The Heterogeneous Effects of the Minimum Wage on Employment Across States*

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Abstract

This paper studies the relationship between the minimum wage and the employment rate in the US using the framework of a panel structure model. The approach allows the minimum wage, along with some other controls, to have heterogeneous effects on employment across states which are classified into a group structure. The effects on employment are the same within each group but differ across different groups. The number of groups and the group membership of each state are both unknown a priori. The approach employs the C-Lasso technique, a recently developed classification method that consistently estimates group structure and leads to oracle-efficient estimation of the coefficients. Empirical application of C-Lasso to a US restaurant industry panel over the period 1990 - 2006 leads to the identification of four separate groups at the state level. The findings reveal substantial heterogeneity in the impact of the minimum wage on employment across groups, with both positive and negative effects and geographical patterns manifesting in the data. The results provide some new perspectives on the prolonged debate on the impact of minimum wage on employment.

JEL Classification: E24, C33, C38.

Keywords: Classification, C-Lasso, Latent group structures, Minimum wage, Unemployment.

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1 Introduction

The relationship between the minimum wage and employment rate has been widely studied in labor economics; see Brown (1999) for a summary. Conventional economic theory suggests that a rise in the minimum wage should lead to reduced employment and thus a higher unemployment rate. This assertion is challenged by empirical evidence in different ways, depending on what methodology is employed.

As Dube, Lester, and Reich (2010) remark, the minimum wage literature in the United States can be classified into two categories. One is based on traditional national level studies, and the other is based on case studies. National level studies such as Neumark and Washer (1992, 2007) use all cross-state variation in minimum wages over time to estimate the effects of an increase in minimum wage on employment. Case studies such as Card and Krueger (1994, 2000) and Neumark and Wascher (2000) typically compare adjoining local areas with different minimum wages around the time of a policy change. In both kinds of studies, the conclusions are mixed. For example, using survey data for 410 fast-food restaurants in New Jersey and Eastern Pennsylvania, Card and Krueger (1994) find that an increase in the minimum wage causes an increase in employment. In contrast, Neumark and Wascher (2000) re-examine the issue for the same two states by using administrative payroll data but find negative effects of a minimum wage rise on employment. Dube, Lester, and Reich (2010) show that both approaches may generate misleading results when unobserved heterogeneity is not properly accounted for. By using the restaurant industry panel data set which ranges from the first quarter of 1990 to the second quarter of 2006 (66 quarters) for 1380 counties across the United States, they construct contiguous county-pairs to control factors other than the minimum wage and find that there are no adverse employment effects from minimum wage increases.

Dube, Lester, and Reich (2010) assume that the increases in minimum wages have constant effects on employment across states. But the United States is a large country that exhibits enormous diversities in terms of economic development. This diversity may generate unobserved heterogeneity in the effects of minimum wages on employment. In particular, as Autor, Manning, and Smith (2016) argue, minimum wages have different degrees of 'bindingness' across different states and their effects on employment can induce heterogeneous responses.

This paper adopts a panel structure model to account for such heterogeneity in the effects of minimum wage on employment. In the panel structure model, cross sectional units form a number of groups. Within each group the slope coefficients are the same, whereas across groups the slopes differ. Both the number of groups and each individual unit's group membership are unknown a priori. Given the background of controversy in the minimum wage and employment literature, this paper argues that the versatility of the panel structure model in accommodating heterogeneity in behavior by means of data-determined grouping offers a new look at this longstanding issue.

The econometric approach employed is a recently developed classification method called C-Lasso (Su, Shi, and Phillips, 2016, SSP hereafter) that provides a consistent method of estimating the unknown group structure and delivers oracle-efficient estimates of the coefficients in each group. [**In this paper, we adapt SSP's method to provide an versatile way of modelling heterogeneity in hierarchical data.**[1]] Empirical application of this technique to a US restaurant industry panel identifies four separate groups at the state level, revealing marked heterogeneity in the impact of the minimum wage on employment across groups. The primary findings show: (i) that the effect of the minimum wage is positive in some groups and negative in others; and (ii) that some geographical patterns are evident in the data, with a notable distinction in response behavior between the southeast and northwest regions of the US.

The rest of the paper is organized as follows. Section 2 extends the panel structure model and C-Lasso technique of SSP (2016) to allow for latent group structures across different states for the USA's county level data. Section 3 describes the data employed in the empirical application. Section 4 reports the findings and Section 5 concludes.

2 The model and methodology

This section introduces the panel structure model and describes the econometric methodology that is used in the empirical analysis.

2.1 The model

The model is adapted from the SSP's panel structure model and takes the following form

$$y_{it} = x_{it}'\beta_{s_i} + \phi_i + \tau_t + \varepsilon_{it},\ i = 1, \ldots, N,\ t = 1, \ldots, T, \tag{2.1}$$

where i and t denote county i and period t, respectively, s_i denotes the state which county i belongs to, β_{s_i} is $p \times 1$ vector of slope coefficients for state s_i, ϕ_i and τ_t are individual fixed effects and time fixed effects, respectively, and ε_{it} is the idiosyncratic error term. A latent

[1] For example, in a panel dataset, each company has few periods of observations. So the classification on firm-level is very diffcult. But the companies come from different industries. If we are interested in the classification of industries, then we might impose the panel structure on the industry-level rather than the firm-level. In the literature, Hu (2002) considers black-white racial differences and classifies men and women into two groups in studying earnings dynamics. Subramanian and Wei (2007) suppose GATT/WTO has different impacts on different groups of country-pairs in international trade.

