Identification and Estimation in "Minimum Wages and Rents"

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1 Towards a Stacked Event Study Model

Empirical Strategy

In an attempt to make our results robust to treatment heterogeneity and use more credible comparisons we developed an alternative strategy that relies on event stacking, following Cegniz et al. (2019). We constructed datasets keyed at the ZIP code, month, and event level. To construct those we proceed as follows.

1. We identify all ZIP code-months that have a change in the statutory MW.
2. We define an event at the CBSA-month if in that month at least one ZIP code that had a change in the statutory MW. For each of the treated CBSA-months we assign a unique event ID.
3. For each event, we take a window k, and we keep all months within that window for the ZIP codes that belong to that CBSA.
4. If a ZIP code has missing data for some month within the window, we drop the entire ZIP code so that each event-level dataset is balanced.

Then we estimate models of the form:

$$\Delta \ln r_{hit} = \delta_{ht} + \gamma \Delta \underline{w}^{res}_{hit} + \beta \Delta \underline{w}^{exp}_{hit} + \Delta \epsilon_{hit}$$

where h, i and t index events, ZIP codes, and calendar time, respectively.

Table 1: Stacked regressions

	Change log rents		
	$w = 3$	$w = 6$	$w = 9$
Change residence minimum wage	-0.0421	-0.0267	-0.0212
	(0.0265)	(0.0156)	(0.0165)
Change workplace minimum wage	0.0767	0.0736	0.0649
	(0.0585)	(0.0386)	(0.0406)
P-value equality	0.1626	0.0616	0.1312
R-squared	0.0838	0.0847	0.0858
Observations	65,222	106,345	146,569

Notes: The table shows estimates of the stacked model under different balancing periods w. To construct the samples we proceed as follows. First, we identify all ZIP code months that have a change in the binding MW. Then, we call a CBSA-month as treated if in that month has at least one ZIP code that had a change in the binding MW. For each of the treated CBSA-months we assign a unique event ID. For each event, we take a window w, and we keep all months within that window for the ZIP codes that are within the treated CBSA. If a ZIP code has missing data for some month within the window, we drop the entire ZIP code.

Results

The table below we show results for windows $k \in \{3, 6, 9\}$. Standard errors are clustered at the CBSA level.

We observe qualitatively similar results to our baseline estimation strategy, with workplace minimum wage tending to a positive effect, and residence MW to a negative effect.

Figure 1 shows the results of our estimation adding leads and lags of the workplace minimum wage variable.

Questions

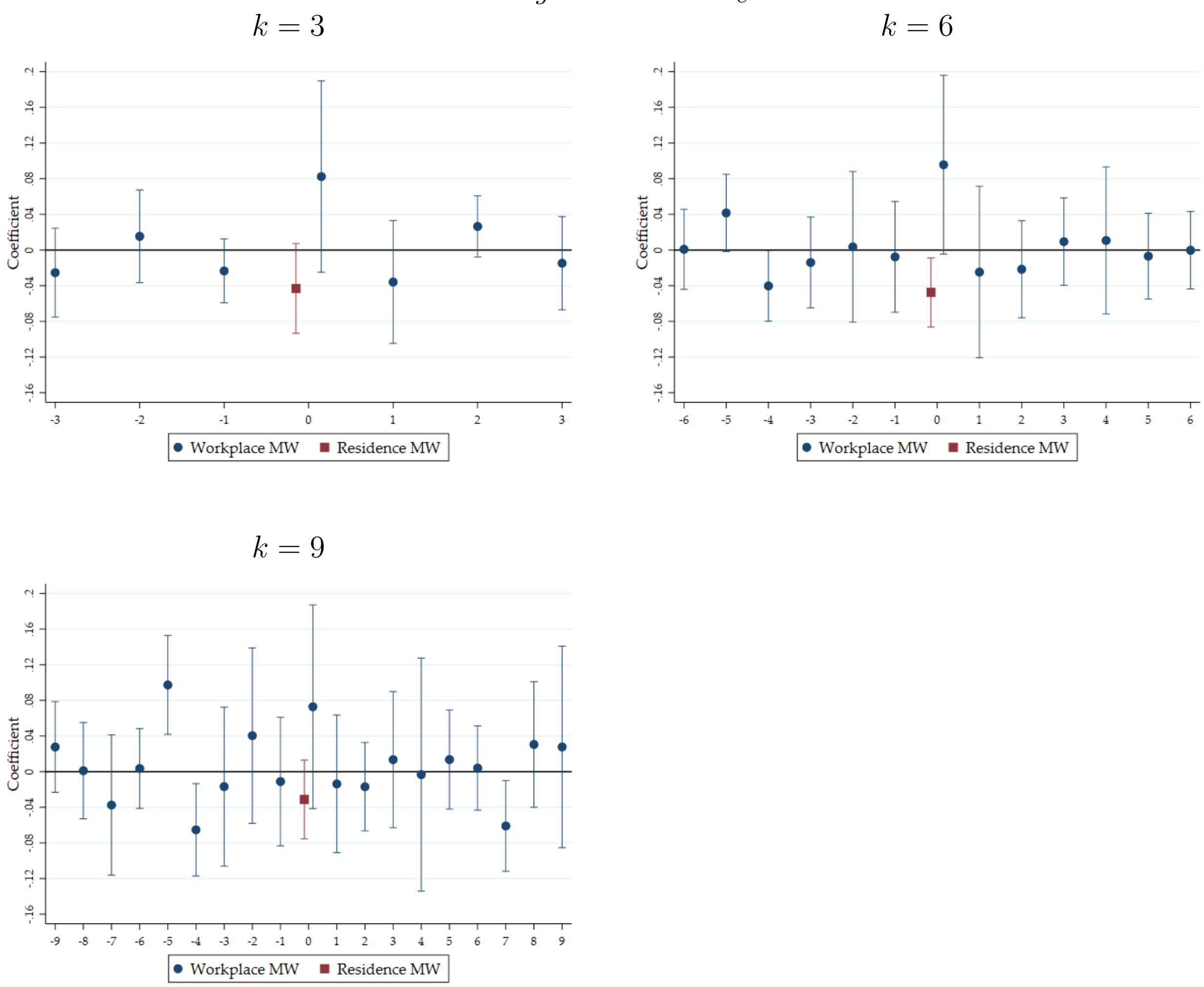
1. Is this strategy sensible? How can we improve it?

