	.53	.6	.77
Niigata	.64	.48	.63	.81
Toyama	.81	.51	.61	1.07
Ishikawa	.65	.51	.67	.75
Fukui	.73	.52	.74	.74
Yamanashi	.67	.46	.66	.83
Nagano	.64	.49	.6	.77
Gifu	.64	.46	.54	.67
Shizuoka	.64	.49	.5	.78
Aichi	.61	.39	.52	.65
Mie	.63	.39	.54	.75
Shiga	.62	.43	.5	.83
Kyoto	.7	.51	.67	.82
Osaka	.65	.49	.6	.7
Hyogo	.67	.48	.56	.77
Nara	.59	.4	.49	.71
Wakayama	.58	.44	.54	.68
Tottori	.68	.42	.61	.78
Shimane	.69	.49	.71	.78
Okayama	.6	.45	.56	.66
Hiroshima	.59	.45	.55	.65
Yamaguchi	.58	.32	.61	.71
Tokushima	.68	.46	.59	.89
Kagawa	.61	.33	.54	.76
Ehime	.63	.49	.62	.74
Kochi	.59	.31	.52	.67
Fukuoka	.61	.4	.61	.69
Saga	.61	.33	.49	.69
Nagasaki	.58	.31	.63	.76
Kumamoto	.71	.43	.51	1.22
Ohita	.62	.44	.59	.67
Miyazaki	.62	.46	.54	.66
Kagoshima	.51	.27	.51	.7
Okinawa	.64	.41	.52	.74
Total	.6367661	.4467094	.5769003	.7643339

Note: This table summarises statistics from plant-level observations. Estimates are obtained from translog production function estimations.The translog production functions are estimated separately for each industry group. The estimation procedure follows System GMM. The estimated production function estimates are then used to calculate η_i by using median values for other input variables within each prefecture-industry group (see section 3.2). The data comes from Census of Manufactures (METI).

Appendix Table 3:
Predicting Proportions of minimum wage Workers with Administrative Wage Records

	(1)	(2)
	$proportion(wage_t < 1.2mw_{t+1})$	$proportion(wage_t < 1.2mw_{t+1})$
$(wagebill/worker)$	-0.00733***	-0.00887***
	(0.000106)	(0.000111)
$(wagebill/worker)^2/10^3$	0.0154***	0.0181***
	(0.000313)	(0.000349)
$(wagebill/worker)^3/10^6$	-0.0134***	-0.0154***
	(0.000384)	(0.000445)
$(wagebill/worker)^4/10^{11}$	0.399***	0.456***
	(0.0166)	(0.0198)
$plantsize/10^3$	-0.0514***	
	(0.00286)	
$plantsize^2/10^6$	0.0240***	
	(0.00186)	
$plantsize^3/10^{11}$	-0.330***	
	(0.0350)	
$plantsize^4/10^{13}$	0.00133***	
	(0.000184)	
Ratio of regular workers	0.258***	
	(0.00401)	
Constant	1.201***	1.557***
	(0.0132)	(0.0122)
N	82,509	82,509
Adjusted R-squared	0.658	0.652

Note: Robust standard errors clustered at the prefecture level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each column represents the estimates from a plant-level linear regression to predict a proportion of minimum wage workers at each plant. *wagebill/worker* indicates average annual wage bill per worker. *plantsize* indicates a number of employees at each plant. The data come from administrative wage records, Basic Survey on Wage Structures (BSWS). See section 3.3 for details.

Appendix I.
Variable Construction for Production Function Estimation.

1. Gross Output

Gross Output is measured as the sum of shipments, revenues from repairing and fixing services, and revenues from performing subcontracted work. Gross output is deflated by the output deflator taken from the Japan Industrial Productivity (JIP) Database 2011 and converted to values in constant prices of 2000.

2. Intermediate Input

Intermediate Input is defined as the sum of raw materials, fuel, electricity and sub-contracting expenses for consigned production used by the plant. Using the corporate goods price index (CGPI) published by Bank of Japan, intermediate input is converted to values in constant prices of 2000.

3. Capital Input

Capital Input (K_{pt}) is measured as real capital stock, defined as follows:

$$K_{pt} = BV_{pt} * \frac{INK_j^t}{IBV_{jt}}, \tag{17}$$

where BV_{pt} is the initial net book value of plant p, INK_{jt} represents the initial net capital stock of the whole industry in constant 2000 price, and IBV_{jt} is the initial net book value of the whole industry. That is, $\frac{INK_j^t}{IBV_{jt}}$ stands for the ratio of real value in constant 2000 price to book value of capital stock of the whole industry in year t. INK_{jt} is calculated as follows. First, as a benchmark, we took the data on the book value of tangible fixed assets in 1975 from the Financial Statements Statistics of Corporations published by Ministry of Finance. We then converted the book value of year 1975 into the real value in constant 2000 prices using the investment deflator provided in the JIP 2011. Second, the net capital stock of industry j, INK_{jt}, for succeeding years is calculated using the perpetual inventory method.

$$INK_j^t = INK_j^{t-1}(1 - \delta_{jt}) + I_{jt}, \tag{18}$$

I_{jt} stands for the real investment in industry j and in year t.We used the investment deflator in the JIP 2011. The sectoral depreciation rate (δ_{jt}) used is taken from the JIP 2011.

4. Labor Input

For labor input, we use the total number of workers at each plants.

- Blue collars and white collars, full-time and part-time. We could estimate production functions separtely for these groups as data is available in limited years. Should we ignore the differential skill levels across worker group to avoid complexities such as substitution, etc?
- We ignore intensive margin adjustments (labour hour) to accommodate the literature that focuses on the overall employment effect.

5. Value Added

Value Added is defined as the difference between gross output and intermediate input.

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