'state-specific' group structure is imposed on the β_{s_i} as follows

$$\beta_{s_i} = \begin{cases} \alpha_1 & \text{if } s_i \in G_1 \\ \vdots & \vdots \\ \alpha_K & \text{if } s_i \in G_K \end{cases}, \tag{2.2}$$

where $\{G_1, \ldots, G_K\}$ forms a partition of the set of S states $\{1, \ldots, S\}$, $S = 51$ for the United States data,[2] and $\alpha_k \neq \alpha_\ell$ for $k \neq \ell$. Intuitively, the above model says that states (and hence counties within those states) in the same group G_k share the same slope parameter α_k, and states in different groups have slope parameters that differ from each other. [**Added Motivation for the Model Specification: Note that we do not want to assume the parameters β_{s_i}'s to be county-specific because minimum wage laws are typically imposed at the state or Federal level. Within a state, the minimum wages are typically the same across counties. In the two-way fixed effects model considered here, minimum wages are completely explained by the time fixed effects for a state. A county usually adopts the maximum of the federal minimum wage and its state minimum wage. For policy makers, it is much more meaningful to consider the group structure on states rather than on counties. And in the dataset, there are 1780 counties, which are much larger than the number of time periods $T = 66$. Both in the theoretical analysis and in simulations of SSP, we know that when the number of individuals is much larger than the time periods, the C-Lasso classification results perform not so well. Considering all these points, we impose the latent group structure on the state level. But for comparison purpose, we also report the classification results for the county level group structure in the Supplementary Appendix.**]

[**The model (2.1) is very versatile. When $s_i \equiv s$, then (2.1) is the traditional two-way fixed effects panel data model. And when $s_i = i$, it is the conventional panel structure model.**]

2.2 The methodology

For equation (2.1), we first eliminate the individual fixed effects to obtain

$$\tilde{y}_{it} = \tilde{x}_{it}'\beta_{s_i} + \tilde{\tau}_t + \tilde{\varepsilon}_{it}, \tag{2.3}$$

where $\tilde{y}_{it} = y_{it} - T^{-1}\sum_{s=1}^{T} y_{is}$, $\tilde{x}_{it} = x_{it} - T^{-1}\sum_{s=1}^{T} x_{is}$, $\tilde{\tau}_t = \tau_t - T^{-1}\sum_{s=1}^{T} \tau_s$, and $\tilde{\varepsilon}_{it} = \varepsilon_{it} - T^{-1}\sum_{s=1}^{T} \varepsilon_{is}$. Note that equation (2.3) is different from the equation (4.2) in Lu and Su (2017) because here the β_{s_i} are not individual i-specific but state-specific. Noting that different

[2] The District of Columbia is included in the data and treated as a state.

states might contain different number of counties, we cannot eliminate the time fixed effects as in Lu and Su (2017). Here, we treat the time fixed effects as incidental parameters and define the $T \times (T-1)$ matrix

$$\tilde{\Gamma} = \begin{bmatrix} -\frac{1}{T} & \cdots & -\frac{1}{T} \\ 1-\frac{1}{T} & \cdots & -\frac{1}{T} \\ \vdots & \ddots & \vdots \\ -\frac{1}{T} & \cdots & 1-\frac{1}{T} \end{bmatrix}.$$

Let $\tilde{Y}_i = (\tilde{y}_{i1}, \ldots, \tilde{y}_{iT})'$, $\tilde{X}_i = (x_{i1}, \ldots, x_{iT})'$, and $\tilde{\varepsilon}_i = (\tilde{\varepsilon}_{i1}, \ldots, \tilde{\varepsilon}_{iT})'$. Noting that $\sum_{t=1}^{T} \tilde{\tau}_t = 0$, it is easy to reparametrize the $\tilde{\tau}_t$ so that equation (2.3) can be written in observation form as

$$\tilde{Y}_i = \tilde{X}_i \beta_{s_i} + \tilde{\Gamma}\gamma + \tilde{\varepsilon}_i, \tag{2.4}$$

where $\gamma = (\gamma_1, \ldots, \gamma_{T-1})'$ is a $(T-1) \times 1$ vector such that $\tilde{\tau}_1 = -\frac{1}{T}\sum_{s=1}^{T-1} \gamma_s$ and $\tilde{\tau}_s = \gamma_{s-1} + \tilde{\tau}_1$ for $s = 2, \ldots, T$. Then the objective function can be written as

$$S_{1,NT}(\beta, \gamma) = \frac{1}{NT}\sum_{i=1}^{N}(\tilde{Y}_i - \tilde{X}_i\beta_{s_i} - \tilde{\Gamma}\gamma)'(\tilde{Y}_i - \tilde{X}_i\beta_{s_i} - \tilde{\Gamma}\gamma),$$

where $\beta = (\beta_1', \ldots, \beta_S')'$.

Next, we want to eliminate the incidental parameter γ. Without loss of generality, we suppose the first i_1 individuals are in state 1, the following i_2 individuals are in state 2, and so on. Define the N-vector $\iota_N = (1, \ldots, 1)'$, set $\tilde{Y} = (\tilde{Y}_1', \ldots, \tilde{Y}_N')'$ and $\tilde{\varepsilon} = (\tilde{\varepsilon}_1', \ldots, \tilde{\varepsilon}_N')'$, and define the $NT \times Sp$ matrix

$$\tilde{X} = \begin{bmatrix} \tilde{X}_1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{X}_{i_1} & 0 & \cdots & 0 \\ 0 & \tilde{X}_{i_1+1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \tilde{X}_{i_1+i_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \tilde{X}_{(\sum_{j=1}^{S-1} i_j)+1} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \tilde{X}_N \end{bmatrix}.$$

The stacked form of (2.4) is then

$$\tilde{Y} = \tilde{X}\beta + (\iota_N \otimes \tilde{\Gamma})\gamma + \tilde{\varepsilon}.$$

