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.

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 et al. (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 Wascher (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 et al. (2010) show that both approaches may generate misleading results when unobserved heterogeneity is not properly accounted for. By using the restaurant industry panel dataset 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 et al. (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 et al. (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 long-standing issue.

The econometric approach employed is a recently developed classification method called C-Lasso (Su et al., 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. This method has been extended in Su and Ju (2018), Su et al. (2018), Huang et al. (2018a), and Huang et al. (2018b) to allow for cross-sectional dependence, time-varying slope coefficients, nonstationarity, and nonstationarity and cross-sectional dependence, respectively. In this paper, we adapt SSP’s method to provide an versatile way of modeling heterogeneity in hierarchical data. 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 analysis. 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

\[ y_{it} = x_{it}' \beta_{s_i} + \phi_i + \tau_t + \epsilon_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T, \]  

where \( i \) and \( t \) denote county and period respectively, \( s_i \) denotes the state which county \( i \) belongs to, \( \beta_{s_i} \) is a \( p \times 1 \) vector of slope coefficients for state \( s_i, \phi_i \) and \( \tau_t \) are individual fixed effects and time fixed effects respectively, and \( \epsilon_{it} \) is the idiosyncratic error term. A latent ‘state-specific’ group structure is imposed on the \( \beta_{s_i} \) as follows

\[ \beta_{s_i} = \begin{cases} \alpha_1 & \text{if } s_i \in G_1 \\ \vdots \\ \alpha_K & \text{if } s_i \in G_K \end{cases} \]  

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, \( \alpha_k \neq \alpha_s \) for \( k \neq \ell \).

Intuitively, the above model says that states (and hence counties within those states) in the same group \( G_i \) share the same slope parameter \( \alpha_k \), and states in different groups have slope parameters that differ from each other.

The model in (2.1) is a hierarchical model. Note that we assume the parameters \( \beta_{s_i} \)'s to be state-specific instead of county-specific for several reasons. First, minimum wage laws are typically imposed at the state or Federal level so that a county usually adopts the maximum of the federal minimum wage and its state minimum wage. As a result, the minimum wages are typically the same across all counties in a state so that there is little or no variations of minimum wages across the counties within a state. The only exception is California in which San Francisco has different minimum wages from the other counties for the period from 2004Q1 to 2006Q2. If we assume \( \beta_{s_i} \) differ across counties, this will create serious multicollinearity between the matrix generated by the time fixed effects and the block diagonal data matrix associated with the slope coefficients \( \beta_{s_i} \). Second, since minimum wage laws are imposed at the state or Federal level, in terms of policy implications, it is much more meaningful to consider the group structure at the state level than the county level. For example, if a state government knows that the increase of minimum wage has a positive impact on employment in its state, then it would have more incentives to raise the minimum wage than other states. Third, SSP’s C-Lasso method does not work well if the number of cross sectional units (N) is much larger than the number of time periods \( T \). In the dataset to be used for our empirical analysis, there are 1780 counties and 66 quarters of observations. \( N \) is approximately \( T^2/3 \), which makes it hard for the C-Lasso method to perform well.

For these reasons, we focus on the hierarchical model in (2.1). For comparison purpose, in the online supplement we consider the models where the latent group structure is imposed at the county level.

The model (2.1) is quite versatile. At one extreme, when \( s_i \in s \), then (2.1) is the traditional two-way fixed effects panel data model. At the other extreme, when \( s_i \neq s \), it is the conventional panel structure model studied by SSP.

2.2. The methodology

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

\[ \bar{y}_{it} = \bar{x}_{it}' \bar{\beta}_{s_i} + \bar{\tau}_t + \bar{\epsilon}_{it}, \]  

where \( y_{it} = y_{it} - T^{-1} \sum_{t=1}^{T} y_{it}, \quad \bar{x}_{it} = x_{it} - T^{-1} \sum_{t=1}^{T} x_{it}, \quad \bar{\tau}_t = \tau_t - T^{-1} \sum_{t=1}^{T} \tau_t, \) and \( \bar{\epsilon}_{it} = \epsilon_{it} - T^{-1} \sum_{t=1}^{T} \epsilon_{it} \). Note that Eq. (2.3) is different from Eq. (4.2) in Lu and Su (2017) because here the \( \beta_{s_i} \) are not individual i-specific but state-specific. Noting that different 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

\[ \bar{\Gamma} = \begin{bmatrix} -1 & \cdots & -1 \\ \vdots & \ddots & \vdots \\ -1 & \cdots & -1 \end{bmatrix}. \]