2. Are there better ways to constrain the comparisons in our model?

3. What is the correct level of clustering for the standard errors here?

Figure 1: Distributed lags in the stacked event study

Average skill levels $\bar{\mathbf{x}}_c$



2 Identification with continouos treatment and spillovers across units

Consider the causal model for rents given by

$$r_{it} = Y_{it}\left(\{w_{zt}\}_{z\in\mathcal{Z}}\right)$$

where w_{zt} gives the treatment ZIP code i receives from ZIP code z at time t, and $\mathcal{Z}$ is the total number of units. We impose some structure by assuming that

$$Y_{it}(w_{1t}, ..., w_{it}) = \alpha_i + \delta_t + \gamma w_{it} + \beta \sum_{z\in\mathcal{Z}} \pi_{iz} w_{zt} + u_{it}$$

where α_i and δ_t are fixed effects, $\pi_{iz} \in [0, 1]$ is the (fixed) share of i residents that work in z, known to the econometrician, u_{it} is an unobserved shock, $\gamma, \beta \in \mathbb{R}$ are scalar parameters. Note that this model assumes a direct effect of treatment equal to $\gamma + \beta\pi_{ii}$ and the effect of treatment somewhere else equals $\beta\pi_{iz}$.

A general approach to discuss identification

Consider a marginal change in the binding MW in some set of ZIP codes in this region, $\mathcal{Z}_0 \subset \mathcal{Z}$. We can identify two groups in a given metropolitan area:

- ZIP codes treated both directly and indirectly, $z \in \mathcal{Z}_0$,
- ZIP codes treated only indirectly, $z \in \mathcal{Z} \setminus Z_0$.

We are interested in two parameters. The average treatment effect on the first group

$$E\left[\Delta Y_{it}\left(\{w_{zt}^{\text{Post}}\}\right) - \Delta Y_{it}\left(\{w_{zt}^{\text{Pre}}\}\right) | z \in \mathcal{Z}_0\right]$$

and the average treatment effect on the second group

$$E\left[\Delta Y_{it}\left(\{w_{zt}^{\text{Post}}\}\right) - \Delta Y_{it}\left(\{w_{zt}^{\text{Pre}}\}\right) | z \in \mathcal{Z} \setminus Z_0\right].$$

We want to derive parallel trends assumptions required to identidy these parameters.

Questions

1. Are these the parameters that we should try to relate to γ and β?

References

Cegniz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer 2019. The Effect of Minimum Wages on Low-Wage Jobs.