Let $M_{\tilde{\Gamma}} = I_{NT} - (\iota_N \otimes \tilde{\Gamma})[(\iota_N \otimes \tilde{\Gamma})'(\iota_N \otimes \tilde{\Gamma})]^{-1}(\iota_N \otimes \tilde{\Gamma})'$, $\ddot{Y} = M_{\tilde{\Gamma}}\tilde{Y}$, $\ddot{X} = M_{\tilde{\Gamma}}\tilde{X}$, and $\ddot{\varepsilon} = M_{\tilde{\Gamma}}\tilde{\varepsilon}$. Eliminate γ by partitioned regression giving

$$\ddot{Y} = \ddot{X}\beta + \ddot{\varepsilon},$$

and the corresponding objective function

$$S_{2,NT}(\beta) = \frac{1}{NT}(\ddot{Y} - \ddot{X}\beta)'(\ddot{Y} - \ddot{X}\beta). \tag{2.5}$$

C-Lasso estimation of β involves nonlinear penalized estimation to obtain a data-determined 'state-specific' group structure in β of the form (2.2). In particular, the C-Lasso estimator minimizes the objective function

$$Q^{(K)}_{1,NT,\lambda}(\beta, \alpha, \gamma) = S_{1,NT}(\beta, \gamma) + \frac{\lambda}{S}\sum_{s=1}^{S} \Pi_{k=1}^{K} \|\beta_s - \alpha_k\|, \tag{2.6}$$

or, equivalently,

$$Q^{(K)}_{2,NT,\lambda}(\beta, \alpha) = S_{2,NT}(\beta) + \frac{\lambda}{S}\sum_{s=1}^{S} \Pi_{k=1}^{K} \|\beta_s - \alpha_k\|, \tag{2.7}$$

where $\lambda \equiv \lambda_{NT}$ is a tuning parameter and $\alpha = (\alpha'_1, \ldots, \alpha'_k)'$. The criteria $Q^{(K)}_{1,NT,\lambda}(\beta, \alpha, \gamma)$ and $Q^{(K)}_{2,NT,\lambda}(\beta, \alpha)$ yield the same estimates of β and α, which are denoted $\tilde{\beta} = (\tilde{\beta}'_1, \ldots, \tilde{\beta}'_S)'$ and $\tilde{\alpha} = (\tilde{\alpha}'_1, \ldots, \tilde{\alpha}'_K)'$. Let $\tilde{G}_k = \{s \in \{1, \ldots, S\} : \tilde{\beta}_s = \tilde{\alpha}_k\}$ for $k = 1, \ldots, K$.[3] Based on the estimated group structure $\tilde{G}_1, \ldots, \tilde{G}_K$, we obtain the post-classification estimates $\hat{\beta}$ and $\hat{\alpha}$. Specifically, for each group $\tilde{G}_k$, $k = 1, \ldots, K$, we use OLS to estimate the common slope parameters $\hat{\alpha}_k$ and set $\hat{\beta}_s = \hat{\alpha}_k$ for all $s \in \tilde{G}_k$.

2.3 The information criterion

Let $\hat{\sigma}^2(K, \lambda) = S_{2,NT}(\hat{\beta})$, where the dependence of $S_{2,NT}$, and thus $\hat{\sigma}^2$, on K and λ is made explicit. When K is unknown, we follow SSP (2016) and choose (K, λ) to minimize the following BIC-type information criterion:

$$\text{IC}(K, \lambda) = \ln[\hat{\sigma}^2(K, \lambda)] + Kp\frac{1}{\sqrt{NT}}. \tag{2.8}$$

[3] Let $\tilde{G}_0 = \{1, \ldots, S\} \backslash (\cup_{k=1}^{K} \tilde{G}_k)$. SSP show that $\tilde{G}_0$ is an empty set asymptotically. In finite samples, $\tilde{G}_0$ might not be empty and we can force each element in $\tilde{G}_0$ to one of the K groups. For $s \in \tilde{G}_0$, if $k^* = \arg\min_k\{\|\tilde{\beta}_s - \tilde{\alpha}_k\|, k = 1, \ldots, K\}$, then s is re-classified into $\tilde{G}_{k^*}$.

3 Data

Minimum wages directly affect only a small part of the labor force and overall economy. The restaurant industry is of special interest in the minimum wage literature because it is both the largest and the most intensive user of minimum wage workers. This feature of the industry has motivated a vast literature on local case studies by using fast food restaurant data.[4]

In this paper, we follow Dube, Lester and Reich (2010) and consider the restaurant industry. [**DLR and we both consider how to identify the accurate effects of minimum wages on employment. They adopt the county-pair approach to control the local economic conditions and find no adverse employment effects. As an alternative method, we consider the heterogeneous effects of minimum wages on employment across states.**] We use their dataset and explore how log employment ($\ln(emp_{it})$) responds to log minimum wage ($\ln(mw_{it})$), where i and t refer to county and time. Other control variables are log population ($\ln(pop_{it})$) and log total employment ($\ln(emp_{it}^{TOT})$). We confine attention to the restaurant industry because minimum wages are known to have relatively larger effects in this industry. The panel data set ranges from the first quarter of 1990 to the second quarter of 2006 ($T = 66$) for 1380 counties ($N = 1380$) across the United States. The total number of observations is 91080 when we do not control $\ln(emp_{it}^{TOT})$ in the regression.