Let \( \bar{Y} = (\bar{y}_{11}, \ldots, \bar{y}_{S1})', \bar{X} = (\bar{x}_{11}, \ldots, \bar{x}_{S1})', \) and \( \bar{\epsilon} = (\bar{\epsilon}_{11}, \ldots, \bar{\epsilon}_{S1})' \). Noting that \( \sum_{t=1}^{T} \bar{\tau}_t = 0 \), it is easy to reparameterize the \( \bar{\tau}_t \) so that Eq. (2.3) can be written in observation form as

\[ \bar{y}_{it} = \bar{x}_{it}' \bar{\beta}_{s_i} + \bar{\Gamma}' \gamma + \bar{\epsilon}_{it}, \]

where \( \gamma = (\gamma_{11}, \ldots, \gamma_{S1})' \) is a \( (T-1) \times 1 \) vector such that \( \bar{\tau}_t = -\frac{1}{T} \sum_{t=1}^{T} \gamma_t \) and \( \bar{\epsilon}_s = \gamma_{s1} + \bar{\tau}_t \) for \( s = 2, \ldots, T \). Then the
objective function can be written as
\[
S_{1,NT}(\beta, \gamma) = \frac{1}{NT} \sum_{i=1}^{N} (\tilde{Y}_i - \tilde{X}_i \beta_i - \tilde{F} \gamma) (\tilde{Y}_i - \tilde{X}_i \beta_i - \tilde{F} \gamma),
\]
where \( \beta = (\beta'_1, \ldots, \beta'_i, \gamma).

Next, we want to eliminate the incidental parameter \( \gamma \). Without loss of generality, we suppose the first \( t \) individuals are in state 1, the following \( i_2 \) individuals are in state 2, and so on. Define the \( N \)-vector \( \epsilon_N = (1, \ldots, 1)' \), set \( \bar{Y} = (\bar{Y}_1, \ldots, \bar{Y}_N) \) and \( \bar{\epsilon} = (\bar{\epsilon}_1, \ldots, \bar{\epsilon}_N) \), and define the \( NT \times Sp \) matrix
\[
\bar{X} = \begin{bmatrix}
\bar{X}_1 & 0 & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
0 & \bar{X}_{i_1+1} & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
0 & 0 & \cdots & \bar{X}_{(\sum_{i=1}^{k})+1} \\
0 & 0 & \cdots & \bar{X}_N
\end{bmatrix}
\]
The stacked form of (2.4) is then
\[
\bar{Y} = \bar{X} \beta + (\epsilon_N \otimes \bar{F}) \bar{\epsilon}.
\]
Let \( M_{\bar{Y}} = I_N - ((\epsilon_N \otimes \bar{F})(\epsilon_N \otimes \bar{F})^{-1}(\epsilon_N \otimes \bar{F})) \), \( \bar{Y} = M_{\bar{Y}} \bar{Y} \), \( \bar{X} = M_{\bar{F}} \bar{X} \), and \( \bar{\epsilon} = M_{\bar{F}} \bar{\epsilon} \). Eliminate \( \gamma \) by partitioned regression giving
\[
\bar{Y} = \bar{X} \beta + \bar{\epsilon},
\]
and the corresponding objective function
\[
S_{2,NT}(\beta) = \frac{1}{NT} \|\bar{Y} - \bar{X} \beta\| \|\bar{Y} - \bar{X} \beta\|. \tag{2.5}
\]