When $\ln(emp_{it}^{TOT})$ is included in the regression, N becomes 1378 because two counties have missing observations for $\ln(emp_{it}^{TOT})$. For Tolland county (countyreal: 9013) of Connecticut and Adams county of Illinois, their $\ln(emp^{TOT})$ data are missing for the periods 2002Q2–2006Q2 and 2003Q3-2003Q4, respectively. To yield a balanced panel for ease of coding, we drop these two counties and the corresponding total number of observations becomes 90948.

We refer readers to Section III in Dube, Lester, and Reich (2010) for a detailed description of the data.

4 Main results

We employ the same benchmark Model (1) of Dube, Lester, and Reich's (2010) which has the following two forms

$$\ln(emp_{it}) = c + \eta \ln(mw_{it}) + \gamma \ln(pop_{it}) + \phi_i + \tau_t + \varepsilon_{it}, \text{ and} \tag{4.1}$$

$$\ln(emp_{it}) = c + \eta \ln(mw_{it}) + \gamma \ln(pop_{it}) + \delta \ln(emp_{it}^{TOT}) + \phi_i + \tau_t + \varepsilon_{it}, \tag{4.2}$$

[4]Researchers have also considered specific subsectors of this labor market, such as teenager workers – see, e.g., Brown, Gilroy, and Kohen (1982).

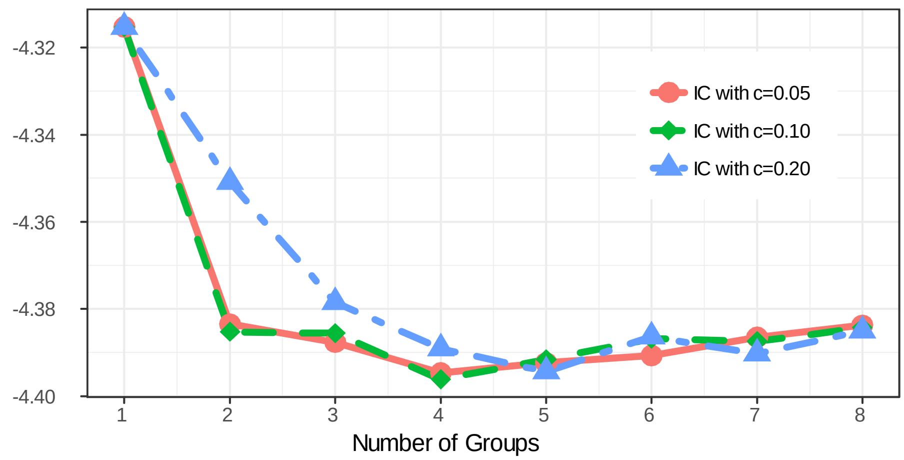

Figure 1: The horizontal axis marks the number of groups and the vertical axis marks the corresponding information criterion value.

where c denotes the common intercept term. By combining this benchmark specification with the panel structure formulation that allows state specific coefficients, we consider

$$\ln(emp_{it}) = c + \eta_{s_i} \ln(mw_{it}) + \gamma_{s_i} \ln(pop_{it}) + \phi_i + \tau_t + \varepsilon_{it}, \text{ and} \tag{4.3}$$

$$\ln(emp_{it}) = c + \eta_{s_i} \ln(mw_{it}) + \gamma_{s_i} \ln(pop_{it}) + \delta_{s_i} \ln(emp_{it}^{TOT}) + \phi_i + \tau_t + \varepsilon_{it}, \tag{4.4}$$

which allows for the state-wise slope coefficients $(\eta_{s_i}, \gamma_{s_i}, \delta_{s_i})$. Following SSP (2016), we allow the parameters $(\eta_{s_i}, \gamma_{s_i})$ in (4.3) or $(\eta_{s_i}, \gamma_{s_i}, \delta_{s_i})$ in (4.4) to exhibit certain latent group structures.

4.1 Model (4.3)

We use C-Lasso to identify the panel structure in (4.3). The tuning parameter is chosen as $\lambda = c \times T^{-1/3}$, and c takes three candidate values, namely, 0.05, 0.10, and 0.20. The maximum number of groups adopted here is 8. For each combination of the number of groups K and the tuning parameter c, we calculate the information criterion value according to equation (2.8). Figure 1 plots the information criterion values for $c = 0.05$, 0.10, and 0.20 and $K = 1, 2, \ldots, 8$. The lowest point is obtained in the green dashed line when the number of groups is 4 and $c = 0.10$. Their numeric values are relegated to the Supplementary Appendix.

Applying C-Lasso on the dataset we find 4 latent groups. The left panel in Table 1 reports the post-Lasso regression results for each group in (4.3) and the pooled regression in (4.1). Table 1 suggests that the estimates of γ (the slope coefficient of $\ln(pop_{it})$) are relatively stable across the four groups and are always positive. The latter is as expected given the positive

Table 1: Regression results

	Model (4.3)					Model (4.4)				
	Group 1	Group 2	Group 3	Group 4	All samples	Group 1	Group 2	Group 3	Group 4	All samples
$\ln(mw_{it})$	0.534^c	0.047^c	0.077^c	-0.221^c	-0.211^b	0.555^c	-0.033^c	0.059^c	-0.255^c	-0.177^a
	(0.014)	(0.011)	(0.011)	(0.009)	(0.096)	(0.013)	(0.010)	(0.009)	(0.010)	(0.097)
$\ln(pop_{it})$	1.521^c	1.239^c	0.678^c	0.997^c	1.035^c	0.626^c	0.603^c	0.338^c	0.465^c	0.526^c
	(0.019)	(0.009)	(0.013)	(0.011)	(0.060)	(0.016)	(0.013)	(0.015)	(0.014)	(0.086)
$\ln(emp_{it}^{TOT})$						0.513^c	0.606^c	0.410^c	0.534^c	0.524^c
						(0.011)	(0.008)	(0.009)	(0.010)	(0.044)
Observations	12078	31416	23298	24288	91080	18414	30030	23364	19140	90948

Note: ^{a}, ^{b}, and ^{c} correspond to 90%, 95%, 99% significance levels.

correlation between total population and employment. In contrast, the estimates of η (the slope coefficient of $\ln(mw_{it})$) vary across the four groups substantially and even alter signs. For Groups 1–3, the estimate of η is positive, which means, counter to economic intuition, that increasing the minimum wage has a positive effect on employment. But for Group 4, the estimate of η is negative, which is consistent with theory and conventional wisdom. These results from C-Lasso estimation suggest that responses of employment to increases in minimum wages are highly heterogeneous across different groups of states. When the minimum wage increases by 1%, employment increases by 0.534%, 0.047%, and 0.077% in Groups 1, 2, 3, respectively, but decreases by 0.221% in Group 4. If we pool Groups 1–4 together and estimate the model in (4.1), then we find that a 1% increase in the minimum wage decreases employment by 0.211% for the full dataset. This pooled estimate can be interpreted as a weighted average of the four group-specific estimates. But this weighted average remains silent about the latent heterogenous pattern in responses that exists across state groups that is revealed by the C-Lasso regression using the panel structure formulation. Such heterogenous effects of minimum wage on employment in different regions of the country surely have useful implications for policy makers in designing legislation at both the state and federal levels.

We use Figure 2 to illustrate the connection between the preliminary estimates and the final groupings for each state. The preliminary estimates are obtained when we minimize the objective function in equation (2.5) without imposing any group structure. The horizontal and vertical axes correspond to the preliminary estimates of η and γ, respectively. Groups 1, 2, 3, and 4 are signified by red circle, green diamond, blue triangle, and purple square, respectively. The results show that, as might be expected from the classification process, those states with close preliminary estimates of the slope parameters are typically more likely to be classified into the same group.

Figure 3 displays the group structure color coded on the map of the United States. States in Group 1 are mainly in the southeast of the United States. The states in the other groups also have some clustering pattern but the pattern is mainly localized clusters. In other words, geographical location plays some role in the minimum wage and employment relationship based on a panel structure regression using the specification (4.3) but the role takes the form of certain regional and localized clusters.

Table 2 reports the descriptive statistics for each group and all samples. We find that the minimum wage is the highest for Group 4 and the lowest for Group 1. Besides, Group 4 also has the highest Restaurant average weekly earnings, Retail average weekly earnings, Overall private average weekly earnings, and Manufacturing average weekly earnings, despite the fact that none of that information on average earnings is used in the C-Lasso classification.

Our findings suggest that the effect of the minimum wage on employment is non-monotonic.

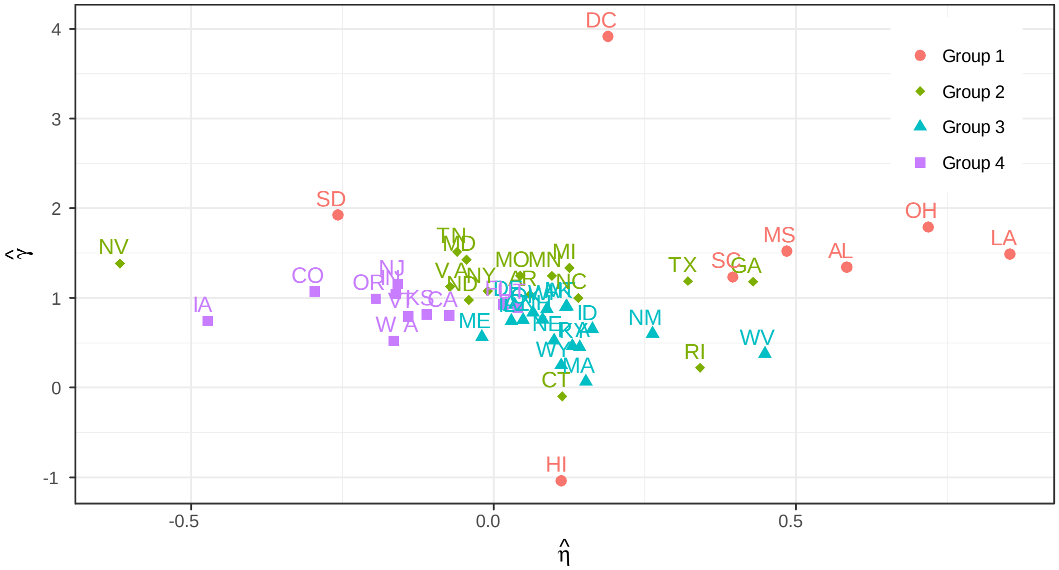

Figure 2: The horizontal and vertical axes correspond to the preliminary estimates of η and γ, respectively. Each point represents a state, marked by the standard state abbreviation. For Groups 1, 2, 3, and 4, we use red circle, green diamond, blue triangle, and purple square to denote them, respectively.