C-Lasso estimation of \( \beta \) involves nonlinear penalized estimation to obtain a data-determined ‘state-specific’ group structure in \( \beta \) of the form (2.2). In particular, the C-Lasso estimator minimizes the objective function
\[
Q^{(K)}_{1,NT,\lambda}(\beta, \alpha, \gamma) = S_{1,NT}(\beta, \gamma) + \frac{\lambda}{5} \sum_{i=1}^{S} \Pi^{K}_{i=1} \|\beta_k - \alpha_k\|, \tag{2.6}
\]
or, equivalently,
\[
Q^{(K)}_{2,NT,\lambda}(\beta, \alpha) = S_{2,NT}(\beta) + \frac{\lambda}{5} \sum_{i=1}^{S} \Pi^{K}_{i=1} \|\beta_k - \alpha_k\|, \tag{2.7}
\]
where \( \lambda \equiv \lambda_{NT} \) is a tuning parameter and \( \alpha = (\alpha'_1, \ldots, \alpha'_i)' \). The criteria \( Q^{(K)}_{1,NT,\lambda}(\beta, \alpha, \gamma) \) and \( Q^{(K)}_{2,NT,\lambda}(\beta, \alpha) \) yield the same estimates of \( \beta \) and \( \alpha \), which are denoted \( \hat{\beta} = (\hat{\beta}'_1, \ldots, \hat{\beta}'_i)' \) and \( \hat{\alpha} = (\hat{\alpha}'_1, \ldots, \hat{\alpha}'_i)' \). Let \( G_k = \{ s \in \{1, \ldots, S\} : \beta_s = \hat{\alpha}_k \} \) for \( k = 1, \ldots, K \). Based on the estimated group structure, \( \hat{G}_1, \ldots, \hat{G}_K \), we obtain the post-classification estimates \( \hat{\beta} \) and \( \hat{\alpha} \). Specifically, for each group \( \hat{G}_k \), \( k = 1, \ldots, K \), we use OLS to estimate the common slope parameters \( \hat{\alpha}_k \) and set \( \hat{\beta}_k = \hat{\alpha}_k \) for all \( s \in \hat{G}_k \).

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 \( \lambda \) is made explicit. When \( K \) is unknown, we follow SSP (2016) and choose \((K, \lambda)\) 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. 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.\(^3\)

In this paper, we follow Dube et al. (2010, DLR hereafter) and consider the restaurant industry. DLR consider how to identify the marginal effects of minimum wages on employment. They adopt the contiguous border 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 (\( \ln(\text{emp}_t) \)) responds to log minimum wage (\( \ln(\text{mum}_t) \)), where \( i \) and \( t \) refer to county and time. Other control variables are log population (\( \ln(\text{pop}_{it}) \)) and log total employment (\( \ln(\text{emp}^{TOT}_{it}) \)). We confine attention to the restaurant industry because minimum wages are known to have relatively larger effects in this industry. The panel dataset 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 \( \ln(\text{emp}^{TOT}_{it}) \) in the regression.

When \( \ln(\text{emp}^{TOT}_{it}) \) is included in the regression, \( N \) becomes 1378 because two counties have missing observations for \( \ln(\text{emp}^{TOT}_{it}) \). For Tolland county (countyreal: 9013) of Connecticut and Adams county of Illinois, their \( \ln(\text{emp}^{TOT}_{it}) \) 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 3 in DLR for a detailed description of the data.

4. Main results

We employ the same benchmark Model (1) of Dube et al.’s (2010) which has the following two forms
\[
\ln(\text{emp}_t) = c + \eta \ln(\text{mum}_t) + \gamma \ln(\text{pop}_{it}) + \phi_1 + \tau_1 + \epsilon_{it}, \tag{4.1}
\]
\[
\ln(\text{emp}_t) = c + \eta \ln(\text{mum}_t) + \gamma \ln(\text{pop}_{it}) + \delta \ln(\text{emp}^{TOT}_{it}) + \phi_1 + \tau_1 + \epsilon_{it}. \tag{4.2}
\]
where \( c \) denotes the common intercept term. By combining this benchmark specification with the panel structure formulation that allows state specific coefficients, we consider
\[
\ln(\text{emp}_t) = c + \eta_s \ln(\text{mum}_t) + \gamma_s \ln(\text{pop}_{it}) + \phi_1 + \tau_1 + \epsilon_{it}, \tag{4.3}
\]
\[
\ln(\text{emp}_t) = c + \eta_s \ln(\text{mum}_t) + \gamma_s \ln(\text{pop}_{it}) + \delta_s \ln(\text{emp}^{TOT}_{it}) + \phi_1 + \tau_1 + \epsilon_{it}. \tag{4.4}
\]
\(^3\) Let \( G = \{1, \ldots, S\} \setminus \bigcup_{k=1}^{K} G_k \). SSP show that \( G_k \) is an empty set asymptotically. In finite samples, \( G_k \) might not be empty and we can force each element in \( G_k \) to one of the \( K \) groups. For \( s \in G_k \), if \( k^* = \text{arg min}_{k} \|\beta_s - \hat{\alpha}_k\|, k = 1, \ldots, K \), then \( s \) is re-classified into \( G_{k^*} \).\(^4\) Researchers have also considered specific subsectors of this labor market, such as teenage workers — see, e.g., Brown et al. (1982).
which allows for the state-wise slope coefficients \( (\eta_s, \gamma_s, \delta_s) \). Following SSP (2016), we allow the parameters \((\eta_u, \gamma_u)\) in (4.3) or \((\eta_u, \gamma_u, \delta_u)\) 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 Eq. (2.8). Fig. 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 Table A1 in the Online Supplement.