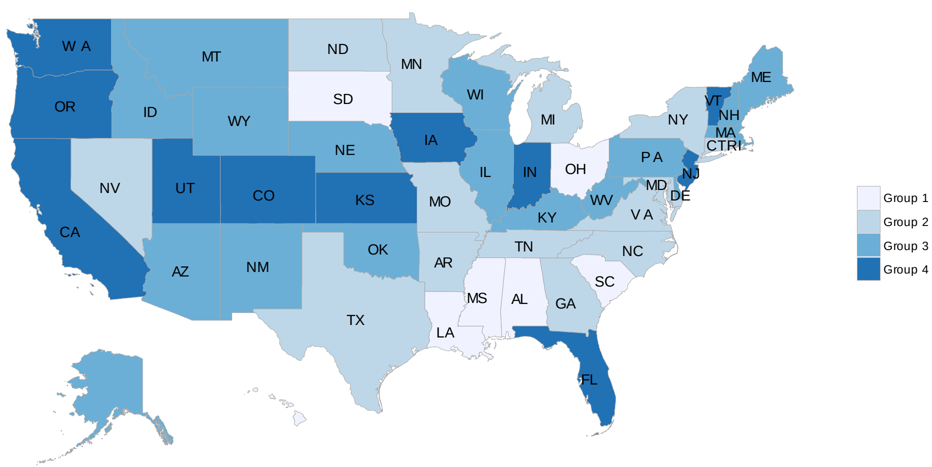

Figure 3: This map color codes the group classification results. Group 1 member states appear in light blue and Group 4 member states appear in deep blue.

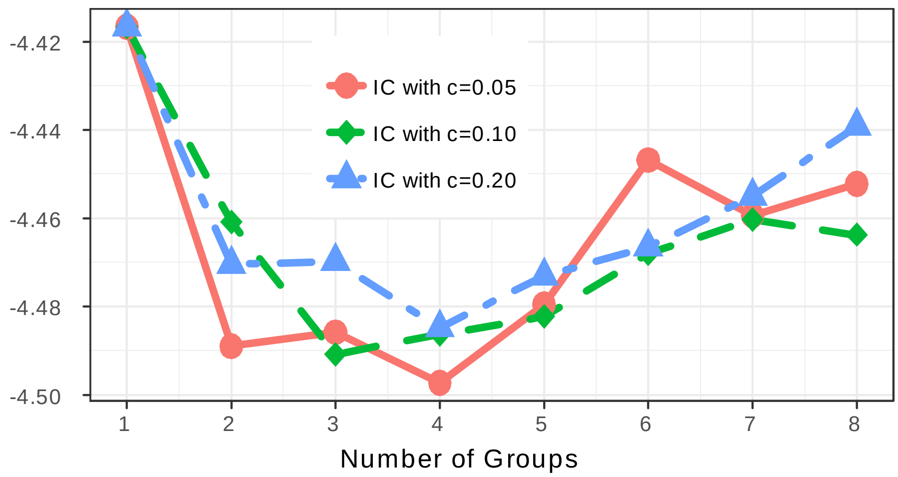

Figure 4: The horizontal and vertical axes mark the number of groups and the corresponding values of the information criterion, respectively.

A possible explanation is the presence of threshold effects. When the minimum wage is too low, some unemployed low-skilled individuals may choose not to work; but a slight increase in the minimum wage in this case may be sufficient to encourage these individuals to choose to work, thereby raising employment. The increase in employment in this case is mainly driven by the supply side. On the other hand, if the minimum wage is already high, further increases lead to rising labor costs which are sufficient to motivate employers to layoff some low-skilled workers. In this case the decrease in employment is mainly driven from the demand side. A formal supply and demand analysis of potential threshold effects of this type on the effect of minimum wage increases on employment seems worthwhile given these empirical findings but is beyond the scope of the present note.

4.2 Model (4.4)

Here we use C-Lasso to identify the panel structure in model (4.4). Figure 4 plots the information criterion function where the horizontal and vertical axes mark the number of groups and the information criterion values, respectively. The lowest point is achieved in the red line when the number of groups is 4 and $c = 0.05$.

By applying C-Lasso, we still find 4 latent groups for the model (4.4). The right panel of Table 1 reports the regression results for each group in model (4.4) and the pooled model in model (4.2). The estimates of γ (the slope coefficient of $\ln(pop_{it})$ and δ (the slope coefficient of $\ln(emp_{it}^{TOT})$) have the same signs for all groups and the pooled one, which implies that the increase in population or/and total employment is positively associated with the increase in

Table 2: Descriptive statistics for 4 groups and the pooled one

	Group 1		Group 2		Group 3		Group 4		All samples	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Population, 2000	134106	181387	185170	343004	152146	375761	226539	603640	180983	423425
Population density, 2000	291	734	750	4110	275	892	363	1186	465	2553
Land area (square miles)	638	312	831	1330	1592	2551	1231	1612	1107	1761
Overall private employment	25267	64117	29272	102266	27313	109218	49175	177533	32179	119363
Overall private average weekly earnings ($)	438	124	438	135	431	138	444	138	437	135
Restaurant employment	3727	6128	4534	9040	3774	9102	5568	14467	4508	10521
Restaurant average weekly earnings ($)	164	35	175	44	163	38	176	50	171	44
Retail employment	3771	8697	4240	12175	4104	13591	7040	21755	4703	14642
Retail average weekly earnings ($)	296	65	307	76	299	73	318	88	306	77
Manufacturing employment	6032	10594	5961	13899	6148	18885	8830	33369	6608	20323
Manufacturing average weekly earnings ($)	581	205	560	205	568	190	598	205	573	202
Minimum wage	4.73	0.51	4.76	0.57	4.80	0.63	5.02	0.82	4.84	0.66
Number of counties	183		476		353		368		1380	
Number of states	8		15		17		11		51	

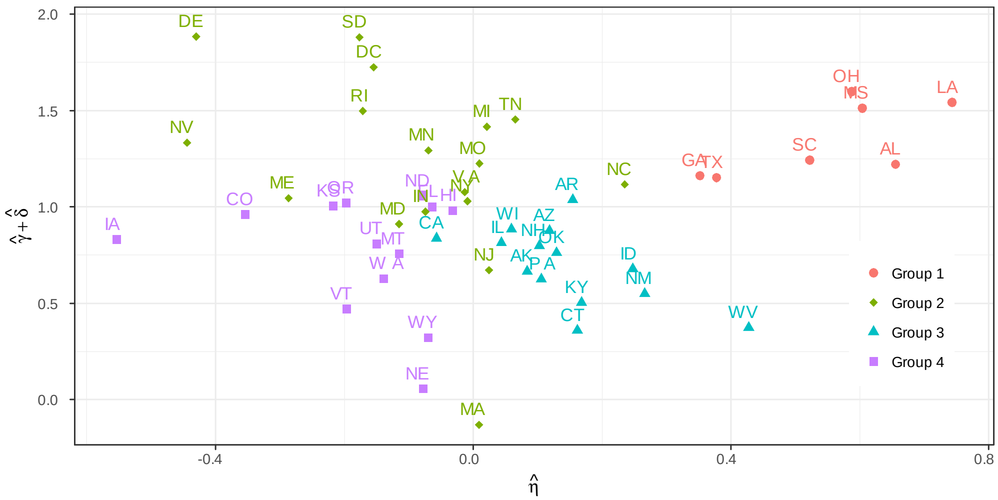

Figure 5: The horizontal and vertical axes correspond to the preliminary estimates of η and $\gamma + \delta$, respectively. Each point represents a state, marked by the standard state abbreviation. Groups 1, 2, 3, and 4 are shown using red circle, green diamond, blue triangle, and purple square, respectively.

employment in the restaurant industry. The estimate of η (the slope coefficient of $\ln(mw_{it})$) is positive for Groups 1 and 3 but negative for Groups 2 and 4. This suggests that the group structure is stable when we control the impact of total employment despite the fact that the effect of minimum wage on employment now becomes negative in Group 2.

Figure 5 illustrates the connection between the preliminary estimates and the final groupings for each state. Now the horizontal and vertical axes correspond to the preliminary estimates of η and $\gamma + \delta$, respectively. Groups 1, 2, 3, and 4 are displayed using red circle, green diamond, blue triangle, and purple square, respectively. Unsurprisingly, we find that states with close preliminary estimates of the slope parameters are more likely to be classified into the same group.

Figure 6 presents the group structure in the map for the United States. Comparing this map with Figure 3, it is now evident that the Group 1 states locate largely in the southeast and the Group 4 states mostly in the northwest. Group membership does not change much for the members in Group 1.

Table 3 reports the descriptive statistics for each group and all samples. We still observe that Group 4 states have higher minimum wages than the others. But interestingly, the average earnings in all industries become lowest in Group 4.

Table 3: Descriptive statistics for 4 groups and the pooled one

	Group 1		Group 2		Group 3		Group 4		All samples	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Population, 2000	166225	306760	180776	299754	230330	672096	135810	254972	181097	423720
Population density, 2000	281	433	876	4277	327	1144	165	362	465	2555
Land area (square miles)	696	494	766	1367	1568	2653	1477	1501	1107	1762
Overall private employment	25396	91636	36816	102267	41816	180285	22636	73639	32179	119363
Overall private average weekly earnings ($)	439	124	453	146	445	144	404	115	437	135
Restaurant employment	4504	9371	4273	7246	5518	15880	3666	7067	4512	10528
Restaurant average weekly earnings ($)	171	35	175	47	167	41	168	47	171	44
Retail employment	3883	11992	5143	11638	5898	21739	3621	10391	4703	14647
Retail average weekly earnings ($)	303	71	313	77	307	78	295	79	306	77
Manufacturing employment	5819	13773	7063	13729	8509	33499	4175	10322	6608	20327
Manufacturing average weekly earnings ($)	571	209	585	210	575	203	548	170	573	202
Minimum wage	4.72	0.50	4.79	0.59	4.87	0.73	4.97	0.78	4.84	0.66
Number of counties	279		455		354		290		1378	
Number of states	7		17		14		13		51	

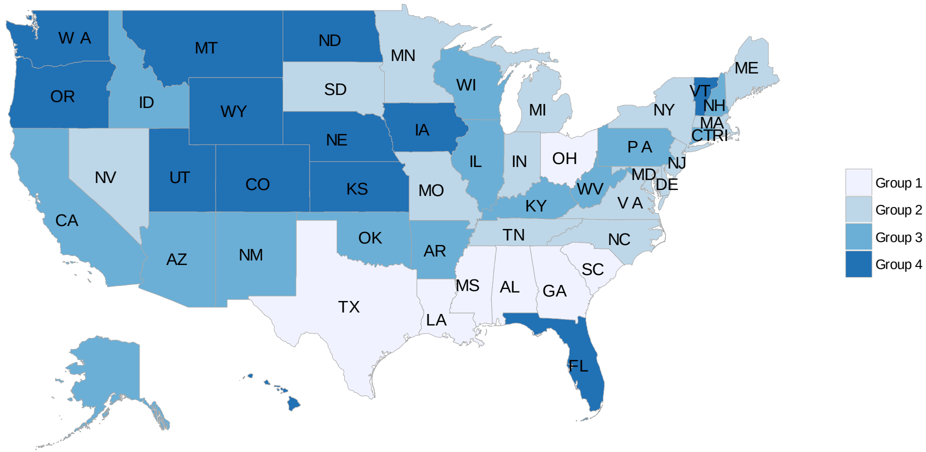

Figure 6: This map displays color-coded group classification results based on model (4.4). Group 1 member states are shown in light blue and Group 4 member states in deep blue.

5 Conclusion

This paper explores the relationship between minimum wages and employment across the US states using new econometric C-Lasso methodology to provide a data-determined approach to the classification of states into common groupings. A panel structure model is used to capture the inherent heterogeneity across states in the US restaurant industry and the C-Lasso mechanism determines the group structure and the number of groups in this industry.