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 \( \gamma \) (the slope coefficient of \( \ln(\text{pop}_i) \)) are relatively stable across the four groups and are always positive. The latter is as expected given the positive correlation between total population and employment. In contrast, the estimates of \( \eta \) (the slope coefficient of \( \ln(\text{mw}_i) \)) vary across the four groups substantially and even alter signs. For Groups 1–3, the estimate of \( \eta \) 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 \( \eta \) 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 heterogeneous pattern in responses that exists across state groups that is revealed by the C-Lasso regression using the panel structure formulation. Such heterogeneous 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.

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Fig. 2 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 1
Regression results.

<table>
<thead>
<tr>
<th></th>
<th>Model (4.3)</th>
<th></th>
<th></th>
<th></th>
<th>Model (4.4)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Group 1</td>
<td>Group 2</td>
<td>Group 3</td>
<td>Group 4</td>
<td>All samples</td>
<td>Group 1</td>
<td>Group 2</td>
</tr>
<tr>
<td>ln(mw)</td>
<td>0.534</td>
<td>0.047</td>
<td>0.077</td>
<td>−0.221</td>
<td>−0.211</td>
<td>0.555</td>
<td>−0.033</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.096)</td>
<td>(0.013)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>ln(pop)</td>
<td>1.521</td>
<td>1.239</td>
<td>0.678</td>
<td>0.997</td>
<td>1.035</td>
<td>0.626</td>
<td>0.603</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.009)</td>
<td>(0.013)</td>
<td>(0.011)</td>
<td>(0.060)</td>
<td>(0.016)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>ln(empTOT)</td>
<td>0.513</td>
<td>0.606</td>
<td>0.410</td>
<td>0.534</td>
<td>0.524</td>
<td>0.606</td>
<td>0.410</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.044)</td>
<td>(0.008)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Observations</td>
<td>12078</td>
<td>31416</td>
<td>23298</td>
<td>24288</td>
<td>91080</td>
<td>18414</td>
<td>30030</td>
</tr>
</tbody>
</table>

- Correspond to 10% significance levels.
- Correspond to 5% significance levels.
- Correspond to 1% significance levels.

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. 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 lay off 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). Fig. 3 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 \( \gamma \) (the slope coefficient of \( \ln(\text{pop}_w) \)) and \( \delta \) (the slope coefficient of \( \ln(\text{emp}_w^{\text{TOT}}) \)) 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 employment in the restaurant industry. The estimate of \( \eta \) (the slope coefficient of \( \ln(\text{emp}_{w_i}^{\text{TOT}}) \)) 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.

Fig. 4 presents the group structure in the map for the United States. Comparing this map with Fig. 2, 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.

## 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 numbers of groups in this industry.

Using the model and data from the study by Dube et al.’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.

As an alternative competitive approach, one may consider applying the C-Lasso method to the contiguous board county-pair sample in the spirit of DLR. But it has some limitations. First, by doing this, one implicitly assumes that the pairwise counties have the same slope coefficients, and it is hard to interpret the group structure on county pairs. Second, the implementation becomes much more tedious than our method because new the C-Lasso penalty term has to be modified to take into account such county-pair comparison. Third, the policy implication for the state government becomes less obvious and one may consider the policy implication for the border counties instead.
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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2018.11.002.

References