Using the model and data from the study by Dube, Lester, and Reich's (2010), our findings reveal 4 state groupings in the restaurant industry. The estimated group structure has certain geographical patterns. For both model specifications employed, we find two major groups which are located in the southeast and northwest of the United States. The findings also reveal substantial heterogeneity in the impact of the minimum wage on employment across groups, with both positive and negative effects manifesting in the data. These results provide some new perspectives about potential impacts on employment that seem relevant to policy makers in designing minimum wage legislation.

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Supplementary Appendix to
"The Heterogeneous Effects of the Minimum Wage on Employment Across States"
(Not for publication)

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The supplement reports some additional empirical results to the paper.

A Some auxiliary empirical results

For Figure 1, we report the numeric information criteria values in Table 4. The number shown in bold in Table 4 denotes the minimum value that is achieved when $c = 0.10$ and $K = 4$.

Table 4: Information criterion values

	$K=1$	$K=2$	$K=3$	$K=4$	$K=5$	$K=6$	$K=7$	$K=8$
$c = 0.05$	-4.315	-4.383	-4.388	-4.395	-4.392	-4.391	-4.387	-4.384
$c = 0.10$	-4.315	-4.385	-4.386	**-4.396**	-4.392	-4.387	-4.387	-4.384
$c = 0.20$	-4.315	-4.351	-4.379	-4.389	-4.394	-4.386	-4.390	-4.385

Table 5 reports the classification results based on the model in (4.3). For Group 1, the increase in the minimum wage is positively correlated with employment. The effect is relatively large – a 1% increase in minimum wages associates with a 0.534% increase in employment. We call Group 1 the 'large positive η, large γ' group, which contains 8 member states. For Group 2, the effect of the minimum wage on employment is significantly positive but very small, and the effect of population is marginally smaller than that in Group 1. So we call Group 2 the 'small positive η, large γ' group, which has 15 member states. Similar to Group 2, the effect of the minimum wage on employment is significantly positive but small for Group 3, but the effect of population on employment is also small for Group 3. So we call Group 3 the 'small positive η, small γ" group, which has 17 member states. Group 4 distinguishes itself from all other groups by having negative correlation between the minimum wage and employment after controlling for population. So we call Group 4 the 'negative η' group, which contains 11 states.

As in Table 4, we report the information criterion values in Table 6 for Figure 4. The number in bold is the minimum value, which is achieved when $c = 0.05$ and $K = 4$.

Table 7 reports the classification results for model (4.4). Groups 1–4 have 7, 17, 14, and 13 member states, respectively. Depending on the values of the η estimates, we name Groups 1–4 respectively as the 'large positive η' group, 'small negative η' group, 'small positive η' group, and 'large negative η' group. The table suggests that the control of total population brings significant changes to the classification results.

Table 5: Classification results of states for model (4.3)

Group 1: 'large positive η, large γ' group ($\lvert\hat{G}_1\rvert = 8$)				
Alabama	District of Columbia	Hawaii	Louisiana	Mississippi
Ohio	South Carolina	South Dakota		
Group 2: 'small positive η, large γ' group ($\lvert\hat{G}_2\rvert = 15$)				
Arkansas	Connecticut	Georgia	Maryland	Michigan
Minnesota	Missouri	Nevada	New York	North Carolina
North Dakota	Rhode Island	Tennessee	Texas	Virginia
Group 3: 'small positive η, small γ' group ($\lvert\hat{G}_3\rvert = 17$)				
Alaska	Arizona	Delaware	Idaho	Illinois
Kentucky	Maine	Massachusetts	Montana	Nebraska
New Hampshire	New Mexico	Oklahoma	Pennsylvania	West Virginia
Wisconsin	Wyoming			
Group 4: 'negative η' group ($\lvert\hat{G}_4\rvert = 11$)				
California	Colorado	Florida	Indiana	Iowa
Kansas	New Jersey	Oregon	Utah	Vermont
Washington				

Table 6: Information criterion values

	$K = 1$	$K = 2$	$K = 3$	$K = 4$	$K = 5$	$K = 6$	$K = 7$	$K = 8$
$c = 0.05$	-4.417	-4.489	-4.486	**-4.497**	-4.480	-4.447	-4.459	-4.452
$c = 0.10$	-4.417	-4.461	-4.491	-4.486	-4.482	-4.468	-4.460	-4.464
$c = 0.20$	-4.417	-4.470	-4.470	-4.485	-4.473	-4.467	-4.455	-4.439

Table 7: Classification Results of States for Model (4.4)

Group 1: 'large positive η' group ($\lvert\hat{G}_1\rvert = 7$)				
Alabama	Georgia	Louisiana	Mississippi	Ohio
South Carolina	Texas			
Group 2: 'small negative η' group ($\lvert\hat{G}_2\rvert = 17$)				
Delaware	District of Columbia	Indiana	Maine	Maryland
Massachusetts	Michigan	Minnesota	Missouri	Nevada
New Jersey	New York	North Carolina	Rhode Island	South Dakota
Tennessee	Virginia			
Group 3: 'small positive η' group ($\lvert\hat{G}_3\rvert = 14$)				
Alaska	Arizona	Arkansas	California	Connecticut
Idaho	Illinois	Kentucky	New Hampshire	New Mexico
Oklahoma	Pennsylvania	West Virginia	Wisconsin	
Group 4: 'large negative η' group ($\lvert\hat{G}_3\rvert = 13$)				
Colorado	Florida	Hawaii	Iowa	Kansas
Montana	Nebraska	North Dakota	Oregon	Utah
Vermont	Washington	Wyoming		